The authors thank the reviewer for his precious time and the constructive comments. Our detailed responses to the editor and referee comments are given below.

General comment

1) This manuscript describes a modeling study of biogenic VOC (BVOC) emissions from Beijing China. Since BVOC emissions are important for determining atmospheric composition and chemistry and are not well understood, this original study has the potential to contribute to the scientific understanding on this significant topic. The manuscript is difficult to understand in many places but that could be addressed with a thorough language editing.

Response: The authors appreciate your precious time and comments. As mentioned in the manuscript, this study is to investigate and discuss the sensitivities of MEGAN model using multiple satellite-based datasets. Therefore, it is necessary to evaluate the effect from input data on the estimation of BVOC emissions. **And the professional language editing has been called before the revised manuscript submitted to solve the language issue.**

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To whom it may concern

The paper "Sensitivity of Biogenic Volatile Organic Compounds Emissions to Leaf Area Index and Land Cover in Beijing" by Hui Wang, Qizhong Wu was edited by Elsevier Language Editing Services.

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2) The authors apply the MEGAN model, driven with WRF meteorology as is typically the case for MEGAN simulations. The most valuable part of the study is the investigation of the two of the main drivers of BVOC emissions: meteorology and landcover. For meteorology, the authors compare temperature to observations and report a bias of cool temperature simulated by the model that is likely because the model does not adequately simulate the impact of the "urban heat island" on temperature. This is one of the more interesting results of the study and is a topic that the authors could potentially explore further with a more detailed examination and discussion of the canopy and leaf temperature simulations. For land cover, the authors compare different satellite based datasets. They do not compare with any in-situ observations so it is a sensitivity study with limited insights regarding accuracy and uncertainties.

Response: The authors appreciate the reviewer's comments. Regarding with meteorology conditions, in the manuscript, we did some validation to indicate the reasonability of simulation to estimate the BVOCs emission. The reviewer mentioned that exploring the impact of Urban Heat Island (UHI) may be an interesting topic, however, the most of available satellite-based land cover datasets, like MODIS 12Q1, can't present the green land among the city region for the limitation of spatial resolution. In this study, only the Finer Resolution Observation and Monitoring of Global Land Cover (FROM-GLC) with 30m resolution could primarily characterize the major green land in the city, but the scattered green space like road greening can't be recognized, which make it not wise enough to discover this topic. The field surveys can provide the more thorough data of urban green space and the multiple studies have adopted such method to discover the relevant topic (Ren et al., 2017;Ghirardo et al., 2016;Chang et al., 2012), and this study focus on the typical landscape, which could be distinguished in the satellite land cover products.

The validations of the land cover datasets were done by the land-cover validation dataset from Zhao et al. (2014), and the baseline period of validation dataset is 2009-2011. The 61 available sample points from the above dataset in Beijing and its surrounding region were used and the results are showed in Table 1. The validation showed that the FROM-GLC has the highest accuracy of 59.67% among these land cover datasets. Since FROM LC has the same benchmark period with validation dataset and close spatial resolution, the FROM LC showed the better accuracy than the other two products. Considering effect of the spatial resolution and benchmark time, the validation results only indicate the reasonability of the land covers coarsely.

Table 1. Accuracies calculated based on the sample points from land-cover validation dataset.

	FROM-GLC	MODIS 12Q1 2013	CCI LC 2013
Accuracy	59.67%	54.10%	50.81%

Specific suggestions and comments:

1) Conclusions #1 to 3 and #6 relate to the total emissions and the contribution of individual seasons. This would be of more interest if the study included some comparisons to BVOC emission measurements, so we have some idea if the emission results are correct. Since the paper does not include any observations of BVOC emissions, the MEGAN predictions of Beijing emissions should not themselves be the major focus of the manuscript. The current manuscript text (in the conclusion and elsewhere) devoted to describing the MEGAN model results (totals, seasonal and spatial variations) is too long and should be provided only as a brief description in the manuscript, and could perhaps be included in more detail in a supplemental section.

Response: Thanks for your comments. We noticed that BVOCs observations that can be found in previous publication (Shao et al., 2009;Xie et al., 2008;Wu et al., 2016;Li et al., 2015) are mainly for the sites in Peking University (PKU) and Yufu, a city site and a rural site. These publications only provided the average value and standard deviation, but are not for year 2013. To evaluate the BVOCs emission and effect, the chemistry transport model (CTM) should be used (Geng et al., 2011;Zhao et al., 2016), but there is no time-serious observation of BVOCs in 2013, and the observation sites are not located in the forest region. According to the reviewer's comments, and partly decreased the descriptions of model results and added more details of the discussion of the sensitivity tests. Meanwhile, we adjusted the standard emission factor based on Ren et al. (2017) to discuss and compare the results of two similar studies.

2) Conclusions #4 (LAI) and 5 (PFT) are the potentially more interesting contributions. However, there are several issues regarding the results and associated conclusions. Page 11, line 24/25 states that MODIS LAI led to a 17.4% decline of total BVOCs compared with baseline in this study, because of the relatively big mask area in the MODIS LAI product. This is not a reasonable comparison. The mask indicates that no data is being provided for the masked region so it doesn't make sense to compare them. The default MEGAN LAI data on the MEGAN website replaces the MODIS LAI in the masked region with values based on an interpolation from the surrounding region. You could use this or some other approach but it is misleading to indicate that the MODIS LAI is lower as indicated in the conclusion section and elsewhere (e.g., Figure3).

