Dear Editor,

Please find attached our revised version of manuscript bg-2018-466 “Global, Satellite-Driven Estimates of Heterotrophic Respiration”.

Reviewer 1 found our new top-down estimates “very novel” and the results interesting, and argued the paper would “no doubt […] be of interest to readers of Biogeosciences”. Reviewer 2, by contrast, did not understand why our new top-down estimates might be useful and cited two main concerns: (1) that the resolution of the CMS-Flux NEP estimates forces the Rh to also have a relatively coarse-resolution, and (2) that globally upscaled Reco estimates are already available that combine Rh with Ra (e.g. through FLUXCOM). Regarding (1), while it is true that the top-down estimates introduced in this paper are coarser resolution than FLUXCOM, they can still be used to estimate regional-scale carbon fluxes. Such regional-scale carbon fluxes (especially in the tropics) provide crucial information about the global carbon cycle consistent with past literature (e.g., Liu et al, 2017, Bowman et al, 2017, and see also other studies cited in our response below). Furthermore, our top-down method could also be applied at much finer resolution over smaller scales, as discussed in Sec 4.2. Regarding (2), the Reco has limited ability to disentangle how specific climate variations effect Ra and Rh, as the sensitivities of the two component fluxes are different. Furthermore, the globally upscaled Reco estimates Reviewer 2 refers to are based on only a small number of observations in the tropics.

The reviewers also asked for a more detailed analysis of the effects of uncertainty in GPP (both reviewers) and in NEP (reviewer 2) on our top-down Rh estimates. We now include in Figure 4 the results of a sensitivity analysis that calculates an alternative version of the top-down Rh estimates by using FLUXCOM GPP instead of the SIF-derived GPP from Parazoo et al. (2014). Because FLUXCOM NEP is known to have a significant global mean bias (as now discussed in the Methods section), we instead used zero mean NEP globally for an NEP sensitivity analysis. This was also one of Reviewer 2’s suggestions. For each of the two sensitivity analyses, we show the spatial variations of the difference in mean Rh, as well as the correlation coefficient between the original Rh and the alternative version. While both analyses show significant sensitivity (particularly in the wet tropics, as expected), the sensitivities exhibited from these analyses are still lower than the difference between our top-down and the bottom-up estimates, suggesting the possible utility of the new top-down estimates despite their large uncertainty. The new sensitivity analyses are extensively discussed in the revised versions of the Methods, Results, and Discussion sections. We also added additional text to the Discussion emphasizing the large uncertainty of the top-down Rh estimates and the need to keep this uncertainty in mind when using the dataset/approach.
In addition, we have addressed several minor comments from Reviewer 1. Based on Reviewer 2’s comment, we also changed the color legend of the RGB colormap in Figure 5 to clarify the meaning of a yellow color. A complete list of changes and point-by-point response to the comments from both reviewers is attached.

Sincerely,

Alexandra Konings (on behalf of all the authors)
Reviewer 1

Reviewer: Konings et al. provide globally distributed estimates of heterotrophic respiration (Rh), both from satellite based observations and from a bottom-up scaling of an empirical model. The satellite based estimates in particular are very novel, and are obtained by combining atmospheric inverse estimates of net ecosystem production (NEP) with global photosynthesis (GPP) estimates informed by solar induced fluorescence data, multiple vegetation models, and empirically upscaled estimates. To combine NEP and GPP to get an estimate of Rh, the authors need to estimate global variations in carbon use efficiency (CUE). The use estimates provided by CARDAMOM, a simple empirical model of carbon fluxes with parameters constrained by global observations. The final estimate of Rh is then taken as [sic] \( \dot{\text{I}} \) SE \( h=\dot{\text{I}} \) \( \hat{\text{h}} \) \] [...]. The authors are to be commended for their heavily data-informed approach, which highlights the potential to use disparate observations to inform global estimates, not just test predictions. The results are interesting and the manuscript is very clearly written and no doubt will be of interest to the readers of Biogeosciences.

Response: We are glad the reviewer believes our new satellite-based approach to estimating Rh is very novel, and that the manuscript will be of interest to Biogeosciences readers.

Reviewer: There are several limitations to the approach, however, and the estimates of Rh should be taken as a first pass of a promising approach rather than a reliable and informative quantification of the global distribution of Rh. As the authors note, the Rh estimates should not be used as a benchmark for other estimates, as their global quantified uncertainty is 50% of the mean flux. There are simply too many uncertainties, some quantified in this manuscript, and some not. Great caution should also be taken in using the approach to quantify trends over time.

Response: We agree that the results of our approach remain uncertain, and tried to be clear about this. In the revised manuscript, we deleted the text about model benchmarking from Sec 4.3 to further emphasize the uncertainty of the method, and have added additional language emphasizing uncertainty to both Sec 4.3 and throughout the manuscript (see below).

Reviewer: The uncertainties stem primarily from the fact that both GPP and CUE are not known, but must be estimated themselves. Global GPP estimates vary a lot between approaches, and although the authors use an approach that combines SIF with DGVMs and upscaled GPP estimates, the relationship between SIF and GPP is poorly understood, and even the magnitude and spatial distribution of GPP has considerable uncertainty. The cited paper on which the GPP estimates are based, Parazoo et al. (2014) does a good job of assessing some of those uncertainties, but important sources of bias persist. For example, Parazoo et al. (2014) used the empirically upscaled GPP from Jung et al. 2012 to constrain the magnitude of GPP to roughly 120 PgC, but recent results of more updated empirical upscaling approaches from the FLUXCOM project (https://www.bgc-jena.mpg.de/geodb/projects/Data.php) show global GPP estimates vary from 108 PgC (neural net based) to 125 PgC (Random forest based), each with an associated uncertainty.
of _8 PgC (standard deviation). It would be worth including an assessment of the contribution of this uncertainty to the global estimates reported here.

Response: We agree that both the global CUE and GPP variability remain poorly understood, and that the Parazoo et al. (2014) approach is influenced by the quality of the Jung et al. (2012) estimates and TRENDY models. We added an additional sentence to the discussion of this dataset in the methods to emphasize its uncertainty. We now include an additional sensitivity analysis testing the effect of GPP uncertainty by using FLUXCOM GPP (and also added a sensitivity analysis using zero-mean NEP based on comments from Reviewer 2). A map of the mean difference between the FLUXCOM-GPP-derived-Rh and the Parazoo-derived-Rh is shown in Fig 4c, while the R² between the two Rh datasets is shown in Fig. 4d. Not surprisingly, changing the GPP product used most significantly changes the dynamics of Rh in the relatively under-constrained tropics, though there are also notable changes in the central American Plains. The results of the sensitivity analysis are discussed extensively in new text in the Results in Sec 3.1.1 and in a new paragraph in the Discussion in Sec. 4.1. The new discussion paragraph reads:

“Among the sensitivity analyses performed, NEP and GPP generally had a greater effect on the resulting Rh than the assumed values of CUE. The primary GPP and NEP datasets used here (those from Parazoo et al (2014) and CMS-Flux, respectively) are sensitive to both observational error (e.g. due to cloud cover) and uncertainties in the retrieval algorithms (including, but not limited to, uncertainties in the relationship between SIF and GPP and, for NEP, in the inversion of atmospheric transport models). As shown in Fig. 4, uncertainties in top-down GPP and NEP can have significant effects on the mean and temporal variability of Rh estimated. Nevertheless, the sensitivity of Rh to alternative GPP and NEP assumptions was still lower than the difference between the top-down and bottom-up Rh estimates everywhere outside the high-latitudes. Thus, despite the large sensitivity of the top-down Rh to the quality of the input datasets (and to a lesser degree, to the assumption of constant CUE), our new approach still provides meaningful new constraints on Rh not available from bottom-up estimation alone.”

Reviewer: The global estimates of CUE are also subject to large uncertainty, though the authors do a great job of assessing the impact on their results. In the absence of a global database of CUE and its seasonal variability, however, the uncertainty is difficult to quantify accurately. It would be worth highlighting in the abstract what these uncertainties indicate regard research needs to improve this approach.

Response: We added a sentence to the abstract that discusses the uncertainty sources:

“Sensitivity and uncertainty analyses showed that the top-down Rh are more sensitive to the choice of input GPP and NEP datasets than to the assumption of a static CUE value, with the possible exception of the wet tropics.”
Reviewer: Detailed comments:

The annual totals for GPP and NEP should be given in the methods section to allow the reader to assess their relationship with the annual total Rh.

*Response:* Good point, thanks. We have added these in page 5, line 13 and page 4, line 27, respectively.

Reviewer: Page 2, line 20 Although the authors are correct that heterotrophic respiration is relatively unconstrained, the same cannot be said for ecosystem respiration, particularly at night. Eddy-covariance observations provide a direct observation of ecosystem respiration at night at 100’s of sites around the world. Consider rewording.

*Response:* We now clarify this as “Thus, while GPP is highly uncertain (Anav et al., 2015), GPP and Reco are far more constrained by observations than Rh, which must be considered among the most uncertain fluxes in the carbon cycle.”

Reviewer: Page 3, line 20: ‘is calculated as’

*Response:* We’ve fixed this typo.

Reviewer: Page 6, line 16: ‘To reduce error, all visual maps are presented after applying a 3 pixel by 3 pixel moving average smoother.’ This does not reduce error, unless the error is randomly distributed around zero. Do you have evidence that there is no systematic bias in spatial distribution of the CMS-Flux predictions?

*Response:* We agree - the moving average smoother was applied to reduce the random component of the error only, and it does not remove biases. We have now clarified this line of the text to clarify: “To reduce the random component of the error, all visual maps are presented after applying a 3 pixel by 3 pixel moving average smoother, as in Liu et al. (2017).”

Reference:


Reviewer: Page 6, line 17: “The NEP is a small number that is the balance of many larger components, so small errors in NEP could lead to large compensating errors in Rh.” This is not clear. A small error in NEP should have little effect on the derived Rh, as NEP itself has a small role in the calculation especially relative to GPP, which is a very large number, and CUE.
Response: This was indeed unclear, so we removed it.

Reviewer: Page 6, line 25: the uncertainty in total annual GPP from the Parazoo et al (2014) paper does not consider methodological uncertainty (see differences between methods in FLUXCOM). How would this affect the results presented here.

