Response to all reviewers

We would like to thank the reviewers for their assessment of our manuscript. Based on suggestions made by the reviewers, we plan on making several modifications to our text, uncertainty approach, figures and references in our revision. Many of the reviewers' suggestions will improve the manuscript. It is important to note, however, that we respectfully and firmly disagree with many of the issues raised in the review of Eric Kasischke. We provide a summary of changes that we plan on and detailed point-by-point responses to each reviewer further below.

This is a summary of changes that we propose to make after incorporating comments from the reviewers:

a) We plan on providing additional context in the introduction that highlights the need for our modeling and remote sensing approach and the dataset presented in our paper. We will also more carefully describe how our study is different from previous work in this field

b) We plan on adding a new paragraph in the Discussion section that more closely relates the advances described in our paper with past work in the field

c) We plan on providing additional analysis and discussion of some of the key uncertainties in our approach. These will include uncertainties that may originate from the land cover classification, scaling factors developed with Consume for other cover types than black spruce, and scaling from 30 m to 450 m.

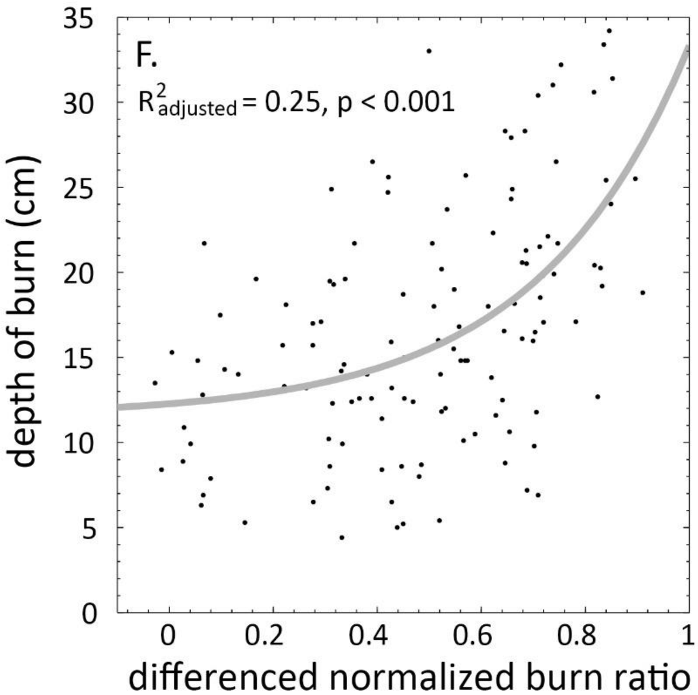
d) We plan on adding several references and provide clarifications of sentences and figures

Given the nature of the review by Eric Kasischke, we will start with highlighting what makes this paper unique and why we feel this is a significant advance in this field. **The Alaskan Fire Emissions Database (AKFED) developed in this study is the first Alaska wide daily burned area and emissions product for all fires since 2001 that is publicly available (from ftp) for atmospheric trace gas, chemistry and aerosol applications.** The database is developed using as much field data that overlaps with MODIS satellite era (from three different publications) and builds on observed relationships between field and remotely sensed variables. Post-fire remote sensing observations are used in synergy with other environmental variables to further constrain carbon consumption estimates. Using MODIS active fire hotspots we are able to retrieve a validated temporal accuracy of one day. Our emissions dataset includes an uncertainty layer that is based on the variability observed in the relationships between field data and environmental variables. We will update this layer based on the revisions made to the uncertainty analysis. Both the carbon consumption and uncertainty estimates are driven by field observations. This considerably advances the state-of-the-art of carbon consumption models for Alaskan fires. To the best of our knowledge, no spatially explicit decadal fire emissions time series with daily temporal resolution has previously been developed for Alaska. Further, no publicly available dataset has included quantitative estimates of uncertainty.

These elements of emissions modeling are crucial for advancing the field, by enabling rigorous comparisons with other modeling approaches, and by allowing for new science in large field campaigns such as NASA's Carbon in Arctic Reservoirs Vulnerability Experiment (CARVE) (https://ilma.jpl.nasa.gov/portal/) and Arctic-Boreal Vulnerability Experiment (ABoVE) (http://above.nasa.gov/) field projects that require estimates of trace gas emissions to compare with top-down aircraft and satellite measurements. A previous manuscript that came closest to this goal was from Kasischke & Hoy (2012). This valuable paper provides a first effort in spatially explicit carbon consumption estimates for a limited number of 75 fire events over the course of four different years. To the best of our knowledge, the resulting data layers have not been made publicly available. We, in contrast, provide consistent and complete Alaska wide spatial coverage and included a total of 629 fires between 2001 and 2012. We recently uploaded our estimates from 2013 at our ftp site and we will continue our data production as part of NASA's CARVE project. Although the carbon consumption model for black spruce ecosystems from Kasischke and Hoy (2012) integrated findings of a valuable prior paper (Turetsky et al., 2011), no direct calibration and/or validation of their model was undertaken using existing and publicly available field data. Their uncertainty approach also relied on 'best-guess' uncertainties of the input layers and was not observation-driven. We extensively discussed differences and similarities between the Kasischke & Hoy (2012) paper and our approach in the manuscript.

We, in contrast, used the available field data to quantify relationships between field data and environmental variables, to calibrate and validate our model, and to derive uncertainties driven by observed variability between field data and environmental variables. Our publicly available dataset will enable, for the first time, research opportunities that require the inputs at the spatial and temporal resolution provided by our dataset. Research opportunities that could benefit from our presented dataset could include a better understanding of controls and limits on fire growth, emission factors, climate feedbacks from changing boreal fire regimes, transport of smoke plumes, and the impacts of smoke on aerosols and human health. Work is already underway to convolve our emissions estimates with air transport models to assess trace gas variability at tower stations in the framework CARVE. Our publicly available data will also be useful within the framework upcoming ABoVE project (http://above.nasa.gov/). If our paper passes through peer review, we plan on making our data available on the ABoVE Science Cloud (http://above.nasa.gov/science_cloud.html).

Two reviewers (anonymous reviewer 2 and Eric Kasischke) expressed reservations about the use of the use of the dNBR to estimate belowground pyrogenic consumption in our study. We are aware of the debate and contrasting previous findings on this topic. It is important to note that we statistically analyzed the utility of the dNBR to estimate pyrogenic consumption. We included the dNBR as environmental variable in the carbon consumption model because our analysis provided mathematical proof that the dNBR's inclusion resulted in a better performance. Following our analysis and Figure 4, we demonstrated that the dNBR was retained as a variable that improved the skill of our depth of burn and belowground carbon consumption models. In addition, as an individual variable, dNBR was significantly related to depth of burn field and belowground carbon measurements ($p < 0.01$) following a nonlinear relationship (Figure S7F and SF8). We want to repeat that we do not recommend using dNBR as a stand-alone predictor, rather we recommend its careful calibration with field measurements and its synergistic use with other environmental variables.



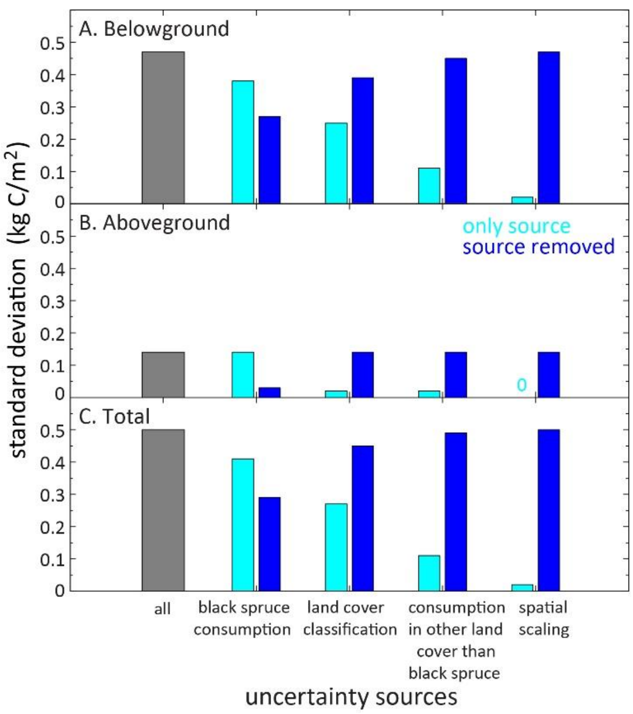
Supplementary Figure 7F. Relationship between dNBR and depth of burn.

We also corroborate with conclusions made in French et al. (2008) and Barrett et al. (2010, 2011). In the abstract of their review paper, French et al. (2008) stated:

'Results from relating and mapping fire/burn severity within the boreal region have been variable, and are likely attributed, in part, to the wide variability in vegetation and terrain conditions that are characteristic of the region. Satellite remote sensing of post-fire effects alone without proper field calibration should be avoided. A sampling approach combining field and image values of burn condition is necessary for successful mapping of fire /burn severity. Satellite-based assessments of fire /burn severity, and in particular dNBR and related indices, need to be used judiciously and assessed for appropriateness based on the users' need.'

We found this review paper an excellent assessment of the difficulties encountered in relating spectral information to fire severity in boreal forest ecosystems and we have fully integrated this knowledge into our study design. We also agree with findings of Barrett et al. (2010, 2011) who demonstrated the predictive power of the combined use of spectral and non-spectral data.

We really appreciated the reviewers' constructive suggestions on the uncertainty approach. We will fully integrate these in our revision. We will provide additional analysis and discussion on uncertainty. We identified four main sources of uncertainty. The first source is the result of the unexplained variance in the black spruce consumption model. The other sources of uncertainty were related to assumptions and data required to extrapolate the model over Alaska. These included uncertainties in the land cover classification, assumptions made for deriving carbon consumption for other land cover types than black spruce, and spatial scaling of a model developed with 30 m data at 450 m resolution. We ran a Monte Carlo analysis and the following new figure summarizes our new findings. This figure will be included in our revision.



New figure that we plan on integrating in the revision: Attribution of uncertainty sources in (A) belowground, (B) aboveground and (C) total carbon consumption estimates. The standard deviation of the consumption estimates from 1000 Monte Carlo simulations was calculated for each scenario.

We responded to the reviewer point-by-point comments in alphabetical order (anonymous reviewer 2 on p. 5-15, Kane Evan on p. 16-18, and Kasischke Eric on p. 19-51) below and we numbered our responses throughout. We apologize for any repitition that may occur in different comments to different reviewers.

Point-by-point responses to anonymous referee 2

Overall Evaluation This manuscript presents the results of a study that develops and applies algorithms to predict fire emissions in Alaska to produce the Alaska Fire Emissions Database (AKFED) that will be updated regularly. The approach of AKFED is similar to that of the Global Fire Emissions Database (GFED), which is not surprising as both databases have been developed with one of the author's (James Randerson's) involvement. The strength of AKFED is that it is daily and will be updated regularly. I was also impressed with the amount of data that were pulled together into the development of the database. However, it was very disappointing to see that there really wasn't any difference in the regional estimates between AKFED and GFED3s (Table S3). No regional uncertainties are presented for either approach, so we don't know if AKFED has reduced uncertainty compared to GFED3s. In my opinion, the authors need to do a more complete job on identifying and quantifying the uncertainties in the AKFED approach. The authors do try to address uncertainties in the Discussion, but I felt that there were some sources of uncertainty that were not adequately addressed in the manuscript. I breakdown these uncertainties into (1) conceptual uncertainties concerning controls, (2) uncertainties associated with possible aggregation errors, and (3) the proper quantification of uncertainty at regional scales. Some of these issues have been highlighted by the other reviewers, but here I provide my perspective. In my opinion, some of these issues will need to be addressed in the Results section, but others can be addressed in the Discussion section (I'll try to be clear about this below).

