We really appreciate the editor and reviewers for their detailed and constructive comments and suggestions. We would love to thank you for allowing us to revise the manuscript and we highly appreciate your time and consideration. We have carefully considered the review comments and revised the manuscript thoroughly. We sincerely hope the revised manuscript is more complete and can be considered for publication. While the changes made can be seen in the revised manuscript, we also present here our detailed responses to the all comments.

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Response to Editor:

No evidence that these DL techniques will work in other regions absent coverage by GF satellite and with different age and resolution of GE images. Very hard to see this used/copied by other users as, e.g., ML benchmark. Access to necessary products not well described, not certain. Manuscripts reads as a reasonably good, perhaps even skillful, description of image processing but not as a data description suitable for ESSD. Please read ESSD guidelines at https://www.earth-syst-sci-data.net/10/2275/2018/ This editor considers possibly it out-of-scope for ESSD, better published elsewhere for other readers/users? Not a helpful guide to future users, not suitable as benchmark product.

Response:

We feel great thanks for your careful review work on our article. According to your suggestions, we have made modifications to the article. We still hope to have the opportunity to being considered by ESSD. And we are prepared to discuss on possible issues if necessary. Here are responses to the major issues mentioned above:

(1) In this paper, we proposed a deep learning framework for large-scale and high-precision UGS extraction, leading to a collection of 1-meter UGS products of 31 major cities in China (UGS-1m). Notably, the framework has introduced the adversarial training to overcome the domain shift between images to help more accurate UGS mapping. Actually, the comparative experiments (at Sect 5.2) have demonstrated the effectiveness of the proposed framework to get over the large shifts between the training set (Gaofen-2 images) and the predicted set (Google Earth images of different cities). The adversarial training strategies is applied in an unsupervised behavior, so no label need to be provided in the target cities need to be predicted. In this study, though we have not applied these DL techniques to other kinds of images, the

potential of the adversarial training strategies has been proved to be used in other images. However, your consideration is very constructive and we think it is necessary to make a supplement based on this question. Therefore, we supplement this point on Sect 5.3, and the relevant sentences are:

"However, the current DL techniques still has limitations. In view of the spatial and spectral diversity of high-resolution remote sensing images, we have not been able to fully evaluate the domain adaptation effect of the adversarial framework for all heterogeneous images with different ages and resolutions. With the emergence of more and more high-resolution satellite images, the adversarial transfer learning of multi-source images remains to be explored."

(2) According to the "6. Code and data availability" part, the UGS-1m can be download from https://doi.org/10.5281/zenodo.6155516, while the other datasets and codes including the UDSNet, UGSet and the original GE images, will be soon openly available at the project link of this paper (https://liumency.github.io/UGS-1m/). Or if necessary, we can try to upload all these files and datasets to Zenodo as a new version (new DOI will be created.). We still believed that once open, our dataset and product will be popular.

(3) We have attempt to revised the manuscripts to make it more clear. We have added a part of "4.4 UGS statistics and analysis on UGS-1m" to elaborate the manuscript as a data description paper. The statistical analysis shows the most intuitive applicability of UGS-1m as a large-scale and refined green space product. And we also prospect some future works on UGS-1m product.

According to your nice suggestions, we have made extensive corrections to our previous draft. Your professional suggestions are very helpful to make our study clearer and more comprehensive. The detailed point-by-point responses are listed below.

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Line 60: Acronym for satellite GF-2 used but not defined.

Response:

Thanks for pointing this out. We have expanded the acronym satellite GF-2 into "GaoFen-2 (GF2)". And add brief descriptions to GaoFen-2 satellite. the Corresponding statements can be found at:

"Liu et al. employed DeepLab v3+ to automatically obtain green space distribution from GaoFen-2 (GF2) satellite imagery" (Line 61).