Response: A full assessment of the methodological uncertainty in any given GPP estimate is difficult without perfect knowledge of the true GPP. For example, even FLUXCOM does not capture all methodological uncertainty as it does not, for example, capture uncertainty related to possible missing input information (which may be part of the reason the uncertainty of the FLUXCOM products is actually lower than that of the Parazoo et al. (2014) estimates). Insofar as there is non-captured uncertainty in GPP, this would have a non-negligible effect on the $R_h$, as shown in Figure 4a-b.

Reviewer: Page 12, line 24: Most plant traits can not be estimated from space, and it is difficult if not impossible to properly characterize the uncertainty associated with estimates of photosynthesis from space as there are no observations of ecosystem photosynthesis. The authors should show some restraint when trying to argue that estimates of photosynthesis, plant traits and $R_h$ from space contain significantly lower sampling errors than bottom-up estimates. Also please clarify what you mean by sampling errors here and how sampling errors relate to total uncertainty.

Response: We removed the phrase “and plant traits” from this sentence.

We agree that remote sensing of photosynthesis (and net carbon fluxes) still has significant sources of error and did not mean to imply in this section that any top-down estimate of an environmental variable will always have lower overall uncertainties. By sampling errors, we mean errors associated with the fact that in situ observations may not be in locations that are representative of environmental conditions across the globe – for example, because they are underrepresented in the tropics, or because they occur more frequently in disturbed areas than ecosystems as a whole, or because they under-sample regions of high topography, etc. We now refer to this as “representativeness error” to clarify. Because they sample across the globe, spaceborne remote sensing estimates would be expected to have significantly lower representativeness errors, although we agree with the reviewer that some errors may remain due to e.g. reductions in accuracy correlated with cloud cover. We have edited the caveat in this paragraph to clarify this. It now reads (page 13, lines 30-31 and page 14, lines 1-2) “While the uncertainties of the remote sensing datasets used for top-down estimation show some variations across different parts of the globe, remote-sensing based estimates of vegetation properties such as photosynthesis and biomass have previously been argued to contain significantly lower representativeness error than bottom-up estimates (Schimel et al., 2015, Saatchi et al., 2015). A similar dynamic is at play for $R_h$.”
Reviewer: Page 14, line 10: measurements of SIF and estimates of GPP. GPP is not measured by TROPOMI.

Response: Thanks, we’ve fixed this.
Reviewer 2

Reviewer: Konings and colleagues aimed to derive global, satellite-driven estimates of heterotrophic respiration.

Here already lies the problem with the manuscript: Konings and colleagues focus too much on deriving the individual ecosystem fluxes that make up Rh top-down. GPP is derived from sun-induced fluorescence (top-down), but the uncertainty from using bottom-up estimates such as FLUXCOM is not evaluated. To my mind it should not matter if all fluxes that can be used to derive Rh top-down are also top-down estimates. Instead of using GPP from SIF also FLUXCOM-GPP (bottom-up) could be used—would that make a difference regarding spatial patterns?

Response: We agree that our approach is sensitive to the GPP dataset used. We now include a sensitivity analysis using FLUXCOM GPP in the revised manuscript. The resulting difference in temporally-mean Rh and the R² between the two Rh variants are mapped in Figs. 4a and 4b and the results are discussed in the text on page 10, lines 9-12:

“When the GPP data source is changed to FLUXCOM (Fig. 4a-b), the temporal dynamics of Rh are most varied in the central American Plains, Australia, and in the tropics, especially in the Amazon. However, other hot spots for a mean difference exist, such as in Central Canada and Eastern Europe.”

The new text also mentions the pros and cons of FLUXCOM GPP (in the Methods, page 6, lines 21-32) and re-emphasizes the uncertainties of the Parazoo et al (2014) GPP dataset we use in a new paragraph in Sec 4.1 of the discussion (quoted below in a later response to the reviewer). The site-based FLUXCOM estimates are based on samples that may not be representative of the whole globe and are highly undersampled in the tropics (for example, only 17 of 225 towers used are in the Southern Hemisphere). While the top-down approaches also have uncertainties, they provide substantially better coverage of global NEP and GPP proxies in traditionally undersampled regions. This motivated us to use top-down approaches for estimating Rh here. We explicitly contrast this to the best-available bottom-up dataset for Rh (that of Hashimoto et al. 2015) and show the uncertainties between both are comparable.

Reviewer: For NEP the authors should discuss the effect of different products, for example Jena CarboScope NEP (http://www.bgc-jena.mpg.de/CarboScope/) or Chevallier et al. (2010) or FLUXCOM (Zscheischler et al., 2017) (how problematic this may be).

Response: An exhaustive discussion of propagated effects of multiple different NEP and GPP product combinations is beyond the scope of this manuscript, which focuses on the comparison between the top-down method and the bottom-up method of Hashimoto et al (2015). However, we have now added an additional sensitivity analysis assuming NEP has value of zero at every pixel and every timestep, as suggested by this reviewer in a later comment. This is now discussed extensively in the text. First in the results (page 10, lines 12-19):
“Changing to using zero-value NEP (Fig. 4c-d) most significantly introduces a mean difference in the Southern Amazon and in Central Africa, though interestingly, the signs of the resulting difference are opposite between the continents. The temporal dynamics of these regions is also the most sensitive to inclusion of actual NEP estimates in the $R_h$ calculation. Despite the fact that NEP’s global mean value is more than an order of magnitude smaller than that of GPP, neglecting NEP causes large changes to the estimated $R_h$ over much of the globe, showing the value of including NEP estimates in the top-down $R_h$ calculation. Note however that the mean deviation in $R_h$ for either the NEP or GPP sensitivity analyses is still smaller than the mean difference between the top-down and bottom-up $R_h$ over most of the world. The only exception to this is in the high latitudes were all differences between estimates are of a similar magnitude.”

We also added a new paragraph to the discussion concerning the new uncertainty analyses for both GPP and NEP:

“The top-down approach introduced here is dependent on the quality of the input datasets used. Among the sensitivity analyses performed, NEP and GPP generally had a greater effect on the resulting $R_h$ than the assumed values of CUE. Among the sensitivity analyses performed, NEP and GPP generally had a greater effect on the resulting $R_h$ than the assumed values of CUE. The primary GPP and NEP datasets used here (those from Parazoo et al (2014) and CMS-Flux, respectively) are sensitive to both observational error (e.g. due to cloud cover) and uncertainties in the retrieval algorithms (including, but not limited to, uncertainties in the relationship between SIF and GPP and, for NEP, in the inversion of atmospheric transport models). As shown in Fig. 4, uncertainties in top-down GPP and NEP can have significant effects on the mean and temporal variability of $R_h$ estimated. Nevertheless, the sensitivity of $R_h$ to the use of alternative GPP and NEP datasets was still lower than the difference between the top-down and bottom-up $R_h$ estimates everywhere outside the high-latitudes. Thus, despite the large sensitivity of the top-down $R_h$ to the quality of the input datasets (and to a lesser degree, to the assumption of constant CUE), our new approach still provides meaningful new constraints on $R_h$ not available from bottom-up estimation alone.”

The results of these new uncertainty analyses are also referred to in a new sentence in the abstract, and Sec 4.3 (the last section of the Discussion, discussing the implications of this approach for carbon-climate feedback studies) has been updated to include several additional references to the uncertainty of the input datasets.

Reviewer: On a similar note, one can get an estimate of $R_h$ from CARDAMOM: this should be very much dictated by data. How does $R_h$ from CARDAMOM compare to the satellite-driven estimates and Hashimoto’s approach?
Response: While CARDAMOM uses model-data fusion to incorporate information from remote sensing products, its soil carbon pools and fluxes are much less well constrained than the aboveground carbon pools and fluxes. The version of CARDAMOM used in this manuscript (the same as in Bloom et al PNAS 2016) predicts heterotrophic respiration only as a function of pixel-dependent base respiration rates, turnover time, and temperature, but does not account for water limitations. As such, while CARDAMOM \( R_h \) and our newly derived \( R_h \) are largely consistent in the mid-latitudes and boreal regions, they actually have opposite seasonality in the dry tropics, where soil moisture limitations are expected to largely drive the seasonal cycle of \( R_h \). This suggests that the CARDAMOM seasonal \( R_h \) variability is unrealistic (because it is solely dependent on temperature).

We emphasize that this does not mean CARDAMOM CUE cannot be used in our top-down method. As we have previously discussed in the manuscript, the allocation fractions that influence the CUE are particularly well-constrained. Indeed, the latitudinal patterns in CARDAMOM are consistent with a recent meta-analysis compiling carbon use efficiency across 415 site-years that has been submitted to Biogeosciences Discussions since the time we originally submitted our manuscript (Tang et al, in review). This paper is now referenced in the Methods (page 6, line 1). Furthermore, as part of unpublished work unrelated to this manuscript, we updated CARDAMOM to account for the effects of soil water limitations on heterotrophic respiration. This had little qualitative effect on the resulting global vegetation CUE maps.

Reference:

Reviewer: How different would global numbers be if NEP was 0 globally? Would spatial patterns change a lot? It seems like that due to the coarse NEP estimates you cannot achieve reasonable resolutions for \( R_h \).

Response: Thanks for the suggestion. As discussed in our response to the reviewer’s earlier comment about the choice of NEP dataset, we now include a sensitivity analysis with NEP equal to zero everywhere and at all times in Fig. 4c-d, to better understand the sensitivity of the \( R_h \) to the choice of NEP.

The reviewer also mentions the relatively coarse resolution of the top-down \( R_h \) product. As the reviewer points out, this is driven by the coarse resolution of CMS-Flux NEP. Our sensitivity analysis shows inclusion of NEP data has a non-negligible effect on the derived \( R_h \), suggesting that inclusion of NEP is useful. While we agree that the relatively coarse-resolution of the top-down \( R_h \) limits inferences to regional scales, heterotrophic respiration and its temporal dynamics is still poorly understood even at these coarser scales. The CMS-Flux NEP (which drives the resolution of the top-down \( R_s \) estimates) has been shown to be scientifically useful both in the tropics and mid-latitudes (Bowman et al, 2017, Liu et al, 2017, 2018). Many other studies have considered carbon fluxes at regional scales. Some examples include: Anav et al J. Climate 2013, Peylin et al Biogeosciences 2013, and Sellers et al, PNAS 2017, etc...
Additionally, as we discuss in Sec 4.2, the method we introduce is not dataset- or resolution- specific and could also be applied using other datasets at finer resolution (and perhaps over a smaller spatial extent). In Sec 4.2, we write: “However, the approach could also be applied at finer resolutions, for example using regional scale atmospheric inversions. If the local carbon use efficiency can be determined (Tang et al., 2019), the method could also be applied at smaller spatial and temporal scales, such as to data from eddy covariance towers”.