1) Our dataset is not only an advance in spatial and temporal resolution compared to GFED3s, a global-scale fire emissions product, it also represents a significant advance for regional fire emission modeling in Alaska. We systematically map all fires since 2001 using a quantitative methodology that is directly driven by field and remote sensing observations and easily extendable in time. The approach and product include an uncertainty layer that is based on the variability observed in the relationships between field data and environmental variables. Based on the reviewers' comments we plan on extending our uncertainty analysis (see other responses). Our publicly available dataset will enable research opportunities that require the inputs at the spatial and temporal resolution provided by our dataset. Research opportunities that could benefit from our presented dataset could include a better understanding of controls and limits on fire growth, emission factors, climate feedbacks from changing boreal fire regimes, transport and exposure of smoke plumes. Work is already underway to convolve our emissions estimates with air transport models to assess trace gas variability at tower stations in the framework of the Carbon in Arctic Reservoirs Vulnerability Experiment (CARVE) project (https://ilma.jpl.nasa.gov/portal/). Our publicly available data will also be useful within the upcoming Arctic-Boreal Vulnerability Experiment (ABoVE) project (http://above.nasa.gov/). If our paper passes through peer review, we plan to make our data available on the ABoVE Science Cloud (http://above.nasa.gov/science_cloud.html). We think that informing global-scale emission models, like GFED, with regionally tuned estimates is valuable to the developers of global products in order to identify discrepancies and develop potential refinements to their global product. We therefore included this comparison as Supplementary Table 3 in our original manuscript. We think that this comparison is valuable within the scope of our work. Given AKFED's region-specific calibration and validation, and its higher spatial and temporal resolution than GFED3s, AKFED is the reference dataset in this comparison. We also found that the reviewer's statement 'that there really wasn't any difference in the regional estimates

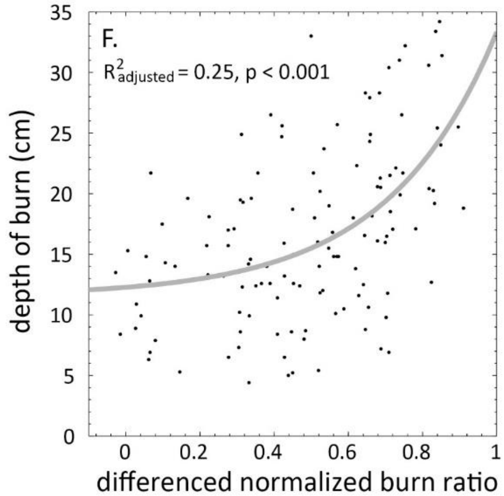
between AKFED and GFED3s (Table S3)' an incomplete judgment. It is true that the burned area estimates from GFED3s and AKFED were fairly similar. Table 3S, however, also shows that aggregated over 2001-2010, AKFED carbon emission estimates were approximately 10 % higher than GFED3s. There were also important differences between AKFED and GFED3s estimates for the large fire years 2004, 2005 and 2009. There was also no correlation between the spatial distribution of carbon consumption from AKFED and GFED3s. These are important nuances to the AKFED-GFED3s comparison that we present, especially for future studies operating at more local scales. The fact that the state wide carbon emissions correlated reasonably well (with an underestimation from GFED3s compared to AKFED) is driven by the similar burned area estimates and the fact that mean carbon consumption estimates (even though their spatial distribution is different) were similar. We find that we provided an honest and nuanced description of the AKFED-GFED3s comparison on p17598l3-24.

We sincerely appreciated the reviewer's comments that pushed for the inclusion of an extended and region wide uncertainty analysis. We will fully integrate these in our revision. We will provide additional analysis and discussion on uncertainty. We identified four main sources of uncertainty. The first source is the result of the unexplained variance in the black spruce consumption model. The other sources of uncertainty were related to assumptions and data required to extrapolate the model over Alaska. These included uncertainties in the land cover classification, assumptions made for deriving carbon consumption for other land cover types than black spruce, and spatial scaling of a model developed with 30 m data at 450 m resolution. We ran a Monte Carlo analysis to estimate the region wide uncertainty and to determine the relative importance of individual uncertainty sources. Details on this analysis and discussion can be found in the responses below.

Conceptual Uncertainties Concerning Controls Similar to referee Kasischke, I was taken aback by the use of dNBR as an explanatory variable in this study given the importance of belowground carbon consumption to fire emissions and the difficulty for a spectral index like dNBR to address this issue. The authors explain this may be because of a correlation between above ground consumption and below ground consumption. I think that this is an important hypothesis to be stated in this study, as the data supporting it is rather limited. A fuller discussion of the use of dNBR is warranted in the Discussion section, as it brought out in the Kasishcke review. Clearly, a call for more data on the issue of the correlation between above and below ground consumption is needed. I was also quite surprised by the differences in the controls identified by this study and those identified by Genet et al. (2013, ERL), given that they were using the same basic data; the Genet et al. (2013) controls are similar to those of Barrett et al. (2010). Genet et al. (2013) indicated that the relative organic layer loss could not be adequately explained by a single regional model for black spruce, and that the data were better explained by developing separate models for flat lowlands, flat uplands, and slopes. Would uncertainties in AKFED be reduced by taking an approach similar to Genet et al. (2013)?

2) We are aware of the debate and contrasting previous findings on this topic. It is important to note that we statistically analyzed the utility of the dNBR to estimate pyrogenic consumption. We included the dNBR as environmental variable in the carbon consumption model because our analysis provided mathematical proof that the dNBR's inclusion resulted in a better performance. Following our analysis and Figure 4, we demonstrated that the dNBR was retained as a variable that improved the skill of our depth of burn and belowground carbon consumption models. In addition, as an individual variable, dNBR was significantly related to depth of burn

field and belowground carbon measurements ($p < 0.01$) following a nonlinear relationship (Figure S7F and SF8). We want to repeat that we do not recommend using dNBR as a stand-alone predictor, rather we recommend its careful calibration



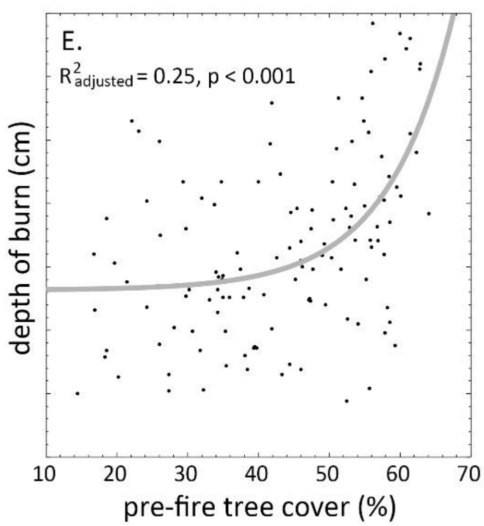
Supplementary Figure 7F. Relationship between dNBR and depth of burn.

with field measurements and its synergistic use with other environmental variables.

We also corroborate with conclusions made in French et al. (2008) and Barrett et al. (2010, 2011). In the abstract of their review paper, French et al. (2008) stated:

'Results from relating and mapping fire/burn severity within the boreal region have been variable, and are likely attributed, in part, to the wide variability in vegetation and terrain conditions that are characteristic of the region. Satellite remote sensing of post-fire effects alone without proper field calibration should be avoided. A sampling approach combining field and image values of burn condition is necessary for successful mapping of fire /burn severity. Satellite-based assessments of fire /burn severity, and in particular dNBR and related indices, need to be used judiciously and assessed for appropriateness based on the users' need.'

We found this review paper an excellent assessment of the difficulties encountered in relating spectral information to fire severity in boreal forest ecosystems and we have fully integrated this knowledge into our study design. We also agree with findings of Barrett et al. (2010, 2011) who demonstrated the predictive power of the combined use of spectral and non-spectral data. In our original manuscript we introduced, analyzed and the discussed the utility of the dNBR for pyrogenic consumption estimates in detail (e.g. dNBR had a separate section in discussion) and we compared our work to all pertinent previously published work on the topic. We will



Supplementary Figure 7E. Relationship between tree cover and depth of burn.

expand this discussion. Our results provide mathematical evidence for the synergistic use of the dNBR in combination with other environmental variables and field data. This is an important contribution to a long-going debate.

We also find that the mechanism behind the inclusion of the dNBR and tree cover as environmental variables is robust, i.e. that aboveground and belowground consumption are related, as can be inferred from the significant relationships between tree cover and depth of burn, and belowground consumption. This idea builds on earlier published work by Rogers et al. (2014) (see Supplementary Figure 3 in their manuscript). Our work considered 126 plots from 3 different publications (Boby et al., 2010; Turetsky et al., 2011; Rogers et al., 2014) encompassing a range of burning conditions (pre-fire tree cover, seasonality, topographic conditions). We fully agree with the reviewer that more data will improve our understanding of these relationship and we will integrate a call for more data in our discussion section.

Based on findings of previous work on this topic (Barrett et al., 2010, 2011; Turetsky et al., 2011; Genet et al., 2013) we fully integrated variables related to topography and drainage into our research design and analysis during AKFED development. We already reported in the original manuscript that, as individual variables, slope was significantly correlated with both depth of burn and belowground C consumption, and northness was significantly correlated with belowground consumption ($p < 0.05$, Supplementary Figures 7 and 8). As reported in the manuscript, inclusion of slope and northness did not result in additional explained variance when using the multiplicative models.

We are aware that previous work has focused on more complex variables that can be derived from a DEM. We have therefore considered and tested such variables in the development of the 30 m consumption model, but they had no relationships with field measurements as individual variables, neither did they contribute to the final model through interactions with other variables. To illustrate this we show the scatter plots between flow accumulation and curvature at 30 m, and the corresponding depth of burn field measurements (Figure below).

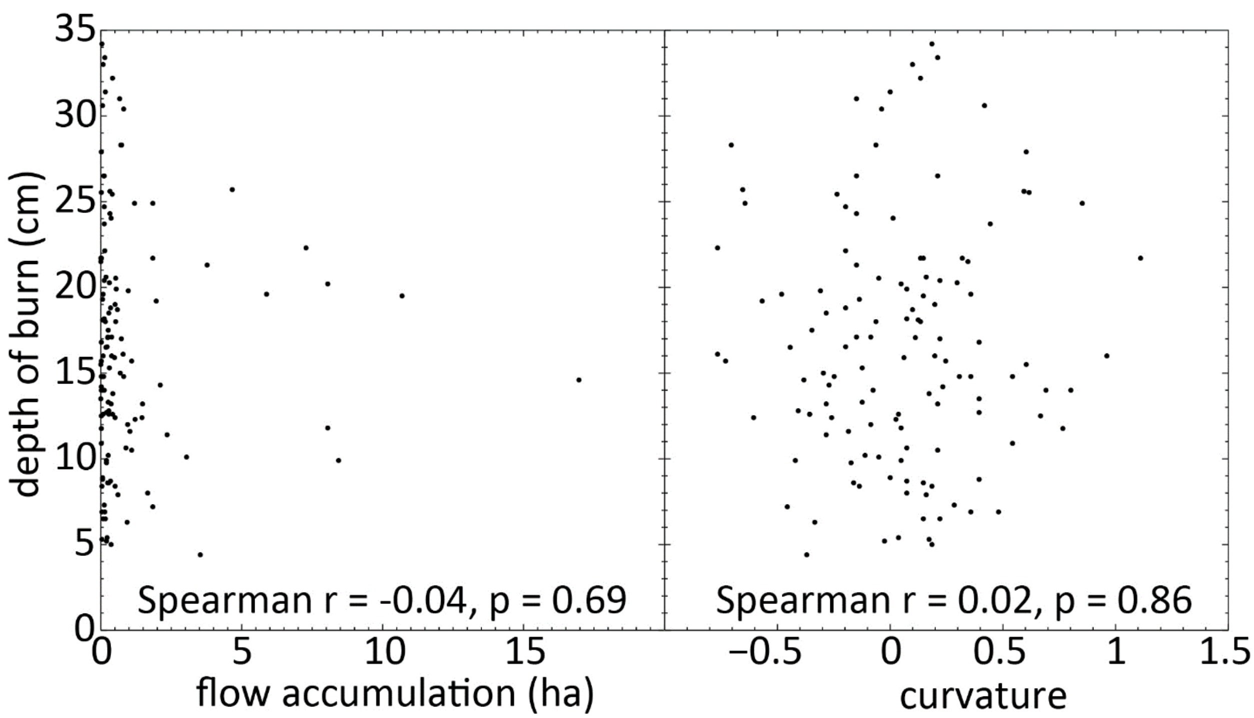


Figure. Scatter plots between depth of burn field measurements and (left) flow accumulation, and (right) curvature extracted from a 30 m DEM.