“These images are collected from 142 images in Guangdong Province, China, as shown in Figure 3, through the Gaofen-2 (GF2) satellite. The GF2 satellite is the first civilian optical remote sensing satellite developed by China with a spatial resolution of about 1 meter, which is equipped with two high-resolution 1-meter panchromatic and 4-meter multispectral cameras.” (Line 130).

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Line 116: Taipei in list, and shown in Fig 1? Also note: Copernicus will attach standard disclaimer about not endorsing geographic boundaries used in figures. I doubt that Copernicus will accept this language; I will recommend that they NOT accept. Neither ESSD nor Copernicus will get involved in domestic territorial issues but neither will we allow false presentation.

Response:

Thank you for your reminder. In order to avoid unnecessary disputes, we decided to change the scope of the study area into the 31 major cities in Chinese Mainland. More specifically, Hong Kong, Macau and Taipei of Taiwan Province were removed from the original 34 cities/areas. At present, the 31 cities included in the study area are widely distributed in various regions of Chinese Mainland, which we believe is sufficient to verify the effectiveness of the method and provide sufficient UGS data products.

To this end, all relevant statements in the article have been changed to “the 31 cities”. And the involved figures (including Figure 2 and Figure 9) have also been revised.

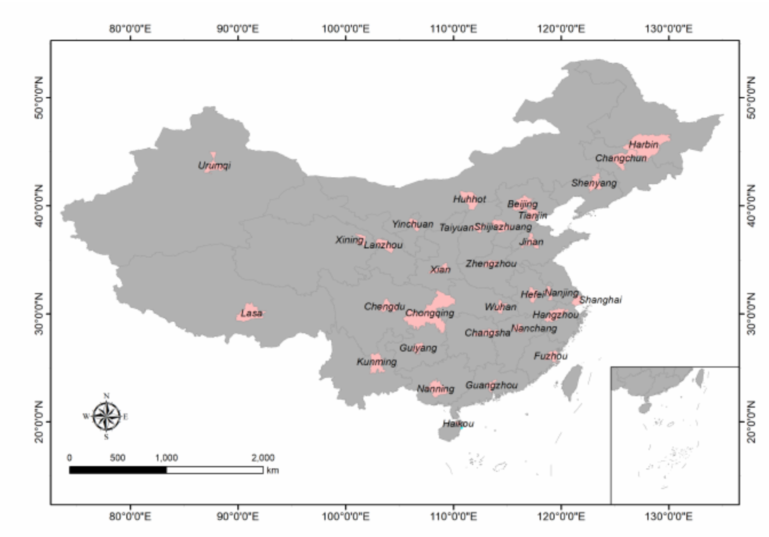

Figure 2. Distribution of the 31 major cities in China.

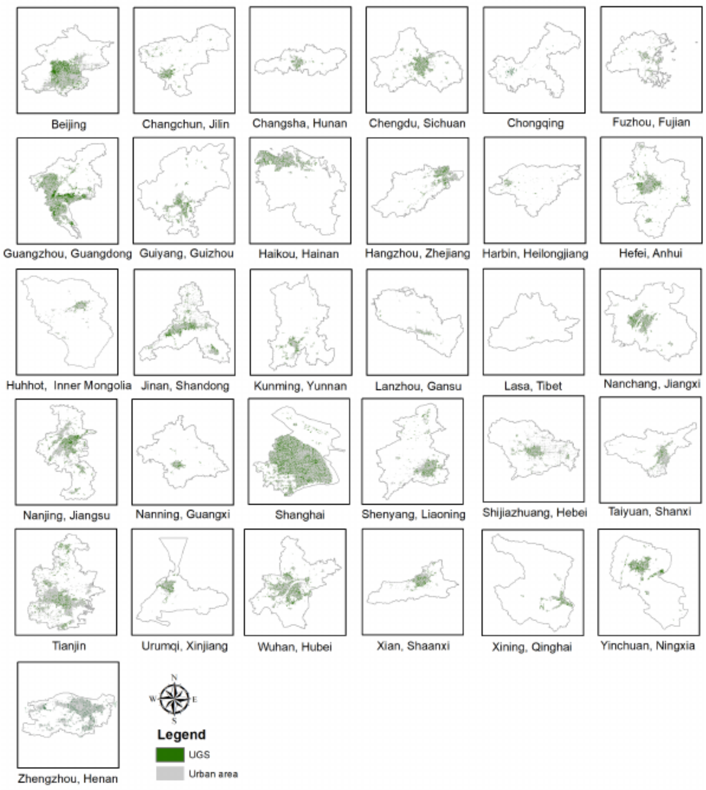

Figure 9. UGS results of the 31 major cities in China (UGS-1m).