Response: Thanks for your comments. We have further compared the effect of LAI products by considering two aspects, masking area and LAI value discrepancy. Firstly, we compared region that is available in MODIS LAI products, and it could explain the effect from the discrepancy of the LAI value on the BVOCs emission estimation. In addition, according to the Xiao et al. (2016), the direct validation with in-situ observation shows that the GLASS LAI has most similar results with the site observation, and the MODIS LAI is the worst. Secondly, the BVOCs discrepancy from the masking area of MODIS LAI is isolated. Since the MODIS adopting the vegetation canopy radiation model to produce LAI products (Knyazikhin et al., 1999), the region assigned as non-pure vegetation type would be treated as a missing value. Meanwhile, in this study, we used L4 level satellite products, and the producer of datasets has finished the work of interpolating the missing value in a reasonable range. Therefore, adopting the method like interpolating for the missing value in MODIS LAI is not helpful to improve the quality of the datasets but lead into new source of error, and we separately discussed the discrepancy within MODIS and other LAI products.

3) Page 11, line 27/28 The statement, "Generally, the uncertainty of LAI is limited under the MEGAN model frame", is unclear but seems to suggest that because the GEO and GLASS LAI data products are similar that means that LAI uncertainties do not contribute substantially to MEGAN BVOC emission uncertainties. This is not necessarily the case as it probably just shows that the two datasets are based on a similar approach (with similar errors).

Response: Thanks for your comments. The authors have followed the reviewer's comments. And this statement has been deleted from the manuscript.

4) Regarding conclusion #5, and the PFT comparison in general, the authors apparently consider only the relative contribution of PFTs to the vegetation covered regions and do not consider the differences in total vegetation cover. I assume this is the case since the PFTs in table 3 add up to 100% but I expect the vegetation cover in Beijing must be less than 100%. How does total vegetation cover differ between the three landcover databases? In addition, the conclusion #5 reports the PFT cover differences but does not provide any insights on which is the most accurate, how uncertain they are, and what the implications are for modeling. For example, how important is it to get the relative PFT correct in comparison to getting total vegetation cover correct or accounting for the variability of emission factors within each PFT (i.e., not all broadleaf trees have the same isoprene emission factor).

Response: Thanks for your comments. The data in table 3 has been corrected to the fractions of area of the different land covers to the total area of the Beijing region. The vegetation distribution is the key determinant of the standard emission factor. Satellite-based land cover products could provide the gridded spatial distribution of major landscapes, but it is limited to provide the further detail of the species information of different vegetation. Therefore, this approach is not suitable to solve the problem, which is mentioned by the reviewer that different species with same PFT have diverse emission factors. But the results based on satellite-based land cover map are gridded and available for the chemistry model directly, and such method is also the most common way for the researches of adopting CTM to investigate the topics about the air quality (Gao et al., 2016;Situ et al., 2013;Wei et al., 2018).

On the other hand, the field surveys can provide more information of species compositions, but the accurate spatial distribution of species is not available. The work done by Ren et al. (2017), mentioned by the reviewer, adopted the statistic species data from field surveys at administrative-region scale. And this approach may be more thorough to estimate the total BVOCs emission, but how to gridded these results and make it suitable for the CTM is not presented in his manuscript.

In general, adopting the satellite-based PFT map would lead to the errors from the species diversity of emission factor, but it is easier to be gridded for the following research. A compromising way is to estimate the emission factor of PFTs based on the statistical data of vegetation species, which presents the average emission factor of the

PFTs. And this method was also adopted by Wang et al. (2011) to provide reasonable parameters for the estimation of regional BVOCs emission.

In addition, the classification of the satellite land cover is also play a key role in determining the emission factor. The PFTs scheme in MEGAN v2.1 are from Community Land Model v4 (CLM4)(Lawrence et al., 2011), and it is significant to convert the diverse land cover classes to the PFTs, which is called cross-walking. The MODIS MCD12Q1 LC and the Climate Change Initiative Land Cover (CCI-LC) adopt the corresponding cross-walking tables to convert its classification system to PFTs. The FROM-GLC product doesn't provide the corresponding cross-walking table, therefore, the converting of FROM-GLC is based on its original classification system. Since pixels of the medium-resolution land cover datasets would contain the information of multiple land cover types and that the cross-walking table is one of the sources of uncertainty in land surface model (Hartley et al., 2017), we treated the 30m resolution FROM-GLC as the baseline land cover in the experiments, and adopted the other two land cover products to discover the impact of the discrepancy of land cover on the estimation of BVOCs emission. And in addition, we also used the CCI-LC to do the sensitivity tests of cross-walking table, and the results will be added to the Discussion section in the revised manuscript and the supplement.

Finally, it is evident that the modeling exercise described in this manuscript generally supports the results and conclusions of a similar study by Ren et al. (http://dx.doi.org/10.1016/j.envpol.2017.06.049) for the same region (Beijing) that covers the same topic more thoroughly. The Ren et al. paper is not referenced in this manuscript which is not surprising since it was only recently published. However, it is important that the authors do compare with and discuss the results and conclusions of the Ren et al. paper and consider whether (and how) their manuscript adds any new information to the existing scientific literature.

Response: The authors thanks for the reviewer's comments. Ren et al. (2017) presented the similar research about the BVOCs emission in Beijing during 2015. The two studies adopting the similar algorithms but different data sources. As mentioned above, Ren et al. (2017) adopted the statistical data of the main tree species and collected thorough parameter of the vegetation, which contains more detail compared with our previous data. Therefore, we adjusted our standard emission factor based on the data from Ren et al. (2017) and recalculated the BVOCs emission. The corresponding results and analysis would be presented in the revised paper. As emphasized by the reviewer, the results of Ren et al. (2017) is more thorough, and the comparison of two studies could be helpful to understand the discrepancy of estimations of MEGAN model and more accurate species-based estimation.

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