We agree that it is interesting that our dataset, which covers data from 3 different independent publications, did not reveal similar topographic controls on consumption compared to previous research. Although these variables did not contribute in our analysis, we do agree that some additional discussion on this topic may be of interest of our readership and we plan on integrating some additional discussion in the revision. We hypothesize that the controls that we identified operate at the regional scale of the state of Alaska, the domain of our study, while local drainage conditions may allow further refinements. This wasn't realized based on the dataset we used, we however do not exclude this possibility, and this again is a call for more data. This comparison with previous work was an interesting point that we already discussed in our manuscript (p17600l8-25):

'Inclusion of the northness and slope variables did not improve our model prediction. This contrasts with the findings of Barrett et al. (2010, 2011) who ranked slope and aspect, and derived drainage indicators, in the top predictors for depth of burn. It contrasts with Turetsky et al. (2011) who found differences in average consumption among different aspect classes. As an individual variable, slope did display some explanatory power (Figure S7B and S8B), but did not contribute to the final model. The contrasting findings of this study compared to Barrett et al. (2010, 2011) and Turetsky et al. (2011) can partly be explained by the scale-dependency of controls on carbon consumption. The model in this study was developed for regional state-wide emission predictions. At this scale, the topographic variable explaining most of the variability in belowground fuel consumption (as a proxy of drainage condition and soil organic layer thickness) was elevation. At a more local scale, for example within one fire, differences in elevation may be smaller, and the variability in drainage conditions and hence belowground fuel consumption may be better captured by including slope and aspect variables. Hollingsworth et al. (2006) found a similar scale-dependency explaining the occurrence and abundance of black spruce types from local to regional scales. Further improvements of the model could include fine scale drainage effects driven by slope and aspect superimposed on the elevation control on consumption.'

Although categorization of continuous variables into a discrete number of classes may help conceptualizations and is sometimes unavoidable (e.g. use of categorical land cover maps) we believe that landscapes should be regarded as much as possible as continuums. Categorization of continuous spatial variability inherently results in a loss of information of spatial heterogeneity. In this case, landscape and drainage conditions can be fully characterized by topographic indices (or by combining different topographic indices). The weak relationships and analyses discussed above demonstrate that in our study such variables (or combination of variables) did not improve model performance, and there is no reason to believe that a class discretization would be helpful here.

While focusing on differences on controlling variables between our work and previous work is important, we please want to note that there are similarities too. Our mathematical analysis demonstrated that one topographic variable (elevation) contributed to the model performance. Day of burning was also included in our model, similar to previous work.

Uncertainties associated with possible aggregation errors Since the algorithms applied in AKFED are based on multiplicative non-linear regression developed at 30 meter resolution, I have a concern about the degree to which aggregation error has been dealt with in the algorithms and how it might affect regional estimates. The authors bring up the issue of scale-dependency in section 5.2.1 of the Discussion (page 17600). However, the specific issue of aggregation error from the development of non-linear relationships at one resolution (30 m) and application of these relationships at another resolution (500 m) is not addressed as completely as it should be. I translation of Landsat dNBR and tree cover to MODIS dNBR and treecover (Supplementary Figure 5) will not solve this issue alone. I think readers just want to get a sense of whether this aggregation error issue is a major source of uncertainty or a minor source of uncertainty (an illustrative test case might help).

3) We are grateful to the reviewer to make us look into the effects of spatial scaling from using a nonlinear model developed at 30 m resolution 450 m resolution. We therefore used all fires with one-year post-fire dNBR assessment from the large fire year 2004. For these fires, we calculated carbon consumption based on two scenarios: 1) carbon consumption derived at 30 m, then spatially averaged to 450 m, and 2) all 30 m input layers spatially averaged to 450 m, then carbon consumption derived at 450 m. The comparison of the estimates of the 2 scenarios allows for the quantification of two important aspects of the spatial scaling: a) systematic biases (slope and intercept of regression lines), and b) uncertainty (SD in slope and intercept of regression lines. We used the regression lines to correct systematic biases introduced by spatial scaling and the uncertainty estimates fed into our revised uncertainty analysis (more detail will be given in response 4). We will update every aspect of our paper that is affected by these modifications based on the spatial scaling analysis.

We plan on introducing the following text in the Methods section:

'We also quantified scaling effects that result from applying a nonlinear model developed at 30 m resolution at 450 m resolution. We therefore selected all cloud-free one-year post-fire observations of the large fire year 2004 from MTBS. We co-registered these with all good-quality observations from the Landsat tree cover layer, the 30 m DEM, 30 m progression maps, and the 30 m land cover map. We then estimated carbon consumption at 30 m and averaged the resulting consumption over 450 m pixels for those 450 m pixels that had complete 30 m dNBR and tree cover coverage within a 15-by-15 box. For these same pixels, we also first averaged all 30 m input layers (dNBR, tree cover, DEM, progression, and land cover) to 450 m, and then estimated carbon consumption at 450 m resolution. The relationship between the carbon consumption at 450 m resolution after averaging 30 m consumption estimates with carbon consumption at 450 m that were derived from spatial averaging of the same input layers allows correction of systematic biases introduced by spatial scaling.'

We also plan on updating the equations that relate to the spatial extrapolation of the 30 m model and will include the following figure in the Supplementary material:

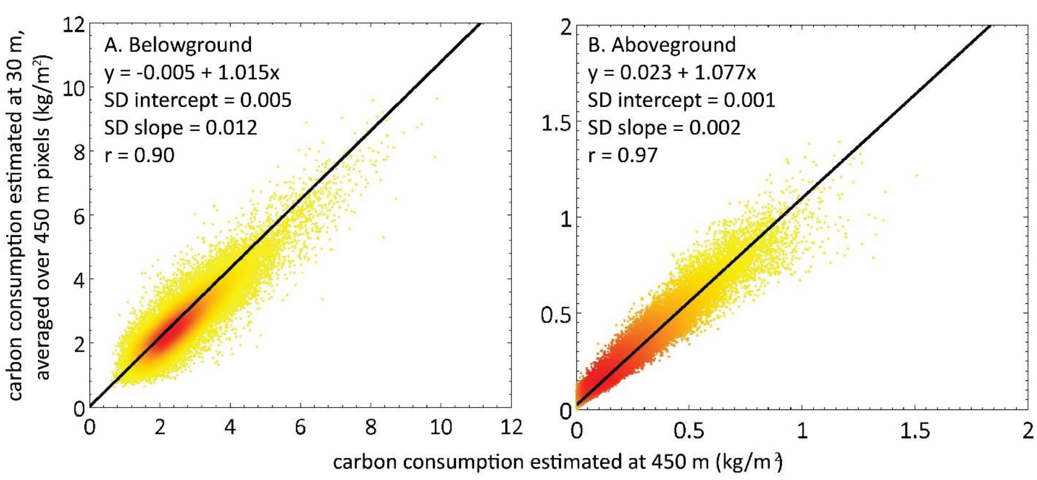


Figure to be integrated in Supplementary material. Scatter plot and linear regression lines between carbon consumption estimated at 30 m resolution that were averaged over 450 m pixels, and carbon consumption estimated at 450 m based on 30 m input layers that were averaged over 450 m pixels. Both estimates use the same 30 m input layers (differenced normalized burn ratio, tree cover, elevation, day of burning and land cover classification). Type 2 regression was used to assess the linear relationship. The regression lines were used to correct for systematic bias resulting from applying a nonlinear model developed at 30 m resolution at 450 m resolution, and the standard deviation in slope and intercept fed into the uncertainty assessment.

The proper quantification of uncertainty at regional scales Similar to the Kasischke review, I have a question about how pixel based uncertainty in consumption was quantified (equation 1, page 17954). There is not description of the components (aboveground and belowground) were calculated, or what it means. If it is the standard deviation of the prediction error, then I'm thinking it might represent a 68% confidence interval at the pixel level. But how is the prediction error estimated? I found it very naïve to state on page 17605 that "per-pixel uncertainties largely average out when scaled over larger areas". This is true if one just randomly samples the positive and negative "errors" from the pixel based estimates. I think a regional model ensemble approach needs to be employed to quantify regional uncertainties. One way to do this is a Monte-Carlo parameter sampling (based on the uncertainty of each parameter) and running the model over the entire region for each parameter set. Do this say 1000 times, and one gets a good idea of the uncertainty in emissions at the regional scale. I think this is an important thing to do in the Results, and it would be nice if it were done for GFED3s over the region as well. I think it is important for other approaches that are developed and applied at the regional scale to be able to compare not only the overall mean/median estimate of fire emissions, but also to have some context of uncertainty in the AKFED regional estimates in the comparison.

4) We are grateful to the reviewer for suggesting a thorough regional uncertainty analysis and we plan on integrating additional analysis and discussion on this topic in the revision. We identified four main sources of uncertainty (see new table below). The first source is the result of the unexplained variance in the black spruce consumption model. The other sources of uncertainty were related to assumptions and data required to extrapolate the model over Alaska. These included uncertainties of the land cover classification, in assumptions made for deriving carbon consumption for other land cover types than black spruce, and from spatial scaling of a model developed with 30 m data at 450 m resolution. We ran a Monte Carlo analyses for different scenarios to quantify region wide uncertainty and the relative importance of uncertainty sources. We will add new uncertainty sections in the Methods and Results, and more discussion on uncertainty.

We will add the following section in the Methods:

'3.4 Uncertainty

We adopted a Monte Carlo approach to assess uncertainties in AKFED. We identified four main sources of uncertainty (Table 2). The first source is the result of the unexplained variance in the black spruce consumption model. The other sources of uncertainty were related to assumptions and data required to extrapolate the model over Alaska. These included uncertainties in the land cover classification, assumptions made for deriving carbon consumption for other land cover types than black spruce, and spatial scaling of a model developed with 30 m data at 450 m resolution. The uncertainty of the black spruce model and spatial scaling was quantified with statistical methods. Due to data paucity we assigned 'best-guess' uncertainties to the land cover classification and scaling factors developed to estimate consumption in other land cover types than black spruce (Figure S6). We ran 1000 simulations in which we randomly added normally distributed uncertainties to the input values. We separated between uncertainties in belowground, aboveground and total carbon consumption. For each run and each uncertainty source, we assumed a uniform spatial distribution of the uncertainty in the simulation.'

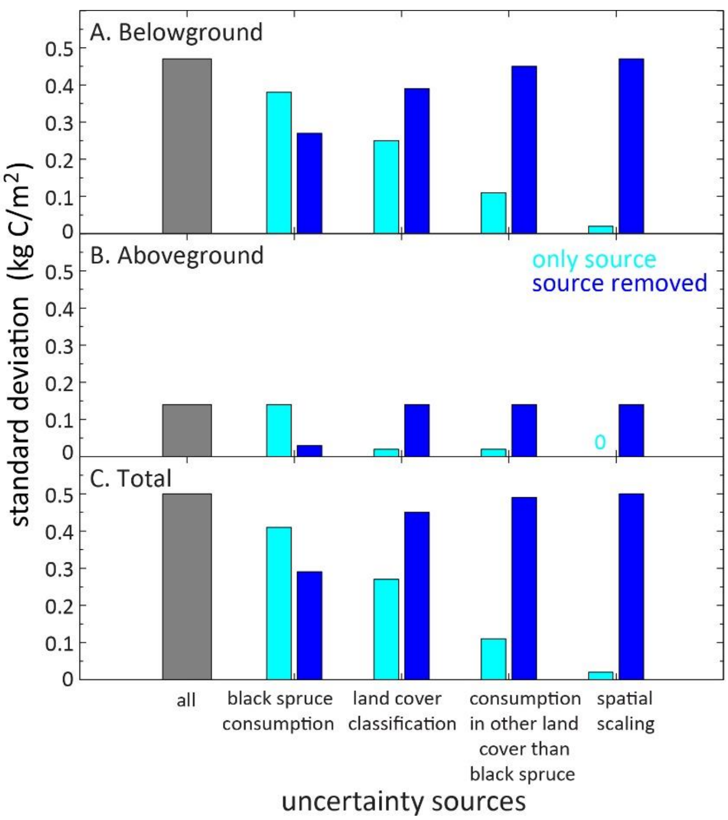
Table 2. Sources and quantification of uncertainty included in the Monte Carlo analysis

source	*standard deviation*
black spruce consumption	*prediction error from regression models (equations 1 and 2)*
land cover classification	*20 % of per-pixel fractional black spruce cover ('best-guess')*
consumption in other land cover than black spruce	*20 % of scaling factors developed for white spruce and deciduous cover (Figure S6) ('best guess')*
spatial scaling	*error in slope and intercept of regression between 30 m and 450 m consumption estimates (Figure S11)*

We plan on adding the following text to the Results:

'*4.3 Uncertainty*

All model means of the different Monte Carlo simulations were within 0.05 kg C m^{-2} of region wide AKFED means between 2001 and 2012 and we therefore focused the uncertainty analysis on the variability within simulations, expressed as the multi-run standard deviation. Uncertainty in total carbon consumption originated primarily from the belowground fraction (Figure 10). The region wide standard deviation of the 1000 simulations that included all uncertainty sources was 0.50 kg C m^{-2} for total carbon consumption. Region wide below- and aboveground uncertainties from all sources were 0.47 kg C m^{-2} and 0.14 kg C m^{-2}. The black spruce model was the main source of uncertainty, followed by the land cover classification. The scaling factors developed to derive consumption in other land cover types than black spruce and spatial scaling introduced smaller uncertainties.'