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Line 139: Figure 4 - legend explains columns but does not explain rows. Close inspection suggests two pairs each, top two plus bottom two. Explain more carefully in legend?

Response:

Thanks for your valuable comments. We have added the explanations of each rows in Figure 4. And we also expand the caption of Figure 4 into:

"Example of the "Image-Label" samples in UGSet (Images were retrieved from Gaofen-2 2019). The first and third rows denote images of the samples, while the second and forth rows provide corresponding labels for these images. Each column denotes different UGS types of the samples, including (a) Park; (b) Green buffer; (c) Square green space; (d) Attached green space; (e) Other green space." (Page 8).

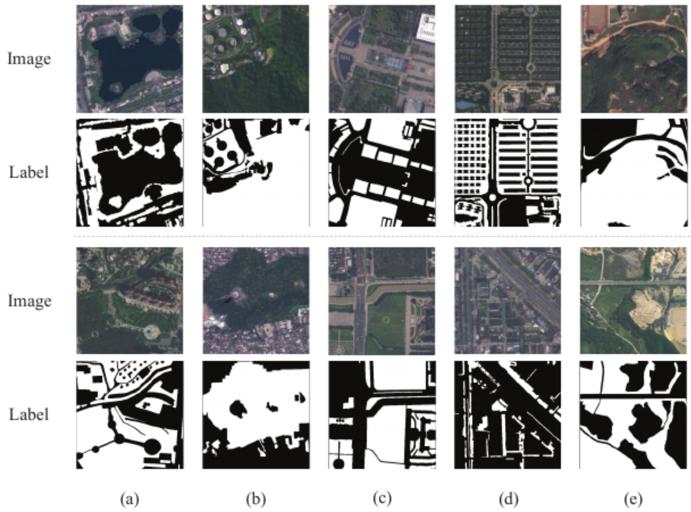

Figure 4. Example of the "Image-Label" samples in UGSet (Images were retrieved from Gaofen-2 2019). The first and third rows denote images of the samples, while the second and forth rows provide corresponding labels for these images. Each column denotes different UGS types of the samples, including (a) Park; (b) Green buffer; (c) Square green space; (d) Attached green space; (e) Other green space.

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Line 143: I worry about provenance and reliability of GE image. For my area, GE image resolution and availability has changed - without notice or traceability - three times in past 12 months. If authors need to rely on GE, they will also need to provide exact subset for subsequent users.

Response:

Thanks for your valuable comments. GE image is one of the most convenient data sources for large-scale and fine-grained mapping, because it can obtain free high-resolution images, has certain historical images and a variety of resolution options. However, as you said, there is some uncertainty in the availability and traceability of GE image. Therefore, we promise to provide the exact subset for subsequent users that we use in our experiment.

We plan to upload the GE subset used in the article to OneDrive for open access, and provide the corresponding link (https://mail2sysueducn-my.sharepoint.com/:f:/g/personal/liumx23_mail2_sysu_edu_cn/EuILVq8vbopKu_juqg4ams8BythT7i1Oe7X-9kQaVn-LAw?e=9aBqSq) in the project address (https://liumency.github.io/UGS-1m/) of the article. However, due to the large dataset (over 800G) and the poor network speed, we have not yet been able to upload all the images. We are truly sorry for this. We will complete the upload as soon as possible, until you return to the next review and opinion.

Or if necessary, we can try to upload all these files and datasets to Zenodo.

