Dear editor and reviewer,

Thank you very much for your great efforts, comments and suggestion! According to your comments and suggestion, we revised the manuscript carefully and thoroughly. Please see, below, our point-to-point response.

Please do not hesitate to let us know if you have additional questions and/or comments.

Sincerely,

Xiaolu Tang, Wenjie Zhang and Sicong Gao, on behalf of all co-authors.

Response to reviewer #1

This manuscript deals with estimation of global belowground autotrophic respiration (RA) in terrestrial ecosystems. I have some questions in this study. 1) Authors compared global RA by data-derived with that by Hashimto et al.(2015). However, authors did not refer the data of Hashimoto et al. (2015) in the manuscript. How did authors get the data from Hashimoto? Please explain the difference between Random forest model and methods of Hashimoto et al. (2015).

Response: we apologize for the unclear statement of Hashimoto RH.

Hashimto RA was publicly available at:

http://cse.ffpri.affrc.go.jp/shojih/data/index.html, therefore, we obtained the annual RA product for our study. Such information was added in text:

"In order to compare with the solely global RA product generated by Hashimoto et al. (2015), which was estimated by a climate-driven model using temperature and precipitation only and obtained from the public available dataset (http://cse.ffpri.affrc.go.jp/shojih/data/index.html)".

Hashimto et al. (2015) proposed a global RA based on the difference of heterotrophic respiration and total soil respiration, and total soil respiration was predicted by a climate-driven model using temperature and precipitation only and global soil respiration dataset. Therefore, Hashimoto RA did not consider other environmental control, such as soil carbon, on RA (Hashimoto et al., 2015).

To fill such knowledge gap, we applied a Random Forest algorithm to model global RA with field observations and 11 environmental variables in terms of different aspects of environmental controls on RA, and we obtained a much higher model efficiency (52%) compared to Hashimoto RA (32%). Furthermore, Random Forest algorithm have great potentials to address the non-linear correlation between RA and environmental variables, and remove auto-correlations among environmental variables.

2) Authors used PgC a-1 or gC m-2 a-1for the unit of RA, but I guess that a-1 should be yr-1. Please correct all unit in the manuscript and figures.

Response: yes, it means Pg C per year. Corrected to "Pg C yr^{-1}" or "g C m^{-2} yr^{-1}" throughout the manuscript and figures!

3) Authors discussed about importance of the dominant environmental factors for estimate spatio-temporal variation in RA. I think that it is important not only environmental factors for plant production but also plant biomass because root respiration would have positive correlation with plant biomass. Why did authors ignore the global pattern of plant biomass??

Response: thank you for the good comments. We agree with you that plant biomass, particularly root biomass, would have positive correlations with RA. However, selecting variables is constrained by the fact that a variable must be available at all sites and at the corresponding global product simultaneously. For instance, if a variable is measured accurately at sites, but with large uncertainties in the corresponding global product, it may be advantageous to exclude this variable from the analysis (Jung et al., 2011).

Although we tried to include global plant or root biomass as a driving variable, we found such product was only available for a single year, or mean values of several years (Huang et al., 2017), or forests (Hengeveld et al., 2015), and there was a lack of time-series global biomass product covering all land covers. Given the fact that plant biomass was highly dynamic due to annual accumulation, using a global biomass for a given year or particularly ecosystem type to represent the biomass dynamics covering all terrestrial ecosystems would cause a great uncertainty to RA estimation. Therefore, the lack of global biomass product constrained the use of plant biomass as a driving variable for RA in this study. Instead, we used MODIS land cover as one of driving variables, which could indirectly reflect the biotic or biomass control on RA to some extent.

Finally, please considering my specific comments and get some English proofreading. In addition, please reconsider carefully about all figures, because I feel that some figures are not important in this manuscript. If authors resolve these questions, I think that this manuscript would be better for global data science.

Response: we answered each of your specific comment carefully, and we improved the English.

As you suggested, see specific comments below, Figure 6c was not important and removed.

Specific comments

Page 3, line 54, "which is almost 5 times of: : :.": I cannot understand relationship between this sentence and preceding sentence. Page 3, line 56, "Therefore, an accurate estimate of : : :": I think that authors did not enough explain the reasons before the sentences. Please add more explanation.

Response: Since the two comments link with each other, we answer the two comments together.