New Figure to be integrated in the revision. Attribution of uncertainty sources in (A) belowground, (B) aboveground and (C) total carbon consumption estimates. The standard deviation of the consumption estimates from 1000 Monte Carlo simulations was calculated for each scenario.

We plan on adding/revising the following text in the Discussion section:

The domain wide uncertainty was slightly lower than 20 % of the region wide mean, which was similar to the fire-wide uncertainty estimate from Rogers et al. (2014). Other studies that have modeled region wide carbon emissions and uncertainties from Alaskan fires have relied on scenarios in which uncertainties of different sources were assigned based on expert knowledge (French et al., 2004; Kasischke and Hoy, 2012). These studies found uncertainties in the range of 5 to 30%, expressed as the coefficient of variation (standard deviation/mean). The most important source of uncertainty in AKFED originated from uncertainties in the belowground carbon consumption estimates from the black spruce model (Figure 10). This corroborates with findings of French et al. (2004) and Kasischke and Hoy (2012) who both identified ground layer consumption as a major source of uncertainty within boreal forest ecosystems. We here quantified this uncertainty source based on the unexplained variance of the carbon consumption model that we developed (Figure 3). This approach provided a quantitative region wide uncertainty assessment for pyrogenic carbon consumption in black spruce ecosystems that was directly driven by observations. Due to a lack of data, we relied on best-guess uncertainty estimates for the land cover classification and consumption estimates in other ecosystems than black spruce. While black spruce forest is the ecosystem most affected by fire in Alaska, other land cover types like white spruce, deciduous, shrub or grass cover also burn (Kolden and Abatzoglou, 2012). We estimated a conifer fraction burned of 61% (39% black spruce and 22% white spruce), a tundra-grass-shrub fraction of 23%, and a deciduous fraction of 14%. The land cover layer and consumption scaling factors for other land covers than black spruce were both necessary steps to allow region wide extrapolation of the pyrogenic carbon consumption model. The land cover layer was used to partition consumption between different land cover types. Due to the data paucity in other land covers than black spruce, we developed scaling factors for consumption in other land cover types based on generalized relationships. Unfortunately, no formal state wide uncertainty assessment has been carried for the FCCS fuel type layer in Alaska, neither can the uncertainty of the scaling factors developed from Consume 3.0 be formally assessed. Best-guess scenarios for these uncertainty sources demonstrated that the uncertainty in the land cover classification, and to a lesser degree the scaling factors for other cover types than black spruce, contributed in a non-negligible way to the region wide uncertainty. We also found that the uncertainty introduced by using a nonlinear 30 m model at 450 m resolution was small. The uncertainty analysis gave insight in the uncertainties and their relative importance of the black spruce model and the assumptions and data required to extrapolate the model over large areas. Our analysis and previous studies (French et al., 2004; Jain, 2007; van der Werf et al., 2010; Kasischke and Hoy, 2012), however, assumed that the uncertainty of each input variable is spatially uniform within each model run. This assumption may not be entirely valid. Uncertainty in for example the black spruce model, the land cover classification and spatial scaling may well have spatial variability. This would not affect pixel-based uncertainty estimates, however, it would affect region wide uncertainty estimates as some of the uncertainties may partly average out over large areas. This was demonstrated by Rogers et al. (2014) who demonstrated that pixel-based uncertainties partly average out over a fire perimeter when assuming spatially random uncertainty in the prediction error of a carbon consumption model. Quantifying the spatial distribution of uncertainty is complex and may not be possible with current data. The assumption of spatially uniform uncertainty represents the 'worst-case' scenario and may therefore overestimate region wide uncertainty. Similarly, the assumption of a spatially random uncertainty distribution, however, would likely underestimate region wide uncertainty.

While we identified and quantified four main sources and their relative importance within AKFED, other sources of uncertainty were not included in our analysis. These include the dNBR threshold used for burned area mapping, the assumption of the same controls on pyrogenic *consumption in non-black spruce ecosystems, consumption of woody debris, and the cumulative carbon storage curves used to convert depth of burn into belowground carbon consumption for the Turetsky et al. (2011) plots. When uncertainties in burned area mapping are large, then this variable can be the most important source of uncertainty (French et al., 2004; van der Werf et al., 2010; Kasischke and Hoy, 2012). We used three independent datasets (ALFD perimeters, and MODIS surface reflectance and thermal anomalies) to map burned area, including burned area outside fire perimeters (1 % of total burned area) and excluding unburned islands within the fire perimeters (18 % of perimeter area). We believe that this approach minimized uncertainties from this source. We recognize, however, that the dNBR threshold of 0.15 introduced some uncertainty and likely resulted in the omission of some partially burned and/or low severity pixels, but minimized the occurrence of commission errors. The carbon consequences of omitting burned pixels with a dNBR lower than 0.15 are likely small. Due to the lack of field data to construct empirical models for other land covers than black spruce, we assumed that the same environmental variables that controlled carbon consumption in black spruce ecosystems also operate for white spruce, deciduous species, grassland and shrub land. This assumption may not entirely be valid but cannot be verified until field data becomes available for these cover types. Consumption of woody debris is hard to quantify. Carbon consumption in this pool is small compared to the consumption of the soil organic layers, but can amount up to 5 to 7 % of the total consumption (Kasischke and Hoy, 2012). Field measurements of fuel loads of woody debris in unburned stands in function of stand age and their consumption in relation to fire weather conditions may allow further optimization of pyrogenic carbon consumption models in boreal forest ecosystems. Finally, the cumulative carbon-depth curves used in this study for the Turetsky et al.(2011) data are based on multiple measurements per landscape class and have an inherent uncertainty (Turetsky et al., 2011). In addition, the source and spatial resolution of the DEM may add some additional uncertainty to the depth of burn to belowground carbon consumption conversion for these field plots. Parts of this uncertainty source are likely reflected in the fact that the belowground carbon consumption model resulted in a slightly lower performance than the depth of burn model, and are as such implicitly embedded in the uncertainty estimates from the black spruce model.*

Several aspects of the uncertainty analysis call for a more comprehensive field dataset to better constrain observation-driven empirical models of pyrogenic carbon consumption in boreal ecosystems. First, additional field efforts could focus on gathering more field data of consumption in black spruce ecosystems. In their sampling design, such field data collections could for example consider layers of pre-fire tree cover and post-fire dNBR in an effort to better represent the distribution of burning conditions (Figure 10), in addition to topographic conditions and fire seasonality. Second, considerable uncertainty within AKFED stemmed from assumptions made to estimate consumption in white spruce, deciduous, grassland, and shrub land ecosystems. Very little data on pyrogenic consumption is currently available for these ecosystems. For white spruce and deciduous ecosystems we developed scaling factors using Consume 3.0 (Figure S6). For grasslands and shrub lands we used the black spruce model because tree cover is one of our predictor variables and our model was calibrated for a range of tree cover between 14 and 64 %. Lower tree cover resulted in lower consumption (Figure 7E) and this may justify the use of the model for non-treed ecosystems until consumption data within these ecosystems becomes available. The initiation of field databases within white spruce, deciduous, grassland, and shrub land ecosystems may allow for the development of similar observation-driven models as developed here for black spruce to further partition consumption models per ecosystem type. These field data collections in other ecosystems than black spruce may consider the same environmental variables as identified here for black spruce, however, other factors may be important as well. Third, regional extrapolation of carbon *consumption model from different ecosystems depends on the underlying land cover classification. To date, the FCCS classification is the only classification that for example distinguishes between black spruce and white spruce in Alaska. No formal accuracy assessment of this layer has been conducted, however, we found that, at its native 30 m resolution, 60 out of the 126 black spruce plots from the field dataset (section 2.2) were misclassified;29 as white spruce, 14 as tundra-grass-shrub, 12 as deciduous, and 5 as non-vegetated. We also found that of eight white spruce-aspen plots from Rogers et al. (2014), seven were classified as black spruce and one as shrub-grass-tundra. The sample size of the land cover ground truth data available was too small to robustly quantify potential over- or underrepresentation of land cover types in the FCCS layer. An improved land cover characterization, including quantitative uncertainty estimates, is thus essential for reducing region-wide uncertainties. An underrepresentation of the black spruce cover in the FCCS would result in lower state wide average consumption estimates and vice versa. While some land cover types, such as spruce and deciduous cover, are likely well separable from remote sensing based on spectral and phenological characteristics, more detailed distinctions, for example between black and white spruce, may be more challenging but not impossible with the combined use of structural and optical attributes (e.g. Goetz et al., 2010). More than a decade after the call from French et al. (2004) for more field data, including from ecosystems that burn less regularly, more field measurements are still required to better constrain pyrogenic carbon consumption in boreal forest ecosystems. The upcoming multi-year Arctic-boreal vulnerability experiment (ABoVE, http://above.nasa.gov/, last accessed March 3, 2015) funded by the National Aeronautics and Space Administration may provide opportunities to fill gaps in existing field datasets.*

Another future improvement could be to operate AKFED at 30 m resolution. This would result in much more spatial detail. The tree cover and dNBR layers currently constrained the development of a 30 m product. The tree cover product at 30 m is now only available for a limited amount of years and this would degrade the annual update of tree cover (up through 2010) that we currently included in AKFED. For the 30 m dNBR, we explored the potential of currently available products like WELD (Roy et al., 2010) and MTBS (Eidenshink et al., 2007), but found that even with these products, it would have been impossible to have consistent post-fire observations for every single burned pixel. We therefore pragmatically decided to use MODIS imagery which facilitated elimination of cloud- and smoke-affected observations thanks to its daily revisit time resulting in useful remote sensing observations for the whole spatio-temporal domain. Further development of WELD and the Google Earth Engine (https://earthengine.google.org/, last accessed March 3, 2015), which also provides access to the Landsat record, could eventually lead to an operational model at 30 m resolution. Further updates of the model may also profit from the availability of active fire data from the Visible Infrared Imaging Radiometer Suite at 375 m which may improve the time of burning estimates.'

The reviewer correctly identified that the pixel-based uncertainty of the black spruce model was expressed at the standard deviation of the model prediction error. Although we agree that an in-depth comparison of several aspects of AKFED and global fire emission products like GFED, including uncertainty, is of interest to developers of global databases, we found that this was out of the scope of our current work. A first comparison was given in Supplementary Table 3 and these results were shortly described in the paper (p17598l3-24).

Point-by-point responses to Evan Kane

Here, the authors developed statistical models to better understand variability in C consumption in stand and soil components on a spatial scale of 500m from 2001-2012. To do this, they relate data from previous field based studies to spatially extensive land cover data from a variety of sources (ASTER, Landsat, MODIS, MOD44B, FCCS, AKFED) and scales (30m-500m), which are then convoluted to a 500m resolution. The authors use the statistical models developed herein to examine the ability of key environmental variables identified in prior research to estimate consumption across boreal Alaska. Of the environmental variables considered, elevation and dNBR were statistically significant in predicting belowground C consumption. The tools developed are heuristically valuable in understanding C consumption patterns at very large spatial scales, and in doing retrospective analyses of C emissions for periods of time where remotely sensed data exist.