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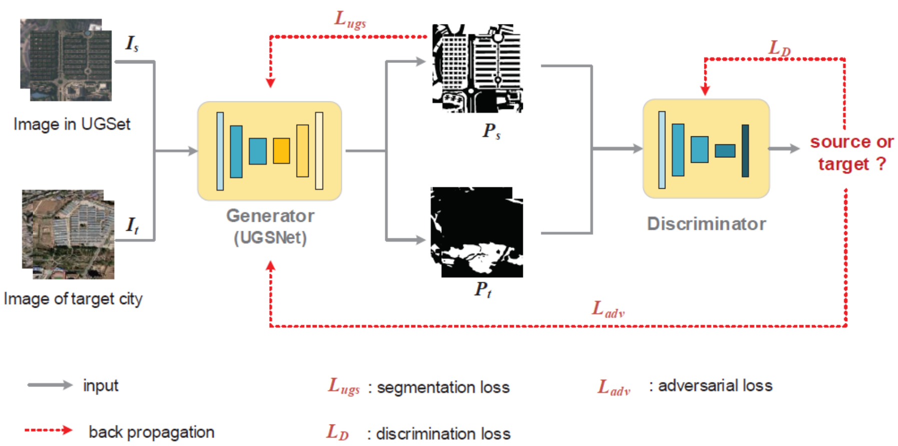
Line 151, legend for Fig 5. Legend does not convey sufficient explanation of figure. In particular, red dashed arrows (e.g. Ladv) not explained. (Not explained until line 239, too long/far for most readers.)

Response:

Thanks for your valuable comments. We have added legend to explain the red dashed arrows and the detailed meanings of the elements. Besides, in order to improve readability, the caption of the Figure 5 has also been expand into

"Figure. 5 Flowchart of the proposed deep learning framework for UGS mapping (The "Image in UGSet" were retrieved from Gaofen-2 2019, while the "Image of target city" © Google Earth 2020). The red dashed lines denote the loss of back propagation for model optimization. The L_ugs, L_D, and L_adv represent the segmentation loss, the discrimination loss, and the adversarial loss, as described in Sect. 3.3.}" (Page 9)



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Line 169: Again, insufficient information in legend for Fig 6. Assume readers will only look at figures; they must gain sufficient information rather than searching randomly through text.

Response:

Thank you for underlining this deficiency. In order to make the figure easier for understanding, we have rearranged Fig 6 and Fig 7. In the new version, Fig 6 displays the structure of the backbone, which includes the ResBlock and ECA module. So the architecture of the ResBlock and ECA module have been put together with the backbone. The Fig. 6 have been changed into:

