Summary of the response letter:

Manuscript ID: ESSD-2021-302

Title: A global dataset of annual urban extents (1992-2020) from harmonized nighttime lights

Dear Editor and Reviewers,

Thank you very much for providing us this opportunity to respond to reviewers' valuable comments that helped us further improve our analyses and the paper. We carefully revised our manuscript to account for the recommended changes by reviewers. The key improvements are as follows. (1) We added details of the methods used in this study as suggested for better understanding; (2) we improved corresponding texts to make the writing more rigorous and standard; (3) we highlighted opinions and insights for clarification; and (4) we updated the references cited in this study with newly published papers after our original submission. We believe the revised manuscript accounts for all reviewers' comments, and it was significantly improved as a result. We are providing detailed responses to all questions and recommendations by the reviewers in the attached letter. Revised manuscripts with and without track changes are attached for your reference.

Sincerely yours,

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Reviewer #1

In this manuscript, the authors developed a global dataset of annual urban extents (1992-2020) using consistent NTL observations and analyzed the spatiotemporal patterns of global urban dynamics over nearly 30 years. The urbanized areas associated with locally high-intensity human activities were mapped from the time-series global NTL imagery using a new stepwise-partitioning framework. The research is significant and meaningful for improving the understanding on global urbanization. My suggestion is minor revision before publication. The comments are presented below.

Response: thank you very much for your insightful suggestions and comments. Below we provide our responses to your comments.

#1-1 How do the authors determine the urban boundary rather than the impervious surface area boundary? In fact, the urban boundary should include the impervious surface region and the permeable surface regions such as green park, water body and bare soil inside the urbans. However, there are many missing land types or hollow areas in the urban boundary of this manuscript such as Figures 6 and 8. Also, we check the dataset (the global time-series urban extents is available at https://doi.org/10.6084/m9.figshare.9828827.v5 in this manuscript) such as annual_urbanMap_global_2009.tif. In this dataset, the urban boundary is still not a complete and contains many hollow regions inside the urbans. This is a minor problem from the subjects of remote sensing and geography.

Response: thank you very much for your comments. It is reasonable and acceptable that there are hollow areas in our NTL-derived urban products. First, it should be noted that the physical meaning of ‘urban extent’ obtained from NTL imagery and other optical remote sensing images (e.g., Landsat and MODIS) are different. The former focuses on depicting the coverage of urbanization and socioeconomic activities with locally high intensity by quantifying the nocturnal lighting at night, while the latter emphasizes human modifications to the landscape from the perspective of land-use types by detecting corresponding spectral features. That is, although both distributed within the urban boundary, settlements exhibiting bright-lit areas (e.g., residential areas) and settlements exhibiting dim-lit areas (e.g., slums or urban villages) reveal completely different intensities of urbanization activities, and thus are identified as urban and non-urban areas respectively in this study. Similarly, other land-use types located within the urban boundary, such as green space and water body, may also be excluded in our NTL-derived urban extents, if corresponding areas exhibit locally dim DNs on the NTL imagery. Therefore, the hollow regions are mainly due to the NTL characteristics. Second, the Landsat-derived urban products also have different definitions of urban areas due to their different classification systems. Most of them focus on built-up land or ISA mapping, and the extracted urban data are spatially broken patches. Differently, the GUB data in *Li et al. (2020)* provide global urban boundaries without hollow regions from the fine ISA data. The additional morphological approach by dilating and eroding the urban patches resulted to another definition of urban. Additionally, *Kuang et al. (2021)* classified the urban ISA and green space within the urban land for better recognition of the urban environment, which indicates that urban land can be identified as not only a single type but different land cover composites. Therefore, the definitions of 'urban extent/urban land/urban areas' vary among studies.

In this revision, we added description for a better understanding of our NTL-derived urban extents. First, we updated the literature review in Section 1 to better compare the major types of urban remote sensing products currently. Second, we further emphasized the difference and uniqueness of NTL-derived urban extents in this study by comparing them with other related studies. Third, we added some explanations about the hollow regions observed in Fig. 8 for clarification.