We apologize for the unclear statement. We revised and added more explanation for it as follows:

"RA could amount roughly up to 54 Pg C yr^{-1} (1 Pg = 10^{15} g, calculating RA as an approximate ratio of 0.5 of soil respiration, more details in Hanson et al., 2000) according to different estimates of global soil respiration (Bond-Lamberty, 2018), which is almost 5 times of the carbon release from human activities (Le Quéré et al., 2018). However, the contribution of RA to soil respiration varied greatly from 10% to 90% across biomes, climate zones and among years (Hanson et al., 2000), leading to the strong spatial and temporal variability in RA. Thus, whether RA varies with ecosystem types or climate zones remains an open question at the global scale (Ballantyne et al., 2017). Consequently, an accurate estimate of RA and its spatial-temporal dynamics are critical to understand the response of terrestrial ecosystems to global carbon cycling and climate change."

Page 8, Figure 2: I cannot understand the meaning of the figure 2c and 2b. Why did authors indicate the standard deviation of temporal variation in RA??

Response: Fig. 2b is the mean value of Hashimoto RA over 1980-2012, while Fig. 2c represents the standard deviation of predicted RA in this study. The figure caption was revised as:

"Spatial patterns of annual mean and standard deviation of belowground autotrophic respiration (RA) from 1980 to 2012 for this study (a, c) and Hashimoto RA (b, d), respectively"

Due to the inter-annual variability of environmental controls on RA, RA varied annually. Although Fig. 6 describes the annual variability of total RA, the spatial pattern of annual variability of RA is lacking. To characterize the spatial pattern of annual variability of RA, the standard deviation of RA from 1980-2012 was employed. Such analysis was also conducted in other studies, e.g. Yao et al. (2018). Therefore, we used standard deviation to represent the temporal pattern of RA.

Page 11, Figure6: what the difference of Fig.6a and Fig.6b? Please add more explanation. And, please make the same value of yaxis in both of Fig.6a and Fig.6b.

And I think that Fig6c is not needed.

Response: Fig. 6a represents the annual variability of predicted RA in this study, while Fig. 6b represents the annual variability of Hashimoto RA. The same value of yaxis from 39 – 45 Pg C yr^{-1} was applied.

Fig. 6c was not important and removed.

We corrected the figure description more clearly:

"Figure 6 Annual variability of belowground autotrophic respiration (RA) for this study (a) and Hashimoto RA (b) from 1980 to 2012. The grey area represents 95% confidence interval."

Page 12, Line 254 to 227, "All the biomes, except: : :, respectively": please rewrite these sentences. Grammatical subject is RA, I think.

Response: we rewrite these sentences:

"RA showed a significantly increasing trend during 1980-2012 ($p_s < 0.01$) in most of the biomes, except temperate forest, savannas and wetland. RA in tropical forests, boreal forests and cropland increased by 0.0076±0.0015, 0.0047±0.0016, 0.0036±0.0014 Pg C yr^{-2}, respectively."

Page 12, Line 259, "a significant increasing trend of: : :": is this "a significant increasing trend of total RA in temperate zones,: : :."??

Response: thank you for your careful revision. Yes, we mean "a significant increasing trend of total RA in temperate zones….". We revised the text:

"there were significant increasing trends of total RA in temperate zones, temperate forest, savannas and wetland of Hashimoto RA, which were not observed in data-derived RA".

Page13, Figure 9: I cannot understand the importance of this figure.

Response: We appreciate your question. Figure 9 showed the relative importance of three main environmental drivers – MAT, MAP and SWR, by colors with RGB plot.

Due to different ecosystem types, or plant functional types or climate zones, the dominant factors may vary. As indicated by Fig. S7, 56% of land area was dominated by precipitation, while temperature and shortwave radiation dominated 19% and 25% of global land areas, which indicated an uneven control of environmental factors on RA. Therefore, Figure 9 showed the spatial variability of dominance of MAT, MAP and SWR on RA. It was found that the dominance of precipitation on RA was globally distributed, particularly dry or semi-arid areas, such as Northwest China, Southern Africa, Middle Australia and America, while temperature controlled RA mainly in in tropical Africa, Southern Amazon rainforests, Siberia and partly tundra, and shortwave radiation dominated high latitudinal areas, e.g. Eastern America and middle and Eastern Russian. Such analysis have been widely used in other studies, e.g. gross primary production (Yao et al., 2018), earth greening (Zhu et al., 2016), vegetation productivity (Seddon et al., 2016).

RGB synthesis (Fig. 9) was performed on stretched values of partial correlation coefficients, an effective way to illustrate the spatial distribution of dominant driving factors of RA (Yao et al., 2018), which could increase our understanding the mechanisms and spatial variability of environmental controls on RA at the global scale.

Page 14, Line 290 “For example, temperature was the: : :Australia” is that the result of Hashimoto et al.(2015)?

Response: thank you for your careful revision again. Yes, we mean “Hashimoto RA”, and revised in text:

“temperature was the main dominant factor for most area of Australia for Hashimoto RA”.

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