References:


Reviewer: Overall, I cannot follow why we need such a coarse estimate of Rh. On page 14 line 7-8, the authors state that estimates of Rh can be helpful as a validation for ESMs. Using Ecosystem respiration as a validation would be enough to my mind. One evaluates temporal and spatial patterns of Reco to deduce if the representation of Ra and Rh can reproduce these patterns. In the approach presented here one ends up with partitioned Rh, but this heavily depends on the prescribed CUE.

Response: In terms of why even coarse top-down Rh data can be useful: studies of carbon fluxes at regional to continental scale are common in the literature, as we showed examples of in the response to the previous comment. Furthermore, global Rs remains a highly uncertain flux, as discussed in detail in Tian et al. (2015) and Bond-Lamberty et al. (2016). Additionally, in the 4 years since it has been published, the bottom-up global Hashimoto et al. dataset (2015) has been cited 73 times. While not all of these citations focused on Rh, we show that the Hashimoto et al. (2015) approach is sensitive to the overfitting that occurred in that dataset for both Rs and Rh. Lastly, our manuscript introduces not just an alternative top-down dataset, but also a method that could be applied over a variety of spatial domains and with a variety of different input datasets.

As to why Rh is preferable to Reco for validating Earth System Models: Ra and Rh can have differential sensitivity to drought and other climatic variations. See, for example, just two papers cited below (Sun et al, 2019; Zhang et al, 2019) that have been published only in the last few months making this point, though of course there are countless others. Thus, while Reco can be used as an indirect constraint on Rh and Ra, knowing only Reco is not enough to unambiguously determine which process representation in the models needs the most improvement and to test possible alternatives. Knowing only Reco could also hide compensating
errors between $R_h$ and $R_a$. While it is true that the input datasets and assumption of constant CUE can affect the interpretation of the $R_h$ datasets derived here (whether in the context of model validation or other studies), this can be partially mitigated by carefully considering and propagating the uncertainty when using the dataset. We have tried to be very transparent throughout the manuscript about the uncertainty in our model and the need to keep it in mind. In the revised version, we also rephrased the last paragraph as a result of the additional GPP and NEP sensitivity analyses to make this even clearer:

“With these and other improvements to remote sensing-driven estimates of GPP and NEP, top-down estimation of $R_h$ may be a promising avenue to better understand the role of $R_h$ fluxes in carbon-climate feedbacks. However, because the temporal variability of the derived $R_h$ varies depending on the quality of the GPP, NEP, and CUE datasets (as well as, to a lesser degree, the assumed constancy of the CUE assumptions), any studies using top-down $R_h$ should carefully consider uncertainty propagation in any hypothesis testing. Nevertheless, with careful consideration of uncertainty, top-down estimation may be a promising approach for understanding or bounding the role of $R_h$ in carbon-climate feedbacks.”

References:


Technical and other comments:

*Page 7, line 13: Hashimoto et al. (2002), I think this should be 2015.*

*Response:* We fixed this.
Figure 5: In the map there are yellow colors. In the RGB legend, however, yellow cannot be seen. Please correct.

Response: Thanks. In the revised version of this figure, we have included a color cube instead of a color triangle to make the yellow more easily identifiable as being between red and green.

References


List of changes to the manuscript

1) A new uncertainty analysis was performed to assess the sensitivity of the top-down Rh to the use of FLUXCOM GPP instead of Parazoo et al.-derived GPP. Figure 4, which previously showed only the results of a sensitivity analysis with respect to CUE, now shows (in six sub-panels) the results of this sensitivity analysis, as well as a new sensitivity analysis for NEP (with NEP assumed 0) and the old CUE sensitivity analysis. For each of the three analyses, the mean difference in $R_h$ (left column) and the $R^2$ between the top-down Rh from the different variants (right column) are shown.

2) The new NEP GPP sensitivity analyses is discussed in the Methods section (new 5th paragraph in Section 2.1.2), the Results section (new second paragraph in Section 3.1.1 and new sentences contrasting the new GPP & NEP sensitivity analysis results with those of the CUE results and contrasting the sensitivity analysis results with the results of the uncertainty analysis in Fig. 5), and Discussion (new third paragraph in Section 4.1, last few sentences of Section 4.3).

3) A sentence has been added to the abstract to summarize the greater sensitivity of top-down Rh to GPP and NEP than CUE, except possibly in the wet tropics

4) A sentence in the second paragraph of the introduction has been edited to clarify that while $R_h$ is globally very poorly constrained by observations, $R_{eco}$ is not.

5) The total average global GPP and NEP of the datasets used in the top-down method has been added to the respective paragraphs discussing each of the datasets in Section 2.1.2

6) The paragraph about the Parazoo et al. (2014) GPP dataset used in Section 2.1.2 has been edited to re-emphasize the uncertainty of this dataset.

7) A sentence was added to the paragraph describing the CARDAMOM CUE data used in Section 2.1.2 to explain the agreement between the CARDAMOM CUE and a recently published bottom-up upscaling of CUE.

8) In Section 2.1.2, a sentence describing the 3x3 smoother applied to all visual maps was edited to clarify that this only reduces the random component of the error.

9) An incorrect sentence about how small errors in NEP could lead to large compensating errors has been removed from Sec 2.1.2 and the same argument has been deleted from Section 4.2.

10) The color legend of the RGB map in Figure 5 has been changed from a triangle to a cube to better clarify the meaning of a yellow color.

11) The title of Sec 4.1 has been clarified to remove duplicate use of the word “uncertain”. It now reads “Top-down and bottom-up approaches are both uncertain.”

12) The first sentence of Section 4.1 was clarified by adding the word “respective”.

13) We added a reference to Eq. 5 in the last sentence of first paragraph 4.1, to clarify the relationship between bottom-up $R_i$ and bottom-up $R_{hi}$.

14) The second paragraph of Section 4.1 has been clarified that top-down methods are expected to have lower representativeness errors than bottom-up estimates, not necessarily lower total error.

15) The last sentence of Section 4.1 was clarified to emphasize that the top-down estimates could be used help constrain, but not benchmark (this word was deleted), bottom-up and other datasets.

16) A sentence in Section 4.2 has been clarified to replace “smaller scales” with “finer resolution”.
17) A sentence about using the new top-down dataset for validating earth system models was deleted from Section 4.3

18) The language in Section 4.3 mentioning TROPOMI has been edited to clarify that TROPOMI measures SIF, not GPP.

The supplementary material remains unchanged.
Global, Satellite-Driven Estimates of Heterotrophic Respiration

Alexandra G. Konings1, A. Anthony Bloom2, Junjie Liu2, Nicholas C. Parazoo2, David S. Schimel2, Kevin W. Bowman2

1Department of Earth System Science, Stanford University, Stanford, CA 94305, USA
2NASA Jet Propulsion Laboratory, California Institute of Technology, Pasadena, CA 91109, USA

Correspondence to: Alexandra G. Konings (konings@stanford.edu)

Abstract. While heterotrophic respiration (R_h) makes up about a quarter of gross global terrestrial carbon fluxes, it remains among the least observed carbon fluxes, particularly outside the mid-latitudes. In situ measurements collected in the Soil Respiration Database (SRDB) number only a few hundred worldwide. Similarly, only a single data-driven wall-to-wall estimate of annual average heterotrophic respiration exists, based on bottom-up upscaling of SRDB measurements using an assumed functional form to account for climate variability. In this study, we exploit recent advances in remote sensing of terrestrial carbon fluxes to estimate global variations in heterotrophic respiration in a top-down fashion at monthly temporal resolution and 4x5° spatial resolution. We combine net ecosystem productivity estimates from atmospheric inversions of the NASA Carbon Monitoring System- Flux (CMS-Flux) with an optimally-scaled gross primary productivity dataset based on satellite-observed solar-induced fluorescence variations to estimate total ecosystem respiration as a residual of the terrestrial carbon balance. The ecosystem respiration is then separated into autotrophic and heterotrophic components based on a spatially-varying carbon use efficiency retrieved in a model-data fusion framework (the CARbon DAta MOdel fraMework, CARDAMOM). The resulting dataset is independent of any assumptions about how heterotrophic respiration responds to climate or substrate variations. It estimates an annual average global average heterotrophic respiration flux of 43.6 ± 19.3 Pg C/yr. Sensitivity and uncertainty analyses showed that the top-down R_h are more sensitive to the choice of input GPP and NEP datasets than to the assumption of a static CUE value, with the possible exception of the wet tropics. These top-down estimates are compared to bottom-up estimates of annual heterotrophic respiration, with new uncertainty estimates that partially account for sampling and model errors. Top-down heterotrophic respiration estimates are higher than those from bottom-up upscaling everywhere except at high latitudes, and are 30% greater overall (43.6 Pg C/yr vs. 33.4 Pg C/yr). The uncertainty ranges of both methods are comparable, except poleward of 45 degrees North, where bottom-up uncertainties are greater. The ratio of top-down heterotrophic to total ecosystem respiration varies seasonally by as much as 0.6 depending on season and climate, illustrating the importance of studying the drivers of autotrophic and heterotrophic respiration separately, and thus the importance of data-driven estimates of R_h such as those estimated here.
1 Introduction

The terrestrial carbon cycle-climate feedback (together with atmospheric processes) is a dominant contributor to the uncertainty of temperature projections in 2100 (Booth et al., 2012). The future effect of carbon-climate feedbacks depends on the climate sensitivity of net terrestrial carbon fluxes, which are a close balance of net primary productivity, disturbance-related fluxes, and heterotrophic respiration ($R_h$). The overall sensitivity of the terrestrial carbon uptake is thus dependent on the climatic response of these fluxes. Model-based estimates of global $R_h$ vary by almost 50% and are highly uncertain (Shao et al., 2013), especially in the tropics (Tian et al., 2015). The climatic sensitivity of $R_h$ is also the primary driver of the large divergence across modeled global soil carbon pools (Tian et al., 2015; Todd-Brown et al., 2013), the largest terrestrial carbon pool (Jobbágy and Jackson, 2000).