"Unlike the temporally consistent but broken patches of artificial impervious areas used for revealing the long-term urbanization process, the global urban boundaries obtained from fine-resolution artificial impervious areas by Li et al. (2020b) provide spatially contiguous boundaries of urban extents without hollow regions. Additionally, a global dataset of intra-urban land cover types with a 5-year interval was developed aiming to provide more details of the key urban composites (e.g., green space and impervious areas) (Kuang et al., 2021b). Therefore, different global urban products based on artificial impervious areas have greatly contributed to revealing the human modifications to the landscape under the background of rapid global urbanization." (Version with track changes, page 2, line 56-62)

"Both of them have advantages in capturing urbanization and socioeconomic activities with high local intensities (Zhao et al., 2019)." (Version with track changes, page 3, line 72-73)

"Besides, several hollow areas can also be observed within the NTL-derived urban extents (see a1, a2, b3 and b4 in Fig. 8d). These hollow areas with relatively lower DNs at the local scales correspond to regions without ISA, and therefore should be considered as non-urban areas." (Version with track changes, page 15, line 322-324)

#1-2 Line 136 "(2) identification of optimal thresholds to delineate annual urban extents;". So, a threshold attachment to identify urbans at the national or regional scales should be provided in the manuscript so that the scholars can accurately repeat the data production process.

Response: thank you very much for your suggestion. The dynamic thresholds for urban mapping over different spaces and time in this study are not simply identified at the national or regional scales, instead, they are determined at the cluster level. As mentioned in Section 3.1, we used the NTL clustering and segmentation approach to divide the 2013 global NTL imagery to obtain the global urban clusters. More than 16,000 potential urban clusters were finally identified for further urban extent delineation. Since each potential urban cluster has an optimal threshold in each year, a record of thresholds for different countries/regions without the location information of each potential urban cluster does not help to repeat the data production. In this revision, we added some details and explanations of the approaches used in the potential urban cluster map generation (Section 3.1) and initial urban extents delineation (Section 3.2) for clarification. More details can be found in our responses to #1-3.

#1-3 Line 144 "(i.e. local areas include urban cores, suburban and rural areas)"? How to identify urban cores and suburban is lacking in this manuscript.

Response: thank you for your question. The key idea of our NTL-based urban mapping framework is to first delineate imagery into potential urban clusters and then extract the urban areas from each urban cluster. When identifying urban clusters from NLT imagery, each potential urban cluster was delineated as an enclosed zone containing spatially contiguous pixels with similar DN values. The DNs of each zone generally increases from the periphery to the center, spatially similar to the process of urbanization activities increasing from rural to urban areas. After we delineated potential urban clusters, we developed the heuristic NTL-based urban mapping approach based on our previous work by *Zhou et al. (2018)* and *Zhao et al. (2020b)*. The key idea of this approach is to capture the characteristics of DMSP NTL spatial variations in each urban cluster over different years. First, we identified the pattern of NTL distributions in each urban cluster in each year as a non-gradual pattern or gradual pattern, by characterizing their NTL quantile curves. Second, we identified the optimal threshold for each case by detecting the feature point of each NTL variation curve. The feature point of the NTL curve for each case has been applied to distinguish urban and non-urban areas because of the difference of DMSP NTL property in urban and non-urban (*Zhou et al., 2018; Zhao et al., 2020b; Ma et al., 2015*). When a non-gradual pattern is observed, the turning point of the NTL quantile curve is identified as a feature point to capture the boundary between urban and suburban, or between suburban and rural, according to corresponding urban cluster categories (See Fig. 4). More details about this approach were presented in Section 3.2.

In the revised manuscript, we made improvements as follows. First, we emphasized that the potential urban cluster is a local zone of areas including urban cores, suburban and rural areas, and our objective is to extract urban extent from each potential urban cluster. Second, we added details of the approaches including the potential urban cluster map generation (Section 3.1) and initial urban extents delineation (Section 3.2).

"A global map of potential urban clusters (i.e., urban domains including urban cores, suburban and surrounding rural areas) was generated using the NTL clustering and segmentation approach. This approach includes two major sections. First, we applied the Marker-controlled Watershed Segmentation algorithm (Parvati et al., 2008) to generate global initial urban clusters of spatially contiguous pixels with similar DN values. The increasing of DNs in each urban cluster from the periphery to the core spatially corresponds to the intensification of urbanization and socioeconomic activities from rural areas to urban cores. Therefore, each initial urban cluster is an enclosed zone constituted by urban and surrounding non-urban areas. Considering that this gray-scale morphology algorithm with dilation and erosion processing is sensitive to the spatial variations of NTL DN values, the filtered NTL imagery in 2013 rather than the latest one was used here to avoid the over-segmentation of urban clusters caused by the slight heterogeneity of simulated DMSP-like NTLs in the urban domain (Li et al., 2020a). Second, we used necessary screening rules to identify and remove non-urban clusters from the initial urban clusters which were unrelated to urbanization. Both the global binary urban reference data mentioned in the datasets and temporal trends of the annual average NTL DNs of each initial urban cluster were designed to screen out the non-urban clusters from the initial ones.