The authors cede that there are several major caveats in considering their conclusions about controls over patterns of C consumption. Primarily, contrasting findings presented in this study and other studies are likely driven by factors related to the scale dependency of controls on carbon consumption. The authors admit that at 500m resolution, the strong controls of slope and aspect on soil moisture and depth of burn are not likely to be realized [e.g., pg. 17600]. At such a large grain size, elevation was the only physiographic variable able to capture fuel moisture controls on burning. For this reason, soil moisture was modeled as a function of elevation and time of burning. So, in effect the authors use elevation as a proxy variable for other (potentially more relevant) drivers of depth of burn. In addition, other studies have varied on consensus of using dNBR as an indicator of depth of burn, but at the scales investigated herein, dNBR could be indicative of belowground consumption. The authors cede that this relationship may be correlative, owing to co-existing trends between depth of burn and occurrence of tree cover. For example, Increases in black spruce standing biomass are also strongly correlated to the total amount of C lost during wildfires in interior Alaska ($R2 = 0.80$, $P < 0.001$, $n = 12$; data from Kasischke and others 2000). The authors admit that fire weather indexes are not intended to be interpreted at 0.5km resolution. The authors also cite potential problems with land cover classification at such a coarse scale, and suggest that improved land cover characterization, including quantitative uncertainty estimates, are necessary to reduce region-wide uncertainty. This of course is important in interpreting the FCCS data, and the Consume outputs, but I think the authors are working with the best data available.

I feel that as long as the caveats stated in the previous paragraph are made clear, this work is significant and should be of interest to the readership of BGD. Perhaps in clarifying the interpretation, a sentence addressing what variables are likely to have muted importance at 500m resolution could be included up front, or in the abstract? Generally, I found the writing to be concise and well researched. The figures are clear and the information is easy to interpret. Admittedly, the remote sensing methods presented here are not in my area of expertise and I defer to other reviewers for input on that, but I think overall the interpretation (caveats and all) is well presented. I otherwise offer general comments throughout, and hope they are useful in revision.

5) We thank Evan Kane for his constructive comments. We would like to clarify some issues raised in this comment.

With regards to the topographic controls on belowground consumption, is important to clarify that we investigated the potential contributions of slope and northness at the 30 m resolution. We reported in the original manuscript that, as individual variables, slope was significantly correlated with both depth of burn and belowground C consumption, and northness was significantly correlated with belowground consumption ($p < 0.05$, Supplementary Figures 7 and 8). However, as reported in the manuscript, inclusion of slope and northness did not result in additional explained variance when using the multiplicative models. We will add a sentence in the Abstract to clarify this. In our response 2 to the anonymous reviewer 2, we show that more complex topographic variables (e.g. flow accumulation and curvature) did not have predictive power in our dataset. We agree that these findings are interesting with respect to previous findings. We hypothesize that the controls that we identified operate at the regional scale of the state of Alaska, the domain of our study, while local drainage conditions may allow further refinements. We think that we provided sufficient discussion on this topic in the manuscript (p17600l8-25).

We agree with the reviewer's assessment on the suitability of the dNBR to estimate belowground carbon consumption on a regional scale. While its synergistic use with other environmental variables and field data is required over large regions, our results show that the dNBR contributed to the belowground consumption model.

In the revision, we plan on integrating additional analysis and discussion on uncertainty. We identified four main sources of uncertainty. The first source is the result of the unexplained variance in the black spruce consumption model. The other sources of uncertainty were related to assumptions and data required to extrapolate the model over Alaska. These included uncertainties in the land cover classification, assumptions made for deriving carbon consumption for other land cover types than black spruce, and spatial scaling of a model developed with 30 m data at 450 m resolution. We ran a Monte Carlo using different scenarios to quantify region wide uncertainty and the relative importance of the different uncertainty sources (see for example the new figure on page 4 of this response). These additional analyses allow a more quantitative discussion than the previous more qualitative discussion of the original manuscript.

17594, 5: I think the inputs for the Consume model would be good to include, even if just in the supplemental. Is there precedent for using the black spruce fuel model as a proxy for tundra and non vegetated pixels? Could this be corrected or evaluated, based on some of the emerging plot-based consumption data for tundra wildfires?

6) We had identified the weather and FCCS code inputs for Consume 3.0 in the caption of Supplementary Figure 6. We will add the following sentence to the caption to specify all input parameters: *'In Consume 3.0 fuelbed type was defined as natural and we assumed 60 % canopy loading consumed (Prichard et al., 2006)'.*

The decision to operate the black spruce model for tundra pixels is driven by the current lack of publicly available data to construct a tundra-specific consumption model. Until more field data becomes available, we justify this assumption by the fact that tree cover is one of our driving variables in the model and we calibrated our model with field data that had a range of tree cover between 14-64 %. Lower tree cover results in lower consumption values and this is conform the expectations for tundra ecosystems. We will clarify this in the revision and we will also devote a new paragraph in the discussion section with a call for more field data on pyrogenic consumption, to better represent burning condition in black spruce ecosystems, and to initiate databases for ecosystems that burn less regularly (e.g. white spruce, deciduous and tundra ecosystems).

17595, 20: ": : :which often burn less severe[ly] and frequent[ly]: : :."
17596, 25: ": : :however, there was considerable spatial variability: : :"

7) We will correct these phrases in revision.

17601, 5-15: Another consideration here is that the Canadian FWI do not account for permafrost or critical drops in water table position, in lowland environments. A good reference addressing this: Waddington et al. 2012. Examining the utility of the Canadian Forest Fire Weather Index System in boreal peatlands. Can. J. For. Res.

8) Thanks for the suggestion, we will integrate this reference in the revision.

17622, fig. 3: This is a really minor point, but shouldn't the independent data (observed) be on the x axis?

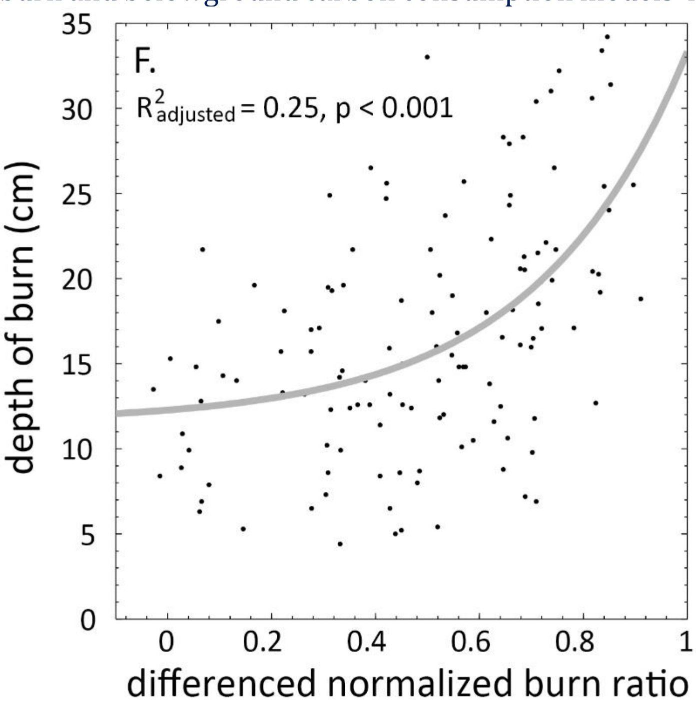
9) We understand the reviewer's confusion. The scatter plots shown do not represent an additional regression analysis. The reported adjusted R^2 refers to the value of the multiplicative regression analyses (equations 1 and 2). Since, the plots thus do not show a regression analysis, there is no dependent and independent variable, and the choice of x and y variables is not dictated by the analysis. We will add the following sentence to the figure caption to clarify this: '*The reported adjusted R^2 values are from the multiplicative nonlinear models (equations 1 and 2).*' We think that the plots give an honest idea of the goodness-of-fit and proximity to the 1:1 line of our estimates.

Point-by-point responses to Eric Kasischke

We are thankful to reviewer Kasischke and his comments contributed to many improvements that we plan on integrating in the revision. Most importantly, this reviewer's comments were very useful in our revised uncertainty analysis and discussion. We, however, also want to summarize several important points that we strenuously contest regarding Kasischke's assessment of our manuscript:

a) Appropriate use of the dNBR spectral index

Eric Kasischke expressed reservations about the use of the use of the dNBR to estimate belowground pyrogenic consumption in our study. We are aware of the debate and contrasting previous findings on this topic. It is important to note that we statistically analyzed the utility of the dNBR to estimate pyrogenic consumption. We included the dNBR as environmental variable in the carbon consumption model because our analysis provided mathematical proof that the dNBR's inclusion resulted in a better performance. Following our analysis and Figure 4, we demonstrated that the dNBR was retained as a variable that improved the skill of our depth of burn and belowground carbon consumption models. In addition, as an individual variable, dNBR was significantly related to depth of burn field and belowground carbon measurements ($p < 0.01$) following a nonlinear relationship (Figure S7F and SF8). We want to repeat that we do not recommend using dNBR as a stand-alone predictor, rather we recommend its careful calibration with field measurements and its synergistic use with other environmental variables. Our results provide mathematical evidence for the synergistic use of the dNBR in combination with other environmental variables and field data. This is an important contribution to a long-going debate.



Supplementary Figure 7F. Relationship between dNBR and depth of burn.

The reviewer incorrectly asserts that we present the stand-alone use of the dNBR as a suitable way to derive carbon emissions. We devoted an entire paragraph on discussing the synergistic use of the dNBR in combination with other variables (p17602l19-p17603l6):

'The relatively high correlations between depth of burn, and dNBR and tree cover suggest that crown fires in high density black spruce plots also cause deeper burning into the ground layer. Burning into the ground layer is primarily controlled by fuel moisture in the ground layer, which was modeled here as a function of elevation and time of burning. For a certain moisture condition of the ground layer, determined by elevation and fire seasonality, dNBR thus adds complementary

power for the prediction of the consumption of the ground layer. This may explain why the dNBR has performed well in studies that focused on one single fire in which the elevation and time of burning were relatively constant (Hudak et al., 2007; Verbyla and Lord, 2008; Rogers et al., 2014). We conclude that the dNBR can well be used as a stand-alone indicator of belowground consumption in boreal ecosystems when drainage and fire seasonality remain relatively constant. When used over large areas and over a range of burn conditions, the synergistic use of the dNBR with other environmental variables is essential for improving model performance. This finding agrees with Barrett et al. (2010, 2011), who found that a combination of spectral and non-spectral data optimized depth of burn prediction in black spruce forest.'

Our conclusion on the suitability of the dNBR for estimating carbon consumption in black spruce ecosystems is thus much more nuanced than the reviewer's assessment. We also corroborate with conclusions made in French et al. (2008) and Barrett et al. (2010, 2011). These three papers were all co-authored by the reviewer. In the abstract of their review paper, French et al. (2008) stated:

'Results from relating and mapping fire/burn severity within the boreal region have been variable, and are likely attributed, in part, to the wide variability in vegetation and terrain conditions that are characteristic of the region. Satellite remote sensing of post-fire effects alone without proper field calibration should be avoided. A sampling approach combining field and image values of burn condition is necessary for successful mapping of fire /burn severity. Satellite-based assessments of fire /burn severity, and in particular dNBR and related indices, need to be used judiciously and assessed for appropriateness based on the users' need.'