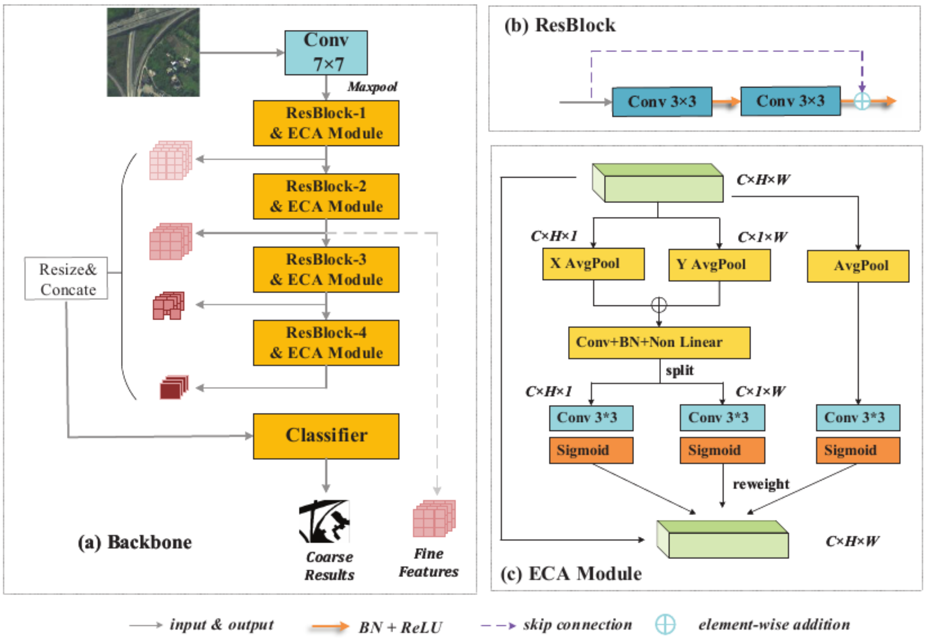

Figure 6. Architecture of the backbone in UGSNet (The image was retrieved from Gaofen-2 2019). (a) Backbone overview. (b) Sketch diagram of the ResBlock. (c) ECA module.

Then, Fig. 7 will introduce the flowchart and goal of the point head in the proposed UGSNet. To make it clearer, the caption of Fig. 7 has been extended to help describe the process in the point head:

"Figure 7. Structure of the point head in UGSNet. Given the fine features and the coarse UGS results from the backbone, the point head will firstly collect N sampling points with lowest certainty to construct point-wise features, which will be input into a MLP for classification and help obtain fine UGS results."

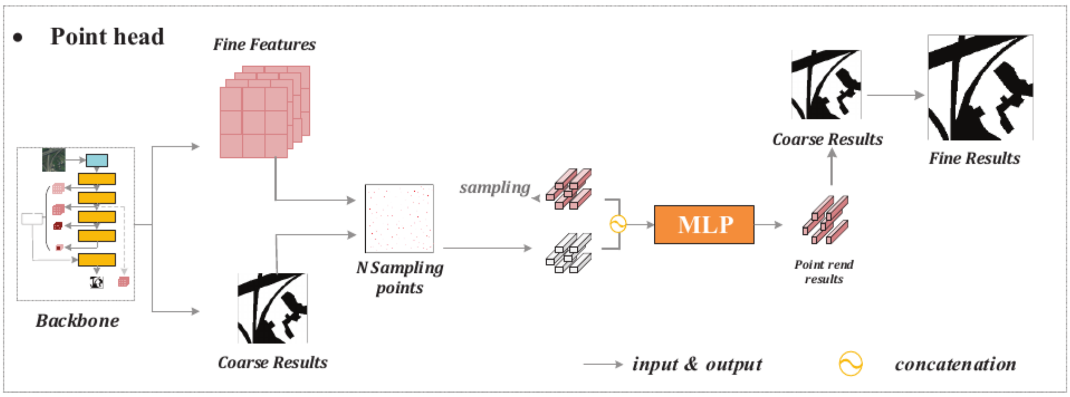

Figure 7. Structure of the point head in UGSNet. Given the fine features and the coarse UGS results from the backbone, the point head will firstly collect N sampling points with lowest certainty to construct point-wise features, which will be input into a MLP for classification and help obtain fine UGS results.

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Overall, focuses on image processing techniques but not on data utility or reliability elsewhere for other users.

Response:

Thanks for your valuable comments. In view of your opinions, we have added a new section, "4.4 UGS statistics and analysis based on UGS-1m", to further explore the utility of the UGS-1m product. Corresponding statements can be found at:

"While the previous evaluation and comparisons have proved the advantages and validity of the UGS-1m, this section would like to explore the potential utility of the UGS-1m product. As mentioned above in the Introduction section, green space equality is one of the keys for the Sustainable Development, which requires fine-grained distributions of UGS as basic data. At this point, compared with the traditional statistical yearbook data, our UGS-1m product can provide a relatively objective and more detailed information about the distribution of green space. Therefore, statistics is conducted on the UGS-1m data to obtain information of the UGS area and the UGS rate in the GUB area, which are summarized in Table 3.