Here, an updated urban binary layer in 2018 overlayed by its binary layer of dense AIA (GAIA percentage > 50%) and corresponding NTL luminance layer (DN > 40), was used to mark the areas associated with dense human settlements and high-intensity human activities, respectively. The initial urban clusters, which exclude such areas or exhibit the abnormal NTL temporal trends unrelated to the urbanization process, were identified as non-urban urban clusters to be removed for generating the potential urban clusters. As demonstrated in Zhou et al. (2015) and Zhou et al. (2018) at the global scale, these associated parameters could jointly determine the screening rules for identifying non-urban clusters. More details about cluster screening are presented in Zhao et al. (2020b)*." (Version with track changes, page 6-7, line 152-158)*

"Both strategies were designed based on the curve feature points of NTL variations from non-urban to urban areas." (Version with track changes, page 8, line 196-197)

"For a cluster with G < 0, its urbanized category in this year was identified as I. For this case, relatively low DN pixels are dominant, the DN value of the turning point essentially reveals the potential boundary between rural and suburban. Hence, the turning point of the NTL quantile curve constituted by remained NTL pixels after the first removal corresponds to the boundary between suburban and urban, if the second pattern of NTL variation is also non-gradual. Therefore, the DN value of the turning point in the second removal (D2) was identified as the optimal threshold for delineating urban extent from the potential urban cluster in this year. The urbanized category was identified as II for a cluster with G > 0 and Q > 0.5. For this case with relatively balanced high and low DN pixels, the estimated threshold is likely to separate urban and suburban. Therefore, the DN value of the turning point in the first removal (D1) was applied to identify the corresponding urban extent in this case. For a cluster with G > 0 and Q ⩽ 0.5, the urbanized category was identified as III. For this case with both dim pixels and strong blooming effect, the estimated threshold in the first removal is relatively low and another removal is necessary when its gradient pattern is again identified as non-gradual. Therefore, the urban boundary was derived after the second removal/iteration using the threshold D2." (Version with track changes, page 9-10, line 222-230)

"Therefore, despite there are no notable changes along the NTL gradient to delineate urban and non-urban, the urban boundary in this type of potential urban clusters can also be captured by

the DN value of urban split point using the parabola-based strategy, as an alternative." (Version with track changes, page 11, line 251-253)

Reviewer #2

The authors developed a global dataset of annual urban extents (1992-2020) using consistent NTL observations in this manuscript. The method is robust and the results are reasonable. Minor comments:

Response: thank you very much for your insightful suggestions and comments. Below we provide our responses to your comments.

#2-1 Section 3.1, the authors use GAIA percentage of 50% and NTL DN of 40 as the thresholds to remove the fake urban clusters. How did the authors determine the thresholds and what is their uncertainty? BTW, the authors mentioned in line 265 the NTL-derived urban areas are consistent with the range of ISA percentages from 20% to 45%. Does this percentage range conflict with the defined fake urban clusters?

Response: thank you very much for your questions. First, the thresholds of GAIA percentage and NTL DN are not the only parameters in identifying the non-urban potential clusters, and the impact on our extracted final urban extents is minor. In this study, we first extracted more than 90,000 initial urban clusters from the global NTL imagery using the Marker-controlled Watershed Segmentation algorithm. Because this segmentation algorithm was designed based on the gray-scale morphology of DMSP NTL imagery, the extracted urban clusters are not all potential urban clusters. To exclude non-urban clusters, several rules were implemented. We developed an urban binary layer with values of 0 and 1 as a reference layer. In this layer, pixels with both GAIA percentage > 50% and NTL DN > 40 were set as a value of 1, and the others were set as a value of 0. Then, by overlaying this reference layer on the initial potential urban cluster layer, we identified urban clusters without at least one pixel with the value of 1 as the non-urban clusters. We have used similar methods (NTL clustering and segmentation approach mentioned in this paper) to delineate the urban clusters at both regional (*Zhao et al., 2020b*) and global scales (*Zhou et al., 2018; Zhou et al., 2015*). The thresholds were chosen based on our experiments in this study, as well as previous related studies *(Zhou et al., 2014; Zhou et al., 2015; Zhou et al., 2018; Zhao et al., 2020b*). We considered that the final thresholds used in this study can both remove non-urban clusters and keep small towns.