We found this review paper an excellent assessment of the difficulties encountered in relating spectral information to fire severity in boreal forest ecosystems and we have fully integrated this knowledge into our study design. We also agree with findings of Barrett et al. (2010, 2011) who demonstrated the predictive power of the combined use of spectral and non-spectral data. More detailed discussion on this point of disagreement can be found in responses 15, 25 and 38.

b) Interpretation of statistics

The reviewer presents three additional statistical analyses that are supposed to demonstrate inconsistencies in the paper. In the first analysis he states that he did not find a relationship between elevation and pre-fire organic layer depth. It remains unclear how this relates to our work since we did not investigate relationship between pre-fire organic layer depth and elevation. In the second analysis, the reviewer found no relationship between depth of burn and elevation. We suggest below that the discrepancy between the reviewer's and our finding may be because he did not consider nonlinearities in his analysis. In the third analysis, the reviewer claims that he did not find a relationship between basal area and depth of burn. We stand behind our finding that showed a significant nonlinear relationships between remotely sensed tree cover and field measurements of depth of burn (Supplementary Figure 7E). We encourage the reviewer to publish his finding that there is no relationship between burn depth and basal area in a future peer-reviewed publication. It does not invalidate our finding that was derived from a different set of observations. Further, we think the conceptual underpinnings are robust – more dense stands are likely to cause greater and more uniform heating of soil organic layer, enabling drying and more complete organic layer combustion. The reviewer also misinterprets several of the statistics that we provided. More detailed comments are given below for each statistical analysis and misinterpretation in responses 21, 22, 23 and 24.

c) Marginally relevant statements to this work in relationship to other studies

At several instances, the reviewer made statements with regards to the amount and quality of previously published material from the authors from this paper and other papers that are, in our opinion, irrelevant for the judgment of this paper. We identified such irrelevant statements in the point-by-point responses 10, 38 and 52.

d) Incomplete consideration of the published literature

The reviewer is selective in describing results from previously published papers that are closely related to the subject matter of our paper. The reviewer's selective handle on the literature is apparent in the dNBR discussion, but is not limited to this topic. We demonstrate examples of this in our point-by-point responses 25, 38, 44 and 52. In our research design and discussion section, we have tried to integrate findings of all available pertinent literature.

Overview

Much research has been carried out over the past two decades to develop and improve approaches to estimate carbon emissions from boreal forest wildland fires, with many studies focused on the Alaskan boreal forest region. An important element of this previous research has been focused on determining the factors that control burning of surface organic layers common to black spruces forests and lowland areas in Alaska, driven by the recognition that the burning of these surface organic layers represent a significant, if not the dominant, source of carbon emissions from fires in this region (see, e.g., French et al. 2005). The manuscript by Veraverbeke et al. represents the second paper by this group in this topic area, and builds to some degree on the previous research carried out on this topic by other researchers.

10) Mentioning how many papers a group already has published in a 'topic area' is in our opinion irrelevant to the judgment of this paper. It remains unclear what the reviewer refers to with 'topic area'. We performed 2 searches on Web of Science (http://apps.webofknowledge.com/, last accessed on March 3, 2015). In our first search with 'boreal fire' as keywords for Topic and 'randerson j' as author, we found a total of 40 papers since 2000. In our second search with 'fire severity' as keywords for Topic and 'veraverbeke s' as author, we found a total of 19 papers since 2010.

On the positive side, the study presented in this manuscript will result in a published dataset of carbon emissions for Alaska which may represent an improvement in terms of spatial/temporal resolution from the global fire carbon emissions database (GFED) that has been created by a group that includes an author of this study. In addition, the use of satellite-derived estimates of the density of forest cover to calculate above-ground C emissions represents an advance over methods used in previous studies.

11) Our dataset is not only an advance in spatial and temporal resolution compared to GFED3s, a global-scale fire emissions product, it also represents a significant advance for regional fire emission modeling in Alaska. We systematically map all fires since 2001 using a quantitative methodology that is directly driven by field and remote sensing observations and easily extendable in time. The approach and product include an uncertainty layer that is based on the variability observed in the relationships between field data and environmental variables. We will integrate additional analysis on uncertainty in our revision. Our publicly available

dataset will enable, for the first time, research opportunities that require the inputs at the spatial and temporal resolution provided by our dataset. Research opportunities that could benefit from our presented dataset could include a better understanding of controls and limits on fire growth, emission factors, climate feedbacks from changing boreal fire regimes, transport and exposure of smoke plumes. Work is already underway to convolve our emissions estimates with air transport models to assess trace gas variability at tower stations in the framework of the Carbon in Arctic Reservoirs Vulnerability Experiment (CARVE) project (https://ilma.jpl.nasa.gov/portal/). Our publicly available data will also be useful within the upcoming Arctic-Boreal Vulnerability Experiment (ABoVE) project (http://above.nasa.gov/). If our paper passes through peer review, we plan on making our data available on the ABoVE Science Cloud (http://above.nasa.gov/science_cloud.html).

Overall, however, I think there are several important issues that need to be addressed before a decision can be made as to whether or not this manuscript merits publication. These issues include: (a) The manuscript fails to provide a framework their approach and results based upon addressing critical uncertainties in previous methods used to estimate C emissions from wildfires in Alaska, in particular, in the introduction, discussion, and conclusions; (b) The performance of the ground-layer C emissions model for black spruce forests is much poorer compared to previous approaches. There are a number of reasons for this, many of which are related to issues with the overall design of the study; and (c) The approach used to estimate uncertainty needs to be clarified and a more thorough discussion of the sources of uncertainty is needed. Details of my concerns in these areas are presented below.

We will summarize our response to the three issue brought up here, and give detailed responses below:

(a) The manuscript fails to provide a framework their approach and results based upon addressing critical uncertainties in previous methods used to estimate C emissions from wildfires in Alaska, in particular, in the introduction, discussion, and conclusions

12) We do not agree with the reviewer that the original manuscript did not provide a motivation and conceptual framework for our analysis. We have a traceable uncertainty approach, which we will expand on in the revision, and we effectively exploit the available field data. We carefully build on and cite a broader published literature in the design of our model. This directly addresses key uncertainties with this scientific challenge. We believe it is overstepping to assert that we need to build our conceptual framework around uncertainties in other modeling systems, as we are designing a new approach. Further, we identified additional drivers of landscape-level variations in fire emissions that have not been addressed in previous work, including the influence of pre-fire tree cover.

We are grateful to the reviewer for suggesting a thorough regional uncertainty analysis and we plan on integrating additional analysis and discussion on this topic in the revision. We will add an entire new section in Discussion to more carefully compare our estimates with previous work, and we will expand our analysis and discussion of key uncertainties in the revision. More detailed responses can be found below.

(b) The performance of the ground-layer C emissions model for black spruce forests is much poorer compared to previous approaches. There are a number of reasons for this, many of which are related to issues with the overall design of the study

13) The assertion that the performance of our model is poor is inaccurate and originates from the use of different statistical methods deployed in different studies. In our manuscript, we compared our approach with the gradient boosting technique used in Barrett et al. (2010, 2011). It is likely that this technique overestimated the *predictive* performance in extrapolating carbon consumption in space and time (Supplementary Figure 4).

(c) The approach used to estimate uncertainty needs to be clarified and a more thorough discussion of the sources of uncertainty is needed

14) We are grateful to the reviewer for suggesting additional analysis and discussion on uncertainty and we plan on this in the revision.

Primary concerns

a. The context of the study in relation to previous research

Reducing uncertainties in fire C emissions from Alaskan boreal forests

Since the mid-1990s, there have been a number of studies whose objectives were to improve understanding of the role of fire on carbon cycling in the boreal forest region of Alaska, which in turn, has provided the basis for improving models of C cycling, as well as models that estimate direct C emissions from fires. This research has focused on improving pyrogenic C-emissions through use of geospatial datasets including, fire perimeters and remotely-sensed products to determine areas burned during fires and fuel types that are burned during fires. Research has also been carried out on mapping of fire severity using satellite imagery, which as discussed below, has not resulted in reliable approaches.

15) We recognize and cite the previous work in estimating carbon emissions from boreal fires, in particular in Alaska. We have tried our very best to integrate these references in our analysis, as part of the study design and/or in discussing our work in relation to previous efforts. We will integrate even more suitable references pointed out by the reviewer in the revision and we believe that our paper correctly acknowledges previous published work on this topic.

We disagree with the reviewer's interpretation of the literature on the reliability of the dNBR in synergy with field data and environmental variables to predict pyrogenic carbon consumption from boreal fires. Following our analysis and Figure 4, we demonstrated that the dNBR was retained as a variable that improved the skill of our depth of burn and belowground carbon consumption models. In addition, as an individual variable, dNBR was significantly related to depth of burn field measurements ($p < 0.001$) following a nonlinear relationship (Figure S7F). We want to repeat that we do not recommend using dNBR as a stand-alone predictor, rather we recommend its synergistic use with other environmental variables.

Considerable research has also focused on collecting field data needed to improve understanding of the factors controlling the burning of surface organic layers in black spruce forests, which represent a significant source of emissions during fires in North American boreal forests. Many studies have been carried out in a coordinated fashion that involves a number of researchers (e.g., see numerous publications on fire impacts on boreal forest carbon emission and carbon cycling research carried out by Barrett, French, Genet, Hoy, Kasischke, Li, McGuire, Turetsky, and Yuan).

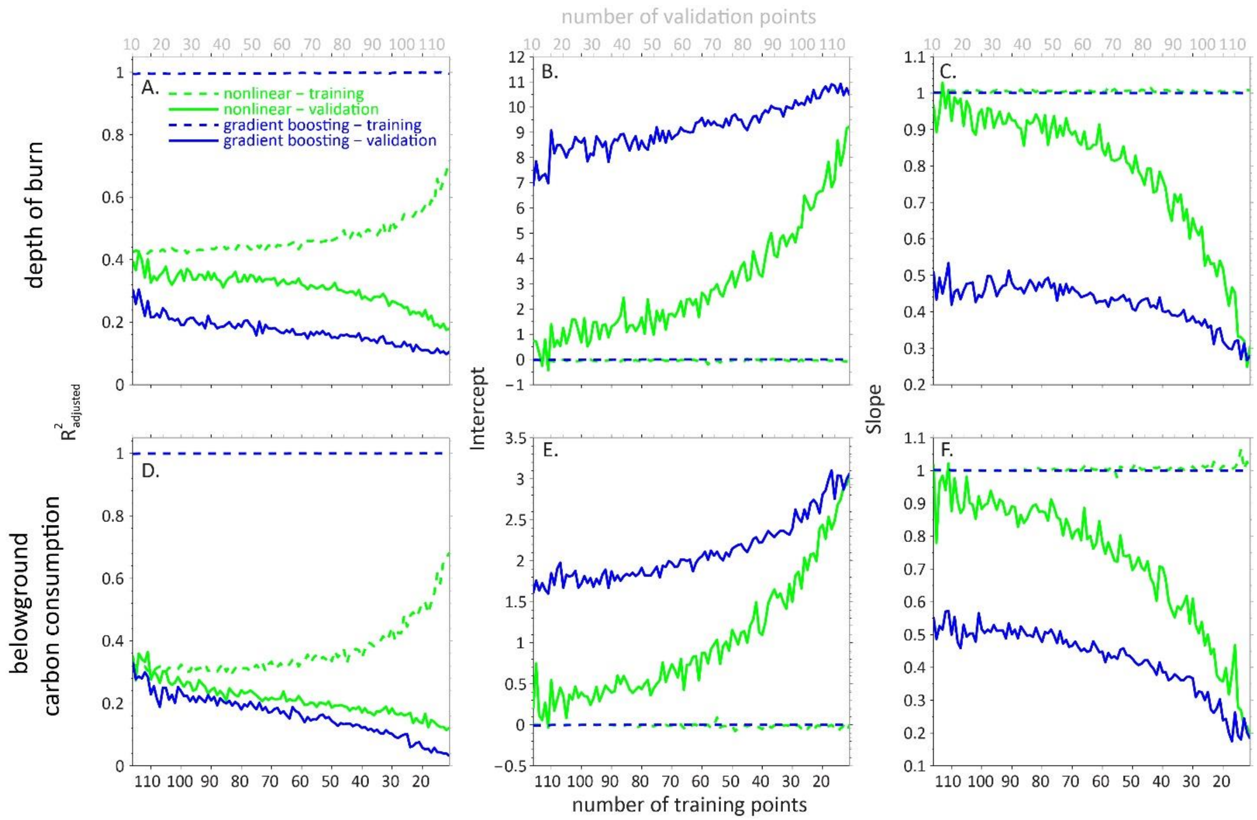
16) We acknowledge the previous work done by the researchers mentioned and our manuscript already included 28 references to papers with one of the identified names as first author. We plan on integrating references to the Genet et al. (2013) and Yuan et al. (2012) papers in our revision.

Our work re-uses previously published field data from the Turetsky et al. (2011) paper, as well as from the Boby et al. (2010) paper. We gratefully acknowledge all contributing authors of these papers for making their field data publicly available.

We would also like to please not that our work is also part of coordinated efforts to understand changes in boreal carbon fluxes as a part of NASA's CARVE campaign.