As shown in Table 3, the area of green space in different cities varies greatly. For example, its obtained that the UGS area of Beijing is the largest among all the 31 cities studied, reaching 1,021.55 square kilometers, while that of Lhasa is the smallest with only 11.41 square kilometers. The statistical area information indicates that the UGS-1m can provide a quick and intuitive comparison of the stock of urban green space in different cities. However, a small UGS area does not always mean the lack of green space due to the restrictions on the city area. Therefore, the UGS rate in the GUB area is further calculated to measure the deficiency and inequality of green space in different cities. At this time, it can be seen that Yinchuan has the highest UGS rate, accounting for 25.35%, while Beijing, which has the largest UGS area, has a slightly lower UGS rate of 20.74%. Besides, the UGS rate of 9.27% in Lhasa, which has the least UGS area, is also slightly better than that of Lanzhou, which has the lowest UGS rate of 8.64%. The results and comparisons further show that the shortage and imbalance of green space cannot be reflected only from the perspective of the stock of green space, and more information and data are often needed for analysis.

The above statistical analysis only shows the most simple and intuitive applicability of UGS-1m as a large-scale and refined green space product, but it is far more than that. Since the high-resolution UGS-1m can provide the detailed distribution of green space, it brings possibility to research in fine-grained scenarios. When considering different datasets or materials, more comprehensive information of UGS can be obtained. For example, by combining high-resolution population (e.g. Worldpop data) with UGS-1m, the availability of residents to green space can be measured, that is, green space equity. Or, combined with the distribution of slums and formal housing space, their differences in green landscape pattern can be studied. We also hope to explore these works in the future." (Line 325-350).

Table 3. Statistical results on UGS-1m of UGS area and rate for the 31 major cities in China.

Id	City	Province	GUB area (Sq.Km)	UGS area (Sq.Km)	UGS Rate in GUB (%)
0	Beijing	/	4925.08	1021.55	20.74
1	Changchun	Jilin	1405.23	331.56	23.59
2	Changsha	Hunan	887.87	162.46	18.30
3	Chengdu	Sichuan	1813.62	336.67	18.56
4	Chongqing	/	1956.56	449.11	22.95
5	Fuzhou	Fujian	1140.41	142.85	12.53
6	Guangzhou	Guangdong	2552.02	561.46	22.00
7	Guiyang	Guizhou	605.05	107.31	17.74
8	Haikou	Hainan	291.81	43.10	14.77
9	Hangzhou	Zhejiang	2217.51	399.74	18.03
10	Harbin	Heilongjiang	1399.12	290.58	20.77
11	Hefei	Anhui	1288.46	281.95	21.88
12	Hohhot	Inner Mongolia	546.26	83.58	15.3
13	Jinan	Shandong	2087.83	424.37	20.33
14	Kunming	Yunnan	1082.19	183.41	16.95
15	Lanzhou	Gansu	444.97	38.46	8.64
16	Lasa	Tibet	123.09	11.41	9.27
17	Nanchang	Jiangxi	637.85	128.35	20.12
18	Nanjing	Jiangsu	1651.83	289.77	17.54
19	Nanning	Guangxi	680.96	116.21	17.07
20	Shanghai	/	4245.44	852.07	20.07
21	Shenyang	Liaoning	1455.37	311.04	21.37
22	Shijiazhuang	Hubei	1844.85	262.28	14.22
23	Taiyuan	Shanxi	817.78	106.38	13.01
24	Tianjin	/	3457.96	496.77	14.37
25	Urumqi	Xinjiang	985.78	199.24	20.21
26	Wuhan	Hubei	1665.88	290.44	17.43
27	Xian	Shaanxi	1330.58	264.33	19.87
28	Xining	Qinghai	262.09	52.89	20.18
29	Yinchuan	Ningxia	612.71	155.35	25.35
30	Zhengzhou	Henan	2311.41	302.04	13.07

* The "/" in Province column denotes a municipality city.

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Hope these responses are clear enough for your further reviewing and we are prepared to discuss on possible issues if necessary.