Second, the percentage range of ISA (20%-45%) does not conflict with the single threshold we used for removing non-urban clusters. The threshold of GAIA percentage (50%) mentioned in Section 3.1 was used to identify whether this 1-km pixel could represent dense human settlements. This threshold is one of the parameters only to identify and remove non-urban clusters. The GAIA percentage data were aggregated from 30-m fine-resolution ISA. The thresholds of GAIA percentage mentioned in Section 4.1.1 were used to characterize the density of human settlements for calculating the total area of human settlements with different densities at different regions. As we discussed in our response to #1-1, the NTL-derived urban extents were defined from the perspective of the intensity of urbanization and socioeconomic activities, and therefore their physical meaning is different from that of artificial impervious areas. Therefore, differences exist between NTL-derived urban extents in this study and ISA-derived areas obtained using different GAIA percentage thresholds. When compared at the regional level, urban areas from NTL might correspond to different ISA percentage levels, and the percentage levels also vary with space and time.

In this revision, we further clarified the removal of non-urban potential clusters for better understanding the related thresholds/parameters.

"A global map of potential urban clusters (i.e., urban domains including urban cores, suburban and surrounding rural areas) was generated using the NTL clustering and segmentation approach. This approach includes two major sections. First, we applied the Marker-controlled Watershed Segmentation algorithm (Parvati et al., 2008) to generate global initial urban clusters of spatially contiguous pixels with similar DN values. The increasing of DNs in each urban cluster from the periphery to the core spatially corresponds to the intensification of urbanization and socioeconomic activities from rural areas to urban cores. Therefore, each initial urban cluster is an enclosed zone constituted by urban and surrounding non-urban areas. Considering that this gray-scale morphology algorithm with dilation and erosion processing is sensitive to the spatial variations of NTL DN values, the filtered NTL imagery in 2013 rather than the latest one was used here to avoid the over-segmentation of urban clusters caused by the slight heterogeneity of simulated DMSP-like NTLs in the urban domain (Li et al., 2020a). Second, we used necessary screening rules to identify and remove non-urban clusters from the initial urban clusters which were unrelated to urbanization. Both the global binary urban reference data mentioned in the datasets and temporal trends of the annual average NTL DNs of each

initial urban cluster were designed to screen out the non-urban clusters from the initial ones. Here, an updated urban binary layer in 2018 overlayed by its binary layer of dense AIA (GAIA percentage > 50%) and corresponding NTL luminance layer (DN > 40), was used to mark the areas associated with dense human settlements and high-intensity human activities, respectively. The initial urban clusters, which exclude such areas or exhibit the abnormal NTL temporal trends unrelated to the urbanization process, were identified as non-urban urban clusters to be removed for generating the potential urban clusters. As demonstrated in Zhou et al. (2015) and Zhou et al. (2018) at the global scale, these associated parameters could jointly determine the screening rules for identifying non-urban clusters. More details about cluster screening are presented in Zhao et al. (2020b).” (Version with track changes, page 6-7, line 161-170)

#2-2 Line 260: "This indicates that identifying urban areas using ISA data rather than NTL data may become more complicated due to the diverse urbanization processes worldwide." This sentence is hard to understand. What do you mean by "complicated" and "urbanization processes"? please consider deleting this sentence.

Response: thank you for your suggestion. We deleted this sentence as suggested.

#2-3 Section 4.1.3, Fig.10: The urban sizes from this study and population from GPW is not very relevant. Please add some explanation and discussion.

Response: thank you very much for your suggestion. In this revision, we added explanation and discussion about the results obtained from this figure.

"Such weak correlations are reasonable because of the complex processes of urban expansion and population growth, which not only interact with each other but are also influenced by other factors such as economic growth, transportation infrastructure, governance and planning controls, as well as the characteristics of the environment. Moreover, it was found that large urban areas in different periods always correspond to high populations, which is consistent with the general cognition." (Version with track changes, page 17, line 357-361)

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