The most comprehensive study based on the research of this group on estimating direct C emissions from boreal forest fires in Alaska is Kasischke and Hoy (2012). In addition, recent efforts have provided newer methods for addressing key uncertainties in estimating C emissions from fire, including modeling of ground-layer consumption in black spruce forests (Barrett et al. 2011; Genet et al. 2013), and accounting for the effects of more frequent reburning of stands (Hoy 2014).

17) We recognized and cited the work of Kasischke and Hoy (2012) in our original manuscript. We made a total of 17 references to this work in our paper. Similarities and differences with this paper were extensively discussed. We also provided comparison by applying statistical methods similar to Barrett et al. (2010, 2011) to similar field and geospatial datasets. We provided a comparison between the nonlinear multiplicative regression technique and a gradient boosting method in Supplementary Figure 4. For easy reference, the figure and caption text is reproduced below. We found that the multiplicative nonlinear regression method was more robust in predicting values that were not included in the training dataset. We therefore selected the multiplicative nonlinear regression technique for our extrapolation in space and time.



Supplementary Figure 4. $R^2_{adjusted}$, intercept and slope for the linear regression between observed and estimated values for training and validation plots in function of the number of training points for the depth of burn (A, B, and C) and belowground consumption model (D, E and F). To assess the robustness of the multiplicative nonlinear regression and gradient boosting techniques in our application to predict carbon consumption by fire in black spruce forests, we varied the number of field plots used as training data between 116 and 10, out of the total of 126 plots, in decreasing steps of one. The remainder of the plots was used for validation. For each combination of the number of training and validation plots, we randomly varied the selection of training and validation plots 100 times. For each combination and selection of training and validation plots, the prediction models were derived and applied on the validation data. The robustness for extrapolation of the models was then assessed as a function of the number of training plots by means of the $R^2_{adjusted}$, slope and intercept of the regression between estimated and observed values of the validation plots, averaged over the 100 random selections. While the gradient boosting technique revealed an apparent high performance ($R^2_{adjusted} \sim 1$) for the training plots alone, its performance for the validation plots was consistently lower compared to the nonlinear regression models. In addition, the intercept and slope values of the linear regression between observed and estimated values for the validation plots deviated substantially from the expect values of zero and one for the gradient boosting technique, while these regression lines followed more closely the 1:1 line for the nonlinear models when at least approximately 70 field points were used for training.

We are thankful to the reviewer for pointing us to the Genet et al. (2013) paper, which we will integrate in our revision. We will integrate a new discussion section to more closely relate our work to previous work, which is discussed in more detail below. We are also grateful to the reviewer for pointing us to the recent dissertation of his former student Hoy. To the best of our knowledge, no peer-reviewed publications have resulted from this work so far, and we look forward to integrating this work once it passes through peer review. One of the main findings of the dissertation is that fire frequency influences pyrogenic carbon consumption in black spruce ecosystems. Interestingly, identification and incorporation of these immature black spruce stands resulted in higher total emissions compared to the prior model presented in Kasischke and Hoy (2012). To some degree, this seems counterintuitive since a longer fire-free interval results in more accumulation of organic matter, and thus more organic matter to burn. That said, we do agree that stand age is a useful predictor of organic layer consumption. Tree cover is also strongly related to stand age in boreal forest ecosystems (Rogers et al., 2013, Figure below). Our inclusion of tree cover in the model thus seems to capture parts of the variability intended by Hoy (2014).

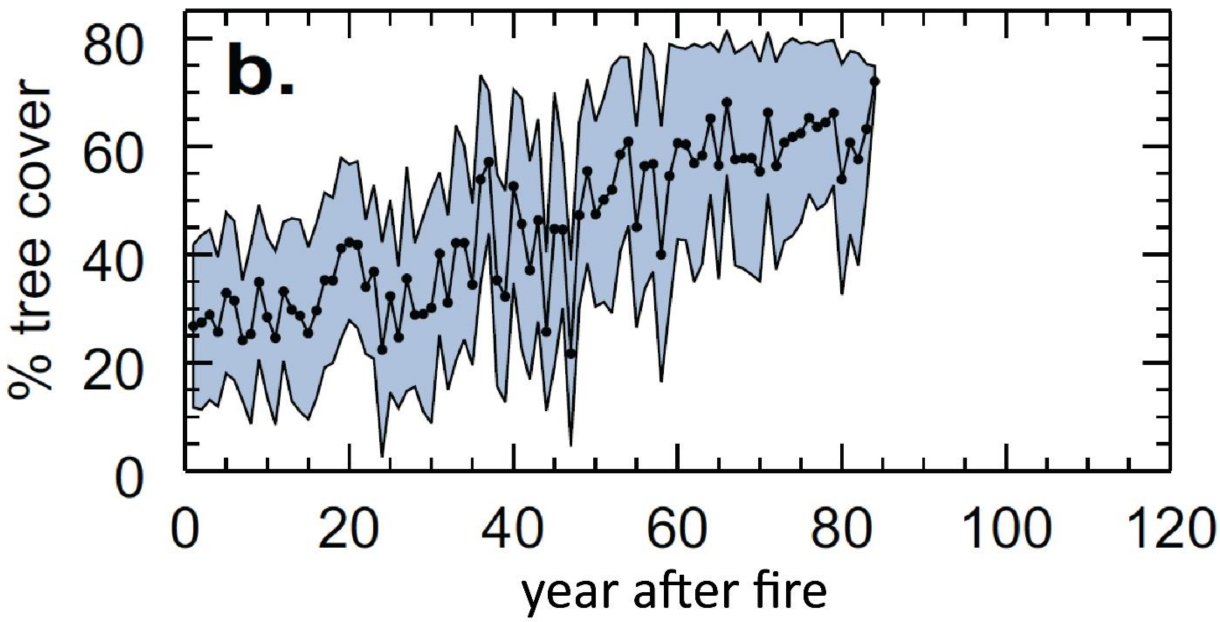


Figure. Relationship between tree cover and stand age in boreal forest ecosystems (Rogers et al., 2013).

This background is presented to make the point that given the degree of systematic research that has been directed towards improving models on the impacts of fires on the boreal forests in Alaska, it is important that new methods to estimate C emissions from fires should be based on identification of approaches that can be used to address existing uncertainties in the previous approaches. In their introduction, the authors do not a discuss what they feel are the key uncertainties in fire C emission estimation approaches, and do not present a rationale for how their alternate methods will address these key uncertainties. Given the breadth and depth of previous work in this area, this context should be provided.

18) We assert that we already provided substantial background for the need of a spatially explicit Alaska wide pyrogenic carbon emissions model with daily temporal resolution. In particular, on p17854l17-p17585l5 we listed examples of applications that require burned area and/or emissions inputs at the spatial and temporal resolution provided by our dataset. Potential applications that may benefit from our dataset may include studies focused on the composition and transport of fire aerosols, fire behavior, and fire modeling.

In view of the reviewer's helpful comment, we plan on elaborating why we think that our paper may result in lower uncertainties in carbon emission estimates from boreal fires in Alaska in our revision by adding the following text in the Introduction:

'Several studies have demonstrated relatively strong relationships between post-fire remote sensing observations and ground layer consumption in boreal forest ecosystems (Hudak et al., 2007; Verbyla and Lord, 2008; Rogers et al., 2014). Identification of such relationships may provide opportunities to constrain pyrogenic carbon emission estimates in boreal forest ecosystems at regional to pan-boreal scales. Quantifying relationships between field data of carbon consumption and post-fire remote sensing observations, in combination with other environmental variables, may minimize the number of assumptions required to extrapolate emissions in time and space. In addition, observed variability in relationships between the field observations and environmental variables may allow for a data-driven uncertainty approach.'

Relation of the results to previous studies

The authors do not provide a detailed enough discussion of the results from their study to those from previous studies. In particular, there should be a discussion of how the performance of their model of ground-layer carbon consumption varies from other recent efforts, including Barrett et al. (2011) and Genet et al. (2013). In addition, the authors do not compare the results from their approach to those from other recent studies, including Kasischke and Hoy 2012 and Tan et al. 2007), and discuss why the results are different. Factors that could lead to differences that need to be discussed include: (a) variations in estimation of burned area for different years; (b) differences in fuel categories used by the different studies; (c) differences in average fuel consumption for different fuel types (e.g., conifer forests, deciduous forests, shrublands, etc.); and (d) differences for different fuel types (e.g., ground-layer fuel versus aboveground fuel). Such a discussion would help the reader understand why different studies produce different estimates of fuel consumption.

19) We thank the reviewer for this constructive comment. We plan on introducing a new section in the Discussion to relate our work to previous estimates in this field, including all papers identified by the reviewer:

'5.3 Comparison with previous work on spatially explicit carbon consumption modeling for boreal fires in Alaska

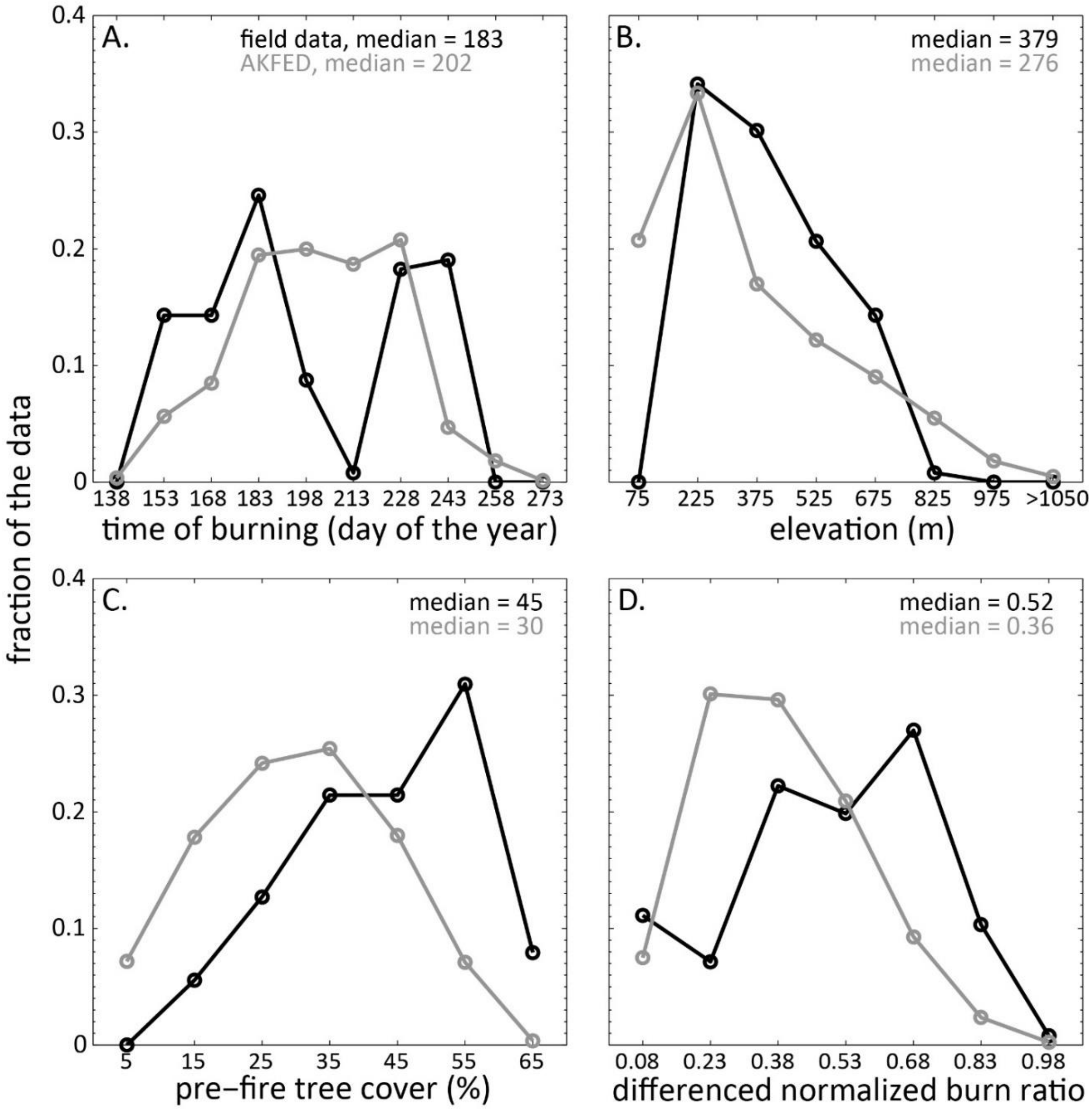
The published spatially explicit estimates from Kasischke and Hoy (2012) and Tan et al. (2007) allow comparison with our study for a limited number of years. Both studies included the large fire year 2004 in their estimates. We estimated a total emission of 69 Tg pyrogenic carbon in our domain in 2004. This is estimate is slightly higher than the estimate of 65 Tg C from Kasischke and Hoy (2012), and both our estimate and the estimate of Kasischke and Hoy (2012) are substantially lower than the estimate of 81 Tg carbon from Tan et al. (2007). We also found agreement between AKFED and Kasischke and Hoy (2012) for the small fire years 2006 and 2008 (estimates of approximately 1 Tg C by both approaches). There was no agreement for the year 2007 were the domain-wide AKFED estimate of 5 Tg C was substantially higher than the estimate of approximately 2 Tg C by Kasischke and Hoy (2012). The discrepancy for the year 2007 is explained by the inclusion of the large Anaktuvuk tundra fire within the AKFED domain, while this fire was excluded in the analysis by Kasischke and Hoy (2012). We also found close agreement in the regional burned area estimates from AKFED and Kasischke and Hoy (2012). For example for the large fire years of 2004 and 2005, AKFED estimated a burned area of 2295 and 1669 kha, compared to estimates of 2178 and 1492 kha burned area by Kasischke and Hoy (2012). The similarities between AKFED and the Kasischke and Hoy (2012) estimates are to be expected since the partly rely on similar input data. For example, both approaches use fire perimeter data in combination with spectral screening for *estimating burned area. In addition, in estimating carbon consumption Kasischke and Hoy (2012) generalized observed relationships by Turetsky et al. (2011) that indicated that ground layer consumption increased with fire season progression. We built on these previous findings by quantifying the relationships between the field data and several environmental variables. We quantified a similar increase in carbon consumption for late season fires based on observations (Figure 6 and 7B) and integrated this relationship in our model structure.*