Few in situ measurements exist to constrain $R_h$, particularly in the tropics (Xu et al., 2016). For example, the international Soil Respiration DataBase (SRDB), which aims to compile data from all published studies of soil and heterotrophic respiration (Bond-Lamberty and Thomson, 2010), includes only 21 sites with $R_h$ information in Central and South America, and only 2 in Africa. The highly limited number of $R_h$ data is likely affected by the relative difficulty and uncertainty of methods for partitioning total soil respiration ($R_s$) fluxes – which can be easily measured using respiration chambers – into autotrophic and heterotrophic components. Performing this partitioning requires isotopic measurements or destructive techniques such as girdling or trenching (Ryan and Law, 2005). Like $R_s$, total ecosystem respiration $R_{eco}$ is also often considered as a counter-part to photosynthetic fluxes, but is rarely partitioned further. However, because most carbon cycle and ecosystem models represent autotrophic and heterotrophic components separately, and because the climatic and soil sensitivities of the autotrophic and heterotrophic components of soil respiration differ (Metcalfe et al., 2010; Scott-Denton et al., 2006), it is challenging to translate soil or ecosystem respiration data to improvements of model representations for $R_h$. Although meta-analyses using data such as the SRDB have been used to understand the sources of spatial variability in soil respiration (Hursh et al., 2016) and heterotrophic respiration (Shao et al., 2013) rates, such studies are limited (by data availability) to consideration of annual respiration fluxes and sparse, discrete points in space. Thus, while GPP is highly uncertain (Anav et al., 2015), $GPP$ and $R_{eco}$ are far more constrained by observations than respiration, especially $R_h$, which must be considered among the most uncertain fluxes in the carbon cycle. Temporally variable and spatially extensive estimates of $R_h$ are therefore needed to better understand its drivers.

Starting several decades ago with Raich & Schlesinger (1992), several authors have tried to upscale sparse measurements to estimate global $R_h$. Most commonly, this is performed using a spatially explicit exponential model of the relationship between $R_h$ and temperature, modified by land cover (Adachi et al., 2017), soil properties (Chen et al., 2013), or soil moisture (Xu et al., 2016) limitations. Recent papers have also used machine learning methods to upscale the relationship between $R_h$ and climate and biogeophysical properties, including random forest models (Jian et al., 2018) and artificial neural networks (Zhao et al., 2017). However, no similar effort has been made for estimating global $R_h$. Only Hashimoto et al. (2015)
have extended a rigorous estimate of global, upscaled $R_s$ to an estimate of global $R_h$. This was achieved by employing a previously noted apparent relationship between annual $R_s$ and $R_h$ at a given site (Bond-Lamberty et al., 2004). However, the Hashimoto et al. approach assumes a specific functional form for the relationship between climate and $R_s$ (and thus, $R_h$), so that investigations of climatic sensitivities of $R_h$ with this dataset are potentially circular. Furthermore, the approach assumes that base respiration rates and sensitivity parameters for temperature and precipitation to soil moisture are constant across the globe. This approach therefore cannot account for known dependencies of heterotrophic respiration on microbial biomass and composition (Johnston and Sibly, 2018; Walker et al., 2018; Wieder et al., 2013; Zhou et al., 2011) and substrate type (Cornwell et al., 2008). Modelling $R_h$ as a function of precipitation alone is also inconsistent with theoretical, laboratory, and field studies that have found $R_s$ to be a function of soil water potential (Manzoni et al., 2012; Moyano et al., 2012, 2013), which is nonlinearly related to precipitation depending on soil properties, vegetation cover, topography, and more.

In this paper, we introduce an alternative approach to estimating $R_h$ at global or regional scales using remote sensing. Rather than a bottom-up approach to aggregating sparse point-based measurements, we propose a ‘top-down’ method that naturally captures average values over large scales. The method derives $R_h$ as the residual of satellite-constrained estimates of the carbon balance: net ecosystem productivity (NEP), gross primary productivity (GPP) and $R_a$. The NEP (the net difference between photosynthetic and respiration fluxes: \( \text{NEP} = GPP - R_a - R_h \)) is based on atmospheric inversions of satellite observations of column $xCO_2$ and $xCO_2$ and GPP is based on upscaling solar-induced fluorescence (SIF). The $R_a$ is calculated based on GPP and carbon-use efficiency estimates from a remote-sensing constrained model-data fusion framework. The top-down approach is applied to the period 2010-2012. Coarse-resolution $R_h$ estimates are difficult to validate using in situ measurements because of representativeness errors. Instead, we rigorously compare the top-down method and its uncertainties to those of bottom-up $R_h$ estimation, in this case as performed by Hashimoto et al. (2015).

2 Methods

2.1 Top-down Estimates

2.1.1 Top-down approach

As summarized in Fig. 1, the top-down $R_h$ at grid-scale is calculated as the residual of observationally-constrained estimates of the carbon balance: \( R_h = GPP - \text{NEP} - R_a \). The combination of NEP and GPP allows calculation of the ecosystem respiration $R_{eco}$, but an estimate of $R_h$ is required to separate $R_{eco}$ into $R_a$ and $R_h$ components. The $R_h$ is calculated based on the GPP and on carbon-use efficiency (CUE). Specifically, the autotrophic respiration $R_a$ is assumed to be proportional to GPP according to a spatially variable but temporally constant CUE, where CUE is defined as the ratio of net primary production (NPP) to GPP. Thus, $\text{CUE} = 1 - \frac{R_a}{GPP}$. Eq. (1) then becomes:
\[ R_h = GPP - NEP - (1 - CUE)GPP, \]

The CUE is commonly assumed constant at a given location (Gifford, 2003; McCree and Troughton, 1966), but has been found to vary depending on ecosystem type, stand age, and forest management (Collalti et al., 2018; Gifford, 2003; De Lucia et al., 2007). Note that by calculating autotrophic respiration as proportional to GPP, we classify the release of CO\(_2\) from decomposition of root exudates by mycorrhizal fungi (Trumbore, 2006) as autotrophic rather than heterotrophic respiration.

This is arguably a misclassification, but is consistent with most in situ methods for measuring heterotrophic respiration (e.g. girdling, trenching, or isotopic measurements) (Ryan and Law, 2005).

The use of this method to calculate spatio-temporal variations in \( R_h \) is enabled by the fact that estimates of each of NEP, GPP, and CUE are available that are based on remote sensing and data assimilation. These datasets are further discussed in the next Section.

2.1.2 Datasets used and implementation

The NEP is determined from an atmospheric inversion of remotely sensed columnar carbon dioxide and carbon monoxide observations in the CMS-Flux system. It is described in detail in Bowman et al. (2017) and (Liu et al., 2017), but summarized here for convenience. It has been validated using methods introduced in Liu and Bowman (2016). CMS-Flux estimates carbon fluxes through a 4D-variational inversion approach that ingests columnar xCO\(_2\) observations from the Greenhouse gases Observing Satellite (GOSAT) and CO observations from the Measurement of Pollution in the Troposphere Instrument (MOPITT) (Worden et al., 2010) into the GEOS-Chem atmospheric transport model and its adjoint (Bey et al., 2001; Henze et al., 2007; Nassar et al., 2010; Sunharalingam et al., 2004). The net fluxes are further decomposed into biomass burning, oceanographic, fossil fuel, chemical sources (including shipping, aviation, and others), and NEP components. The biomass burning emissions are constrained by the MOPITT CO observations and published CO/CO\(_2\) ratios. Anthropogenic and oceanographic priors for the fluxes come from the Fossil Fuel Land Data Assimilation System (Asefi-Najafabady et al., 2014; Rayner et al., 2010) and ECCO2-Darwin oceanographic model (Brix et al., 2015), respectively, and NEP flux priors come from the Carnegie-Ames-Stanford-Approach (CASA) model simulations. As shown in Fig. S1, the posterior and prior fluxes of NEP differ significantly almost everywhere – 42% of pixels have a normalized root-mean-square-difference between the prior and posterior fluxes greater than 1, consistent with a previous observing system simulation experiment for the CMS-Flux system (Liu et al., 2014). The total global NEP averages 5 ± 13 Pg C/yr across 2010-2012, and the uncertainty of the NEP estimates is assumed to be normally distributed with a spatially and temporally varying standard deviation estimated in the atmospheric inversion via a Monte Carlo approach (Bousserez et al., 2015).

The GPP is determined based on an optimal rescaling of SIF observations. SIF is a by-product of photosynthesis and therefore provides direct information about the magnitude of GPP (Porcar-Castell et al., 2014). The information content of SIF
for photosynthesis has been demonstrated using field-scale measurements (Yang et al., 2015) and by comparing satellite-based data to eddy-covariance towers (Ganter et al., 2014; Joiner et al., 2014; Sun et al., 2017; Wood et al., 2017; Zuromski et al., 2018), carbon dioxide mole fractions in Amazonia (Parazoo et al., 2013), and machine-learning based estimates of GPP (Alemohammad et al., 2017). Despite the abundance of evidence that SIF carries information about GPP, the linear constant of proportionality between SIF and GPP depends on the light use efficiency of the vegetation in question as well as the satellite efficiency at capturing photons and is difficult to estimate a priori. Here, we use GPP estimates from Parazoo et al. (2014), which used a Bayesian approach to determine an optimal seasonally and spatially varying scaling parameter between SIF and prior GPP along with explicit uncertainty estimates. Monthly GPP at each grid point is inferred from a precision-weighted minimization of SIF, which is regressed against biome-specific GPP from upscaled flux tower data (Frankenberg et al., 2011; Jung et al., 2011), and prior GPP from eight terrestrial ecosystem models in the TRENDY project (Sitch et al., 2015). This approach has been used to examine regional GPP responses to climate variability and drought, and has been extensively validated against flux tower data (Bowman et al., 2017; Liu et al., 2017; Parazoo et al., 2014, 2015), though it remains uncertain. The average global GPP across 2010-2012 is 114 ± 41 Pg C/yr, and the uncertainty of these GPP estimates is determined as in Parazoo et al (2014) and assumed to follow a normal distribution.

The CUE is determined from a 10-year (2001-2010) run of CARDAMOM (Bloom & Williams, 2015; Bloom et al., 2016), in which uncertainties are explicitly represented as probability density functions computed from an ensemble. CARDAMOM is a model-data fusion system that uses a Bayesian framework to determine global ecological parameter combinations that minimize the mismatch with observations while still satisfying a set of ecological realism and dynamic stability constraints to regularize the inversion. CARDAMOM is built on the underlying Data Assimilation Linked Ecosystem Carbon model version 2, DALEC2 model (Bloom & Williams, 2015; Williams et al., 2005), with assimilation of observations of leaf area index, burned area, tropical biomass, and soil carbon (Bloom et al., 2016). Within CARDAMOM, a constant fraction \( f_a \) of photosynthetic carbon gain is assumed to be allocated to autotrophic respiration (note that \( f_a = 1 - \text{CUE} \)). The fraction \( f_a \) is directly linked to the allocation fractions of photosynthetic carbon to other pools (labile, wood, foliar, and fine root carbon) through conservation of mass. The allocation fractions directly influence the observed quantities used for CARDAMOM parameterization (e.g. LAI, tropical biomass, and soil carbon), and are subject to several ecological realism constraints. The resulting range of global CUE (between 0.35 and 0.6, shown in Fig. 2) is consistent with results found from meta-analyses (Gifford, 2003; De Lucia et al., 2007) and is also supported by theoretical considerations based on conservation of mass (Van Oijen et al., 2010) and plant carbon dynamics (Dewar et al., 1998). Average values of CARDAMOM CUE are generally lowest in the tropics, consistent with previous site-specific observations (Amthor, 2000; Chambers et al., 2004; De Lucia et al., 2007; Piao et al., 2010). The zonal mean variation of CARDAMOM CUE (not shown) also compares favorably with that of a recently produced random forest derived global upscaling of in situ CUE measurements decreasing at low...
Autotrophic respiration may depend on stored supplies of carbon, causing a decoupling between the seasonality of GPP and \( R_h \) and thus temporal variation in CUE. This is particularly common in deciduous trees in mid- and high-latitudes (Epron et al., 2012; Kuptz et al., 2011). Less is known about seasonal variations of CUE in tropics. Although small variations in CUE (e.g. <= 0.05) have been observed in both highland and lowland Amazonian sites, these variations were found to be small relative to seasonal variations in allocation rates to non-respiratory carbon pools (Doughty et al., 2015; Rowland et al., 2014). Nevertheless, the assumption of constant CUE likely adds error to the top-down estimates of \( R_h \). This error is partially accounted for by the wide uncertainty range used for CUE. We further performed a sensitivity analysis in which the \( R_h \) derived using an assumption of constant CUE was compared to the \( R_h \) with a systematic seasonal variability in CUE. Although little is known about the true temporal variation of CUE across the globe, we here assumed a seasonal cycle of CUE proportional to that of GPP, but re-normalized to have a mean equal to the constant CARDAMOM CUE and a standard deviation of 0.1 at each pixel. That is,

\[
CUE(x, y, t) = CUE_{CARD}(x, y) + \frac{0.1}{\text{std}(GPP(x, y, t) - \overline{GPP})} (GPP(x, y, t) - \overline{GPP}),
\]

(3)

where \((x, y)\) determines a pixel location in space, \(t\) is the monthly time vector, \(CUE_{CARD}(x, y)\) is the constant CUE determined from CARDAMOM, \(\text{std}\) refers to standard deviation, and the overbar denotes a time-average over the entire period. The use of a CUE proportional to GPP is chosen so as to provide a structure to the temporal variability of CUE that is potentially realistic for each pixel (i.e. not completely random), even if little is known about the overall controls on temporal variability in CUE. The 0.1 standard deviation magnitude is fairly conservative unless true temporal variation in CUE is much larger than spatial variation – the spatial standard deviation of CARDAMOM CUE across all global land surfaces is 0.06.

Additional sensitivity analyses were also performed to test the sensitivity of \( R_h \) to errors in the GPP and NEP datasets.

To test the sensitivity to GPP, we compared \( R_h \) with an alternative set of \( R_h \) estimates calculated using GPP from FLUXCOM (Tramontana et al., 2016). FLUXCOM estimates of GPP are derived as the median value across an ensemble of estimates from 11 different machine learning models applied to meteorological drivers from reanalysis and remote sensing and trained on eddy covariance observations. The uncertainty of the FLUXCOM GPP is calculated based on the standard deviation across the different machine learning methods. Note that FLUXCOM is a bottom-up method and thus carries many of the same uncertainties as other bottom-up methods (see Sec 4.1), particularly in globally under-sampled regions. For example, only 17 of 225 eddy-covariance tower sites used to train the machine learning models are in the Southern Hemisphere. Furthermore, the FLUXCOM data are sensitive to the quality of the GPP partitioning of the observed tower NEE. Nevertheless, we use the FLUXCOM dataset here to study the sensitivity of \( R_h \) to GPP because it is widely used, well-regarded, and cross-validated against withheld parts of the eddy-covariance record. While FLUXCOM also estimates NEP, its NEP predictions are of lower quality than those of other fluxes (Tramontana et al., 2016). Furthermore, it shows significant bias (Exbrayat et al., 2019).
Instead, taking advantage of the low magnitude of NEP, we test the sensitivity to NEP data quality by computing \( R_s \) assuming NEP is zero everywhere across the globe and across the timeseries. Because an uncertainty in NEP still needs to be assumed, we simply use the same uncertainties from the CMS-Flux product.

When calculating \( R_s \) in either the main or sensitivity analyses, all datasets are averaged to the same monthly temporal and 4° latitude x 5° longitude spatial resolution, the native resolution of flux estimates from CMS-Flux. We use NEP and GPP data over the period 2010-2012, when the CMS-Flux data have been validated in the most detail. However, even at 4° by 5° resolution, the precision of CMS-Flux data can still be poor. To reduce the random component of the error, all visual maps are presented after applying a 3 pixel by 3 pixel moving average smoother, as in (Liu et al., 2018). When calculating \( R_s \), a 4000-member ensemble is used for explicit simulation of the uncertainty distributions of each of the input variables. The NEP is a small number that is the balance of many larger components, so small errors in NEP could lead to large compensating errors in \( R_h \). To reduce the effect of such compensating errors, a constraint on the signs of \( R_h \), \( R_s \), and GPP is used to ensure the estimated \( R_s \) is physically realistic (Bloom and Williams, 2015; Parazoo et al., 2018) – each of these three fluxes is required to be positive. A simple accept-reject sampling scheme is used that rejects ensemble members that violate this criterion. For each of these ensemble members, new samples of the uncertainty distribution of NEP, GPP, and CUE are drawn until each of \( R_s \), \( R_h \), and GPP for that ensemble member are positive. Using such a constraint is equivalent to using a Bayesian scheme with prior distributions for \( R_s \), \( R_h \), and GPP that are 0 for negative values and 1 otherwise.

The uncertainty of the resultant \( R_s \) is a combination of the uncertainty in the three input datasets: NEP, GPP, and CUE. There is some non-linearity to this combination because the positive flux constraints limit what uncertainty combinations are considered to lead to acceptable \( R_s \). To estimate how much each of these datasets contributes to the overall \( R_s \) uncertainty, \( R_s \) is re-estimated three times, but in each case only one of the input datasets is given non-zero uncertainty. The resultant magnitude of the uncertainty in \( R_s \) is then compared.

### 2.2 Bottom-up estimates

#### 2.2.1 Approach

To the best of our knowledge, only Hashimoto et al. (2015) have previously estimated \( R_s \) based on upscaling in situ measurements. Their method is based primarily on estimating \( R_s \) for which a simple functional form adapted from Raich et al (2002) is used:

\[
R_s = F \times e^{aT - bT^2} \times \frac{aP_t(l-a)P_{t-1}}{K + aP_t + (l-a)P_{t-1}},
\]

where \( F \) [gC m⁻² dy⁻¹] is a base rate, \( a \) [C⁻¹] and \( b \) [C⁻²] control the sensitivity to temperature \( T \) [°C]. The \( R_s \) also depends on the current-month precipitation \( P_t \) [cm mo⁻¹] and the previous-month precipitation \( P_{t-1} \) [C⁻¹], with the relative weight of each determined by \( a \) [-]. The \( K \) [cm mo⁻¹] parameter also controls the influence of precipitation. For lack of more information, all
parameters are assumed to be global constant, so that the only spatial variation is provided by variations in the climatic drivers. Hashimoto et al (2015) used temperature and precipitation from the Climate Research (CRU) 3.21 (Harris et al., 2014) and fit the above function to observations from the SRDB using a Bayesian Markov Chain Monte Carlo scheme. To determine the annual average Rh at a location based on annual Rs, Hashimoto et al. (2015) employed a previously determined relationship between annual soil and heterotrophic respiration (Bond-Lamberty et al., 2000):

\[ \ln(R_h) = c + d \ln(R_s), \]  

(5)

where \( c = 1.22 \) and \( d = 0.73 \). While it is in theory possible to apply Eq. (5) to any number of recent bottom-up Rs estimation approaches, we here apply it only to the estimates from Hashimoto et al. (2015) in Eq. (4), both for consistency with the literature and since the data from Hashimoto et al. (2015) are among the most commonly used bottom-up Rs estimates.

2.2.2 Parametrization and Implementation

We implemented Eq. (4) using climate data from the CRU 4.01 and using the maximum a posteriori parameter values from Hashimoto et al. (2015) (that is, \( F = 1.68 \) gC m\(^{-2}\) dy\(^{-1}\), \( a = 0.0528 \) °C\(^{-1}\), \( b = 0.000628 \) °C\(^{-2}\), \( \alpha = 0.98 \), and \( K = 1.20 \) cm mo\(^{-1}\)) to determine monthly resolution estimates of Rs. The Rs estimates were then temporally aggregated to determine annual Rh using Eq. (5). These are referred to as the bottom-up estimates below.

Extrapolating from a limited sample of parameters with multiple fitted parameters carries the risk of overfitting. Fortunately, several measurements of Rs and Rh have been added to the SRDB since the Hashimoto et al. (2015) article; the number of Rs measurements has increased by 20%, from 1638 to 1979. Similarly, the number of measurements of heterotrophic respiration has increased from 53 measurements when Bond-Lamberty et al. (2004) originally derived Eq. (4) to 362 measurements in the most recent SRDB version. To test the applicability of the original parameters, we also implemented the bottom-up approach at the increased number of SRDB location-years available since Hashimoto et al. (2015), i.e. all datapoints in SRDB v20170208. Consistent with the original study, for SRDB experiments for which the observed annual average was determined over a range of years, we used only the middle year in the range. We compared simulated to observed annual Rs and Rh for both the case of the maximum a posteriori parameters from the original Hashimoto et al. (2015) study and for a set of updated model parameters determined by a non-linear least-square fit. For the updated parameters, the coefficients of the \( R_h-R_s \) relationship are also optimized. Because the updated parameters did not perform significantly better (see Sec. 3.2), the original parameters were used in the rest of this study.

No uncertainty was considered in Hashimoto et al. (2015). To determine the uncertainty of the bottom-up estimates, we tested them against SRDB observations. Measurements in the SRDB are highly concentrated in the mid-latitudes – 74% of Rs measurements and 78% of Rh measurements were made at a latitude greater than 30° N. The uncertainty of the bottom-up estimates is therefore likely to exhibit significant spatial and temporal variability due to sampling error alone, on top of errors related to the imposed functional form and its parameterization. To find one or more covariates between the expected
uncertainty of \( R_h \) and other factors, the errors associated with bottom-up implements at the SRDB sites were linearly regressed against the following possible predictors: latitude, longitude, mean and standard deviation of precipitation, mean and standard deviation of temperature, and mean predicted \( R_h \). Several non-linear functions of latitude were also tested. Of these, the mean predicted \( R_h \) and latitude were chosen as predictors because they had the greatest explanatory power (\( R = 0.23 \) when used in combination). Adding more predictor variables does not further increase the adjusted \( R^2 \).

In order to determine a spatio-temporally variable uncertainty range we calculated the 25th and 75th percentile of all 362 \( R_h \) errors associated with using the bottom-up model. These formed a baseline globally averaged confidence interval \( \delta_{base} \) that was then modified linearly based on the modelled \( R_h \) and latitude (consistent with the linear regression tests mentioned above):

\[
\delta_i = \delta_{base} \left( \frac{\gamma_1 + \gamma_2 R_{hb} + \gamma_3 \text{lat}}{\gamma_4} \right),
\]

where \( i \) denotes either the 25th or 75th percent confidence interval, \( R_{hb} \) is the predicted mean bottom-up heterotrophic respiration rate, \( \text{lat} \) is the pixel latitude, \( \gamma_{1-3} \) are regression parameters and \( \gamma_4 \) is the mean error of the bottom-up method across the SRDB dataset. Although the amount of variability in error captured using this method (\( R = 0.23 \)) is still extremely low, no alternative ways of capturing the expected spatio-temporal variability in bottom-up \( R_h \) uncertainty exist, and poorly accounting for this variability is still expected to be more useful than not accounting for it at all.

2.3 Comparison Analyses

We compared the mean and uncertainty estimates of the top-down and bottom-up annual \( R_h \) across latitudes. Because no bottom-up estimates of the seasonal cycle of \( R_h \) are available, we further compared the seasonality of \( R_h \) in different regions to the seasonality of \( R_h \) from bottom-up estimates and \( R_{top} \) from the top-down estimates. Pixels are seasonally aggregated for simplicity and plotting and to reduce noise from the propagation of atmospheric inversion uncertainty. In particular, we consider high-latitude regions (latitude greater than 55°N/S), mid-latitudes (latitude between 30 and 55°N/S), dry tropics (latitude < 30°N/S and mean annual precipitation less than 1500 mm/yr), and wet tropics (latitude < 30°N/S and mean annual precipitation greater than 1500 mm/yr). To calculate the uncertainty of the bottom-up \( R_h \) estimates, a method analogous to that used for determining the 25th-75th confidence interval of bottom-up \( R_h \) was used.
3 Results

3.1 Annual average $R_h$ from top-down and bottom-up estimates

3.1.1 Top-down $R_h$

The annual mean tropical $R_h$ is 450 ± 200 gC/m²/yr. The spatial pattern of mean annual $R_h$ is similar to that of GPP, (Fig. 3a, $R^2 = 0.97$, $p < 0.001$), as expected. More complex dynamics are revealed by considering the coefficient of variation (CV) of $R_h$ (e.g. temporal standard deviation divided by mean per grid cell, Fig. 3b). The CV does not closely follow known spatial patterns in biomes, GPP, turnover times, or other carbon parameters (e.g. (Anav et al., 2015; Bloom et al., 2016; Carvalhais et al., 2014; Hiederer & Kochy, 2011)), as it reflects a combination of all these factors. More information about the temporal variability of substrate availability (e.g. litter and soil organic matter) is needed to disentangle the climatic and biogeochemical controls on $R_h$ dynamics. This is left for a future investigation. Note that the high CV values in semi-arid regions are likely due to the near-zero mean $R_h$ there.

Fig. 4 shows the results of sensitivity analyses for each of GPP (by comparing the $R_h$ estimates with those derived using GPP from FLUXCOM), NEP (by comparing with $R_h$ estimates derived assuming zero NEP) and CUE (by comparing with $R_h$ estimates derived assuming a seasonally varying CUE as described in Sec 2.1). When the GPP data source is changed to FLUXCOM (Fig. 4a-b), the temporal dynamics of $R_h$ are most varied in the central American Plains, Australia, and in the tropics, especially in the Amazon. However, other hotspots for a mean difference exist, such as in Central Canada and Eastern Europe. Changing to using zero-value NEP (Fig. 4c-d) most significantly introduces a mean difference in the Southern Amazon and in Central Africa, though interestingly, the signs of the resulting difference are opposite between the continents. The temporal dynamics of these regions is also the most sensitive to inclusion of actual NEP estimates in the $R_h$ calculation. Despite the fact that NEP’s global mean value is more than an order of magnitude smaller than that of GPP, neglecting NEP causes large changes to the estimated $R_h$ over much of the globe, showing the value of including NEP estimates in the top-down $R_h$ calculation. Note however that the mean deviation in $R_h$ for either the NEP or GPP sensitivity analyses is still smaller than the mean difference between the top-down and bottom-up $R_h$ over most of the world. The only exception to this is in the high latitudes were all differences between estimates are of a similar magnitude.

Lastly, Fig. 4e-f shows the results of the sensitivity analysis assuming a temporally variable CUE. Overall, this sensitivity analysis leads to far smaller changes to $R_h$ than those for GPP and NEP. The magnitude of the $R_h$ change resulting from a change in CUE depends on whether the seasonality of GPP aligns with $R_h$ and whether the changed CUE causes unrealistic flux combinations across any of the ensemble members. The difference in time-average $R_h$ is relatively small - no more than 50 g C m⁻² yr⁻¹ for any pixel. Despite the change in seasonality of CUE, the temporal dynamics of the 36 months of estimated $R_h$ also remain relatively similar in the sensitivity analysis. More than 90% of pixels have an $R^2$ between the $R_h$ from constant CUE and the $R_h$ from seasonally variable CUE greater than 0.8. The largest difference in $R_h$ seasonality occurs in the wet tropics. In these regions, the average GPP is largest, and a change in CUE seasonality corresponds to the greatest absolute change in $R_h$. 

10
Fig. 5 maps the relative contributions of uncertainty in NEP, GPP, and CUE to Rh as calculated by consecutively recalculating Rh assuming in each case that all but one of the three datasets have zero uncertainty. The uncertainty in GPP is the dominant source of uncertainty in Rh across most of the globe, except in parts of the Amazon. Consistent with the CUE sensitivity analysis (Fig. 4c-d), the contribution of CUE to the Rh uncertainty is greatest in the tropics. In many high-latitude regions, NEP also contributes significantly to the overall Rh uncertainty. This contrasts with the results of the zero-NEP sensitivity analysis (Fig. 4c-d) in which NEP effects were no greater in the high-latitudes than elsewhere in the world, because the CMS-Flux NEP is close to zero in mean magnitude in the high-latitudes, but nevertheless relatively uncertain there. Overall, future efforts to improve top-down approaches for Rh estimation would likely benefit most from reduced uncertainty in remotely sensed GPP and NEP estimates.

3.1.2 Bottom-up Rs

The performance of the bottom-up approach at SRDB sites for both Rs and Rh is shown in Fig. 6. The influence of latitude on modelled Rh is stronger than on observed Rh (since the color patterns in Fig. 6 are largely horizontal). The uncertainties of the bottom-up method are high. Indeed, for both the bottom-up Rs and Rh, the root-mean-square error (RMSE) (421 g C m⁻² yr⁻¹ for Rs, 306 g C m⁻² yr⁻¹ for Rh) is only less than 15% lower than the RMSE for a model that simply predicted the average observed respiration value everywhere (RMSE = 488 g C m⁻² yr⁻¹ for Rs, 333 g C m⁻² yr⁻¹ for Rh). The Rs RMSE = 421 g C m⁻² yr⁻¹ is also higher than the 376 g C m⁻² yr⁻¹ RMSE value reported by Hashimoto et al. (2015) when their equation was applied to a smaller subset of the current SRDB dataset. The performance of the bottom-up model may be even worse on a cross-validation dataset that is entirely independent.

To test whether the bottom-up model can be improved, its parameters were optimized using a non-linear least squares fit. The resulting values (\(F = 1.30 \text{ g C m}^{-2} \text{ dy}^{-1}, a = 0.0565 \degree \text C^{-1}, b = 0 \degree \text C^{-2}, \alpha = 9.8, K = 0.0008 \text{ cm mo}^{-1}, c = 0.92, \text{ and } d = 0.75\)) were of a similar magnitude as the original parameters (\(F = 1.68 \text{ g C m}^{-2} \text{ dy}^{-1}, a = 0.0528 \degree \text C^{-1}, b = 0.000628 \degree \text C^{-2}, \alpha = 0.98, K = 1.20 \text{ cm mo}^{-1}, c = 1.22, \text{ and } d = 0.73\)), for all values except \(K\) and \(\alpha\), the two parameters controlling the relationship between precipitation and Rh. This suggests that precipitation is among the most uncertain controls of Rh, consistent with the fact that moisture limitations on Rh are mediated by soil water potential rather than precipitation. However, because using the optimized parameters led to only a 3% reduction in RMSE (from 306 g C m⁻² yr⁻¹ to 294 g C m⁻² yr⁻¹, Fig. S2), the original parameters were used elsewhere in the manuscript. Several constraints and alternative initial conditions were tested for fitting, but these did not lead to a better-performing fit (not shown). Some compensation between parameters is likely occurring when fitting to observations, reducing the quality of the fit.

In the absence of additional information about the bottom-up model uncertainty, the SRDB implementation and the associated errors were also used to determine a model for the uncertainty of the global bottom-up estimates. As shown in Fig. 7, the Rh experiments in the SRDB over-represent mid-latitudes but under-represent low and high latitudes relative to the distribution of global land area. This can also be seen visually in a map of the experimental locations (Fig. S3). As a result,
pixels with low $R_0$ (which are typical in the high-latitudes) are underrepresented in the SRDB, such that the bottom-up model has greater uncertainty there. These factors are accounted for by the dynamic uncertainty model in Eq. (5).

3.1.3 Comparison

The top-down and bottom-up estimates and their uncertainties are compared in Fig. 8. Global maps of the two $R_h$ estimates are also shown in Fig. S4. Except in boreal regions and in Australia, the top-down estimates are greater than the bottom-up estimates. This is reflected in their global averages, with mean $R_0$ rates of 452 g C m$^{-2}$ yr$^{-1}$ for top-down vs. 353 g C m$^{-2}$ yr$^{-1}$ for bottom-up estimates (43.6 Pg C yr$^{-1}$ and 33.4 Pg C yr$^{-1}$ respectively, summed across the globe). The highest magnitude fluxes are in the low-latitude tropics, consistent with findings for $R_s$ by Zhao et al. (2017), and the monotonic $R_h$ - $R_s$ relationship in Eq. (5). The difference between the two estimates is also largest in this region - top-down estimates are an average of 281 g C m$^{-2}$ yr$^{-1}$ larger than bottom-up ones between 30°S and 30°N, but are only 10 g C m$^{-2}$ yr$^{-1}$ larger than bottom-up estimates between 30° and 45°N/°S. When compared against SRDB observations (Fig. 6b), the bottom-up estimates were 500-2000 g C m$^{-2}$ yr$^{-1}$ or more lower than observations at several low-latitude sites, suggesting the bottom-up estimates may be underrepresenting $R_h$ across the region. The tropics is also the region where the relative uncertainties in both top-down

(57% median relative 25-75th confidence interval width) and bottom-up (76% median relative 25-75th confidence interval width) estimates are highest. For the bottom-up estimation, this is due to a lack of representative in situ observations, while for the top-down estimates, this is likely driven by uncertainties in NEP from atmospheric diffusion and satellite sampling in the atmospheric inversions (Liu et al., 2014) and GPP (Parazoo et al., 2014). Remarkably, although uncertainty estimates for both the bottom-up and top-down approaches were conservative, the two estimates are so different at low latitudes that there is almost no overlap in their uncertainty ranges.

The greatest overlap between the two datasets and their uncertainty range occurs between 30° and 50° degrees North, where more than 48% of SRDB observations fall and the bottom-up estimates are likely the most reliable. At high-latitudes (above 55° N), the top-down uncertainty narrows but the bottom-up uncertainty does not. In this region, bottom-up uncertainties are about 30% greater than the uncertainties of the top-down $R_h$.

3.2 Seasonal cycle of respiration components

The bottom-up estimates only provide $R_h$ at annual timescales. To gain insight into the realism of the seasonal cycle of the top-down $R_h$ estimates, they are compared to the seasonal cycle of bottom-up $R_s$ and top-down $R_{net}$ in several regions in Fig. 9. Consistent with the low values of bottom-up $R_s$ (Sec 3.1.3), the top-down $R_s$ are not much lower than $R_h$. There is significant overlap between the uncertainty ranges of both in many region-month combinations, despite the fact that true $R_s$ is always lower than (or equal to) $R_h$ due to the occurrence of belowground autotrophic respiration. Indeed, the bottom-up $R_s$ and top-down $R_h$ nearly overlap in the period January-March in the wet tropics. Remarkably, during boreal winter at high
latitudes, the top-down $R_{co2}$, $R_a$, and $R_h$ all agree. This is likely because the constant CUE assumption assumes that $R_a$ is near-zero in boreal winter when GPP shuts down, which may not be realistic. Previous studies have found that winter-time $R_a$ can provide as much as 20% or more of total boreal soil CO$_2$ fluxes (see overview in Hobbie et al., 2000), but only 5.2% of bottom-up estimated $R_a$ and 8.8% of top-down estimated $R_h$ here occurs between December and February. In the dry tropics, the seasonal cycle of top-down $R_h$ is remarkably flat, and flatter than that of bottom-up $R_a$. This could be explained by the fact that temperature, moisture, and substrate variabilities do not vary the same way across the seasons and may partially compensate for one another. However, more research is needed to determine what controls dry tropical variations in $R_a$ and a detailed investigation of this issue is beyond the scope of this paper.

The ratio of estimated $R_h$ to $R_{co2}$ spans between close to 1 in high-latitude winters and 0.4 in the wet tropics. Similarly, the ratio of $R_a$ to $R_h$ varies from 0.75 to 0.94 for different month-region combinations.

4 Discussion

4.1 Uncertainties in top-down and bottom-up approaches are both uncertain

Top-down estimates of $R_a$ are 30% higher, on average, than bottom-up estimates. At low-latitudes, the top-down estimates of $R_a$ are so much larger than the bottom-up ones that there is almost no overlap between their respective 25th-75th uncertainty intervals, despite efforts to create conservative uncertainty intervals in each case. Consistent with these results, the bottom-up $R_a$ were previously shown to be biased low relative to models from the Climate Model Intercomparison Project 5 (CMIP5) (Taylor et al., 2012) in the low-latitudes, though it is unclear whether this is because CMIP5 models are biased high or because the bottom-up estimates are biased low relative to true $R_a$ (Hashimoto et al., 2015, Fig. 10). Zhou et al. (2009) found that attributing a globally uniform Q$_{10}$ value decreases model-simulated average $R_a$ by 40%, and a similar dynamic may be causing the bottom-up $R_a$ estimates to be too low. It should also be noted that the global average $R_a$ estimates of the bottom-up approach are 10-20 Pg lower than the six other estimates of global $R_a$ published in the last decade (Bond-Lamberty, 2018), and that a lower bottom-up $R_a$ leads to a lower bottom-up $R_h$ (Eq. 5).

The top-down and bottom-up approaches to estimation of $R_a$ have complementary strengths and weakness, as detailed in Table 1. Top-down estimates are indirect, and errors and uncertainties in any of the source datasets can propagate to errors and uncertainties in the retrieved $R_a$. These include the assumption of a temporally constant CUE, which among others, can lead to unrealistically low $R_a$ in boreal winters. Additional uncertainties also include, for example, choices made in the atmospheric inversion (Peylin et al., 2013) or the retrieval of SIF and its scaling to GPP (e.g. whether a constant set of values is used, or whether this scaling is dynamic as in the Parazoo et al (2014) data used here). GPP is the most uncertain of the input fluxes (Fig. 5). Despite their uncertainties, the top-down estimates are globally representative. By contrast, bottom-up upscaling starts with more accurate, direct observations of $R_a$, but suffers from a lack of representativeness: these direct observations are often temporal snapshots covering only a single or few years at a given site, with the time period observed
varying dramatically between sites. More importantly, they under-represent boreal and tropical regions, and may over- or under-sample disturbed sites in different regions. While the uncertainties of the remote sensing datasets used for top-down estimation vary in space, show some variations across different parts of the globe, remote-sensing based estimates of vegetation properties such as photosynthesis and plant traits (Schimel et al., 2015) and biomass (Saatchi et al., 2015) have previously been argued to contain significantly lower sampling error, representativeness error than bottom-up estimates (Saatchi et al., 2015; Schimel et al., 2015). A similar dynamic is at play for Rh.

The top-down approach introduced here is dependent on the quality of the input datasets used. Among the sensitivity analyses performed, NEP and GPP generally had a greater effect on the resulting Rh than the assumed values of CUE. The primary GPP and NEP datasets used here (those from Parazoo et al. (2014) and CMS-Flux, respectively) are sensitive to both observational error (e.g. due to cloud cover) and uncertainties in the retrieval algorithms (including, but not limited to, uncertainties in the relationship between SIF and GPP and, for NEP, in the inversion of atmospheric transport models). As shown in Fig. 4, uncertainties in top-down GPP and NEP can have significant effects on the mean and temporal variability of Rh estimated. Nevertheless, the sensitivity of Rh to alternative GPP and NEP assumptions was still lower than the difference between the top-down and bottom-up Rh estimates everywhere outside the high-latitudes. Thus, despite the large sensitivity of the top-down Rh to the quality of the input datasets (and to a lesser degree, to the assumption of constant CUE), our new approach still provides meaningful new constraints on Rh not available from bottom-up estimation alone.

For the bottom-up approach, the errors associated with sampling bias are likely also exacerbated by the uncertainty in parametrizing a single functional model and the difficulty of parameter optimization. When the model parameters were re-fit on a version of the SRDB that was slightly expanded from that used in Hashimoto et al. (2015), the precipitation-sensitivity parameterization changed dramatically, while the error statistics remained similar, suggesting possible overfitting. Furthermore, even comparing against an SRDB dataset that was similar to that used to derive the original parameters, the bottom-up approach barely had improved error statistics (RMSE of 306 g C m⁻² yr⁻¹) relative to a model that simply ignores spatial variations and everywhere assigns the same value (RMSE of 333 g C m⁻² yr⁻¹). Such results suggest a structural problem with the underlying modelling approach (no good parameters exist), but also call into question whether currently used parameters are truly optimal given the model structure. In a recent study, machine-learning based approaches for estimating Rh were able to explain 60-70% of the Rh variability (Zhao et al., 2017), considerably more than the 35% variability explained in this study using the Hashimoto et al. (2015) approach. If the robustness of machine learning based bottom-up upscaling methods can be further established, they may form a path forward for improved fidelity of bottom-up estimation of Rh, and for allowing estimation of Rh at a temporal resolution finer than the current annual timescales. However, the number of Rh observations in the SRDB - and presumably the literature as a whole - is 5 times smaller than the number of Rs sites. Thus, additional measurements of Rh are needed for this approach, and they must include under-sampled areas. This is unlikely to be possible in the foreseeable future.

Despite the complementary sources of uncertainties in both top-down and bottom-up Rh estimates, the strong overlap between the two estimates and their uncertainty ranges in latitude range 30-50°N (the same latitude range where SRDB
observations are most common, Fig. 7) is encouraging. Indeed, if the uncertainty of top-down estimates can be reduced, they could be used to benchmark, constrain or help parameterize bottom-up models similar to those used in bottom-up R_h estimation compared to here, allowing creation of a longer record than may be possible with top-down observational data alone.

4.2 General applicability of the carbon balance inversion method

This paper introduced a new method for top-down estimation of R_h by calculating it as the residual of the carbon balance. The propagation of uncertainty under realism constraints (in the form of the correct sign on each of the respiration components and GPP) is key to avoiding large errors in this approach because the NEP is of considerably smaller magnitude than the other terms in the carbon balance. In this paper, we used large-scale, regionally available estimates for the carbon balance components, including recently developed atmospheric inversion-based NBE and NEP estimates from CMS-Flux. However, this approach could also be applied at finer resolutions, for example using regional scale atmospheric inversions. If the local carbon use efficiency can be determined (Tang et al., 2019), the method could also be applied at smaller spatial and temporal scales, such as to data from eddy covariance towers. For example, constraints based on estimates of R_h from a carbon balance inversion could be useful in upscaling chamber-based soil respiration measurements to the tower scale, which could help explain inconsistencies between tower and chamber measurements of respiration fluxes (Barba et al., 2017; Phillips et al., 2016).

4.3 Implications for carbon climate feedbacks

The response of terrestrial net carbon fluxes to climate changes is likely to feed back to future climate (Bodman et al., 2013), but the sign and magnitude of this feedback is highly uncertain (Friedlingstein et al., 2014). The tropics likely form a dominant control on global carbon-climate feedbacks (Cox et al., 2000; Schimel et al., 2015). However, in the period 2010-2015, GPP explained less than 1/3 of variations in tropical NEP, suggesting an important role for R_a and R_h in controlling net terrestrial carbon uptake and its climate sensitivity (Sellers et al., 2018). A recent modeling study also suggested that R_h forms a dominant control on NBP at multi-decadal timescales (Zhang et al., 2018). Studies of climate-carbon feedbacks commonly consider either R_a or R_h, but in doing so they confound two separate respiration components (total R_a and R_h, or belowground R_a and R_h, respectively), which have different biogeophysical controls and responses to climate. The large spatial and temporal variations in the ratio of top-down heterotrophic to R_a and R_h in Fig. 8 act as a reminder that heterotrophic respiration should be studied separately from other respiration fluxes in this context. Indeed, data-driven estimation of R_h can be particularly useful for validation of earth system models, as many of these do not even include R_h as a separate variable.

The recent launch of TROPOMI, which has daily coverage and approximately 7 x 3.5 km pixel resolution, will greatly increase measurements of SIF, and hence will also greatly increase the number of estimates of GPP (Kohler et al., 2018), the largest source of uncertainty in the global R_h estimates (Fig. 5). Increased data density from OCO-2 (Crisp et al., 2004)
et al., 2017a) and in the future GeoCarb (Polonsky et al., 2014) should also provide better regional estimates of NEP. With these and other improvements to remote sensing-driven estimates of GPP and NEP, top-down estimation of R_h may be a promising avenue to better understand the role of R_h fluxes in carbon-climate feedbacks. However, because the temporal variability of the derived R_h varies depending on the quality of the GPP, NEP, and CUE datasets (as well as, to a lesser degree, the assumed constancy of the CUE assumptions), any studies using top-down R_h should carefully consider uncertainty propagation in any hypothesis testing. The assumption of constant CUE employed here has a particularly strong effect on the seasonal cycle of R_h in the wet tropics (Fig. 4b) and should be taken in assessing how this assumption propagates to other studies of top-down R_h variations. Nevertheless, temporal CUE variations in previous studies in the tropics have shown that seasonal variations in CUE are 0.05 or smaller (Rowland et al., 2014), less than assumed in the sensitivity analysis performed here. If more light can be shed on the drivers of variations in CUE, nevertheless, with careful consideration of uncertainty, top-down estimation may be a promising approach for understanding or bounding the role of R_h in carbon-climate feedbacks.

Data availability
Data are available at https://github.com/agkonings/ReHet and http://cmsflux.jpl.nasa.gov. Upon acceptance of the manuscript, the heterotrophic respiration data will be further deposited with a DOI.

Author Contributions
AGK, AAB, and DSS conceived of the idea, and AGK, AAB and KWB designed the research. AGK performed the research. AAB, JL, NCP, and KWB contributed remote sensing datasets. AGK wrote the first draft of the manuscript and all authors edited the manuscript and contributed to the interpretation of results.

Competing Interests
The authors declare that they have no conflict of interest.

Acknowledgements
The research was partially carried out at the Jet Propulsion Laboratory, California Institute of Technology, under a contract with the National Aeronautics and Space Administration. KWB, JL, and AAB acknowledge the support of NASA NNH14ZDA001N-CMS. AGK, AAB, JL, DS, and KWB also acknowledge the support of NASA NNH16ZDA001N-IDS.

References


Brix, H., Menemenlis, D., Hill, C., Dutkiewicz, S., Jahn, O., Wang, D., Bowman, K. and Zhang, H.: Using Green’s Functions...
to initialize and adjust a global, eddying ocean biogeochemistry general circulation model, Ocean Model., 95, 1–14, doi:10.1016/j.ocemod.2015.07.008, 2015.


<table>
<thead>
<tr>
<th>Advantages</th>
<th>Disadvantages</th>
</tr>
</thead>
<tbody>
<tr>
<td>Top-down</td>
<td>Inherently global</td>
</tr>
<tr>
<td></td>
<td>Uncertainty in constant CUE assumption</td>
</tr>
<tr>
<td></td>
<td>Uncertainty in NEP and GPP data</td>
</tr>
<tr>
<td>Bottom-up</td>
<td>Based on direct, high-resolution measurements</td>
</tr>
<tr>
<td></td>
<td>Sparse, non-representative sampling</td>
</tr>
<tr>
<td></td>
<td>Based on temporal snapshots in non-consecutive years</td>
</tr>
</tbody>
</table>

Table 1: Advantages and disadvantages of top-down vs. bottom-up estimation methods.
Figures

Figure 1: Schematic diagram of process used to calculate heterotrophic respiration $R_h$. Input datasets are outlined in red, and data sources are described in blue italics. Arrows indicate one flux is used to calculate another. Data sources are described in detail in Section 2.1.2

Figure 2: Global variations in mean carbon use efficiency from CARDAMOM
Figure 3: Spatial variability in top-down $R_h$. Maps of (a) mean $R_h$ [g C m$^2$ yr$^{-1}$] and (b) temporal coefficient of variation of top-down $R_h$, calculated based on monthly data over 2010-2012.
Figure 4: Results of sensitivity analyses for three input datasets. (left) Mean difference [gC m$^{-2}$ yr$^{-1}$] between baseline top-down RH and alternate-input top-down RH and (right) $R^2$ between baseline top-down RH and alternate-input top-down RH. Sensitivity analyses performed include using FLUXCOM GPP (top row), assuming uniformly zero values of NEP (middle row) and assuming CUE varies temporally in a manner proportional to GPP (bottom row). (left) Mean difference [gC m$^{-2}$ yr$^{-1}$] between $R_h$ assuming constant CUE and $R_h$ assuming CUE varies temporally in a manner proportional to GPP and (right) coefficient of variation ($R^2$) between $R_h$ assuming constant CUE and $R_h$ assuming CUE varies temporally in a manner proportional to GPP.
Figure 5: RGB map of relative contributions to $R_h$ uncertainty in each of the input datasets, NEP (red), CUE (blue), and GPP (green).
Figure 6: Comparison of observed annual respiration terms at SRDB sites vs. bottom-up estimates at the same sites for (left) 1979 soil respiration sites and (right) 362 heterotrophic respiration sites. Each point denotes a single experiment and is colored by the experiment’s latitude.

Figure 7: Distribution of all SRDB experiments (red dashed lines) and global land points where top-down retrievals were possible in terms of (left) latitude and (right) bottom-up modelled $R_h$. Modelled $R_h$ rather than observed $R_h$ were used for the SRDB data in the comparison to isolate the differences due to the representativeness of the SRDB experiments relative to the entire global land area, and remove any possible effects of biases in modelled global values and observed SRDB values.
Figure 8: Longitudinally-averaged $R_h$ as estimated from top-down (black solid line) and bottom-up (blue dashed line) estimates, respectively. Shaded areas represent the average 25th-75th uncertainty bars at each latitude.

Figure 9: Comparison between regionally and temporally averaged seasonal cycle of different respiration components: top-down $R_h$ (black solid line and area), bottom-up $R_s$ (blue dashed line and area), and top-down $R_{eco}$ (red dash-dotted line and area). Shaded areas represent the average 25th-75th uncertainty bars at each latitude. (top left) high latitudes (latitude > 55 N/S), (top right) mid-latitudes (30 N/S < latitude < 55 N/S), (bottom left) dry tropics (latitude < 30 N/S and mean annual precipitation < 1500 mm/yr), and (bottom right) wet tropics (latitude < 30 N/S and mean annual precipitation > 1500 mm/yr).
Figure S1: Root-mean-square sum of the normalized difference between the prior and posterior CMS-Flux NEP estimates (where the posterior flux is used for normalization).

Figure S2: Comparison of observed annual respiration terms at SRDB sites vs. bottom-up estimates at the same sites for (left) 1979 soil respiration sites and (right) 362 heterotrophic respiration sites. Parameters in the bottom-up equations are sequentially optimized on the entire $R_s$ dataset. All $R_s$ observations are then used to optimize the parameters of the $R_h$-$R_s$ relationship. Each point denotes a single experiment and is colored by the experiment’s latitude.
Figure S3: Locations of $R_h$ experiments in SRDB.

Figure S4: Mean $R_h$ [gC m$^{-2}$ yr$^{-1}$] from the (left) top-down and (right) bottom-up models.