French et al. (2011) compared 11 different estimates of burned area and carbon emissions for the 2004 Boundary fire. Fire-wide burned area estimates ranged between 185 kha and 218 kha, and carbon emissions between 2.8 Tg and 13.3 Tg. The burned area and carbon emissions estimates from AKFED were 205 kha and 6.0 Tg C. Our carbon emissions estimate for this fire was slightly higher than the estimates of WFEIS (5.3-5.7 Tg C), and also slightly higher than the reported field-based study by E. Kasischke (4.8 Tg C) in French et al. (2011). The difference between AKFED and the latter estimate is at least partly explained by the lower burned area estimate from that study (185 kha).

Differences in the carbon estimates between approaches result from differences in the methods and input data to quantify burned area, fuel type and fuel consumption. We demonstrated in supplementary Figure 4 that, in our application, the nonlinear multiplicative regression model outperformed other statistical methods for extrapolating carbon consumption in space and time that others have found useful for this purpose (Barrett et al., 2010, 2011). Our depth of burn model achieved an $R^2_{adjusted}$ *of 0.40, which is similar to the explained variance of 49.6% in estimating relative loss of the organic layer by Genet et al. (2013). An important difference between these estimates is that Genet et al. (2013) aggregated multiple field locations within the same fire per topographic class. We aimed at preserving the within-fire variability of environmental variables, most notably dNBR and tree cover (Figure S12), in our spatiotemporal extrapolation of carbon consumption. The representation of these higher resolution dynamics in fuel and consumption variability may partly explain our slightly lower model performance.'*

Beginning on 25 of page 604, the authors present a discussion of the relationship of the average ground-layer fuel consumption derived from field studies to those derived from their model, and discuss the need for further measurements of depth of burning based upon the results from their study. This entire passage illustrates a shortcoming of this manuscript in that it fails to correctly relate the research in this paper to research conducted previously. For example, Turetsky et al. (2011) recognized the need to develop a sampling scheme for collection of field data on depth of burning that (a) accounts for factors controlling depth of burning (e.g., topographic position and seasonal timing of fires) and (b) that allowed for scaling of the field results to regional scales through comparison with geospatial information provided by combining information derived from geospatial data. In discussing the design of their study, the authors fail to determine whether or not the dataset they created captures the factors that are known to control depth of burning in black spruce forests Thus, the observations by the authors that the average model predicted values are different from the field observed averages should not be surprising at all, and is a direct product of the design of the study. Later on page 607, lines 10-12, the authors state that currently available field data are biased towards high consumption sites further illustrates their lack of understanding of existing data. In particular, the authors only used a fraction of the data from Turetsky et al. (2011), which includes additional data from sites that did not burn under high burning conditions that were not used in this study. A review of the data used by Turetsky et al. (2011) shows that this database on depth of burning in black spruce forests is robust for most of the burn conditions that occur in interior Alaska, except for immature black spruce forests and for sites that burned during late season fires in small fire years.

20) We strenuously object to the characterization that we do not understand the field observations used in our analysis. We selected all available field data from three different publications (Boby et al., 2010; Turetsky et al., 2011; Rogers et al., 2014) during the MODIS era. We then retained all available field data that had a one-year post-fire dNBR value in the MTBS database since 2001. Field data from before 2001 were excluded from the analysis since AKFED relies on MODIS active fire data to estimate the day of burning. We also optimized this day of burning retrieval for this specific application (Supplementary Figure 3). Thus, we used all available field data from fires covering the same period like AKFED. Given the data limitations, we found this a consistent approach that allows us to assess the representativeness of field data for the same time period as AKFED. For the time period studied and considering data limitations, we found that the field data were biased towards high consumption, in part, because many of these sites were collected at locations with high tree cover and dNBR. These are critical variables not controlled for in previous work. Tree cover may be directly connected to aboveground fire intensity (Rogers et al., 2015), and we demonstrated a linkage between tree cover and depth of burn (Supplementary Figure 7E). We strongly believe is this a new finding, and one that is critical for successfully modeling fire emissions. It is not, as the reviewer suggests, a result of our improper use of understanding of the observations. We will move up this figure (Supplementary Figure 11, shown below) in the current text, to the main text in our revised paper given the importance of this finding.



Supplementary Figure 11. Distribution of (A) time of burning, (B) elevation, (C) pre-fire tree cover, (D) differenced normalized burn ratio of field observations (n = 126) and region wide Alaskan Fire Emissions Database (AKFED) between 2001 and 2012. The tree cover and differenced normalized burn ratio derived from the Moderate Resolution Imaging Spectroradiometer were converted to their Landsat-like values using the equations in Figure S5. The x-axes are labeled with the center of the binning intervals.

b. Methods to estimate fuel loads/fuel consumption in Alaskan boreal forests - Suitability of factors used to estimate C emissions from burning of surface organic matter

Previous studies have shown that depth of burning (from which C consumption is estimated) in Alaskan black spruce forests is controlled by a combination of factors that regulated variations in soil moisture, including topographic factors controlling site drainage and seasonal permafrost thawing.

While the modeling approach used by the authors (multiplicative, non-linear regression) considered a suite of independent variables that might be related to depth of burning, including (a) slope, (b) aspect, (c) elevation, (d) date of burning, (e) tree cover; and (f) a satellite fire severity index, dNBR, the overall performance of the model does not lead one to believe that it represents an improvement over previous approaches. In particular, the r-squared derived from comparing observed versus predicted values was very low (0.29) (see Figure 3), and the calculated in the equation developed to estimate ground-layer C consumption in black spruce forests (1.99 kg sq m) is 76% of the median ground-layer C consumption produced by the model developed by this study. From Figure 3, there appears to be no relationship between predicted and observed depth of burn for the region where the vast majority of the observations exist (e.g., depth of burn between 10 and 20 cm).

21) We strongly disagree with the reviewer's claim that the performance of our model was 'very low' for this application, i.e. estimating carbon consumption from boreal fires. Our depth of burn model had a $R^2_{adjusted}$ of 0.40, our belowground consumption model 0.29, our aboveground model 0.53. All models were significant at $p < 0.001$. Note that adjusted R^2 values are usually a few percentage lower than the 'normal' R^2 values, however, the adjusted R^2 values allow for unbiased comparison between models with different numbers of input variables. Our depth of burn model ($R^2_{adjusted}$ = 0.40) achieved a slightly lower performance than the model from Genet et al. (2013) that predicted relative loss of the organic layer (49.6% of the variance explained). As explained above, this was likely influenced by the aggregation of field plots used in the latter study, which decreases observed variation. As described above in our reviewer response, we also compared our nonlinear multiplicative regression models with statistical methods (gradient boosting of regression trees) that other have found suitable in a similar application (Barrett et al., 2010, 2011). All of the above papers were co-authored by the reviewer. We demonstrated in supplementary Figure 4 that, in our application, the nonlinear multiplicative regression model outperformed gradient boosting technique for extrapolating carbon consumption in space and time. As previously discussed (response 19), we plan on adding a more close comparison of our model with previous efforts in the Discussion section.

The reviewer also misinterprets the RMSE statistic and incorrectly relates this to statewide average consumption values. We initially chose to report the RMSE values since it allows readers to relate this work to previously published material. However, we now realize that the use of this statistic is not well suited for our application and prone to misinterpretation. Our residual errors from our models do not follow a Gaussian distribution as can be inferred from Figure 3. They have a tail towards higher absolute errors. As a result the Root Mean Squared Error is a suboptimal statistic for this application. We thank the reviewer for giving us the chance to correct this and avoid future misinterpretation. We will express our regression model error as the median absolute residual in the revision. We will replace the RMSE number in Figure 3 with the median absolute residuals for the depth of burn model (3.65 cm), belowground carbon model (1.18 kg C m^{-2}) and aboveground carbon model (0.12 kg C m^{-2}). Even when these values are corrected for the non-parametric distribution of the residuals it is still incorrect to directly relate these residuals to statewide average consumption since we demonstrated that the field dataset used in this study is not fully representative for the statewide burning conditions between 2001 and 2012 (Supplementary Figure 11, given above). Given this observation, there is no reason to believe that the distribution of residuals from the field data would be representative for the distribution of statewide uncertainty estimates between 2001 and 2012.

We respectfully disagree with reviewer's assertion that our model does not provide reliable estimates for the range of depth of burn between 10 and 20 cm. First, the model is calibrated for the range of depth of burn observed in the field observations (4.4-34.2 cm). Second, pixel-based uncertainty estimates are an essential part of our model. Based on 12 years of data, we calculated the mean uncertainty (defined as the standard deviation of the prediction error) in depth of burn for black spruce ecosystems for the 10 to 20 cm cohort. The mean uncertainty equaled 1.06 cm (SD = 0.78 cm). These values were weighted for the fraction of black spruce burning in each 450 m pixel.

The claims made by the reviewer in this comment are thus the result of a misunderstanding and misinterpretation of the methods and statistics presented in our paper.

1. I think the authors need to explore other approaches for estimating ground layer consumption that address the shortcomings of their approach. The reason for this recommendation is based on a review of 3 out of the 4 variables selected to model depth of burning/ground C consumption. In section 2.3.3, the authors assert their selection of environmental variables used to estimate fuel consumption was based on an extensive literature review, summarized in Table 1. Ultimately, four of these factors (elevation, pre-fire tree cover, dNBR, and day of year) were included in their model of ground-layer carbon consumption in black spruce forests. I disagree with their assertion that previous studies support selection of 3 out of the 4 selected variables: elevation, pre-fire tree cover, and dNBR. I used field data from previous studies to evaluate the assertions in this study that depth of burning was controlled by elevation and pre-fire tree cover. I used data from the sites used by by Turetsky et al. (2011), Boby et al. (2010), and Kasischke et al. (2008). These data include pre-fire organic layer thickness, depth of burning, stand basal area for black spruce (which is a measure of pre-fire tree cover), and elevation. I also used depth of burning data and we have collected for additional studies. Using these data, I found that:
a) Depth of the pre-fire surface organic layers was not correlated to elevation in unburned stands (r-squared = 0.001).

22) We did not attempt to compare pre-fire organic layer depth with elevation in our paper, and we do not believe this analysis is relevant for evaluating our paper.

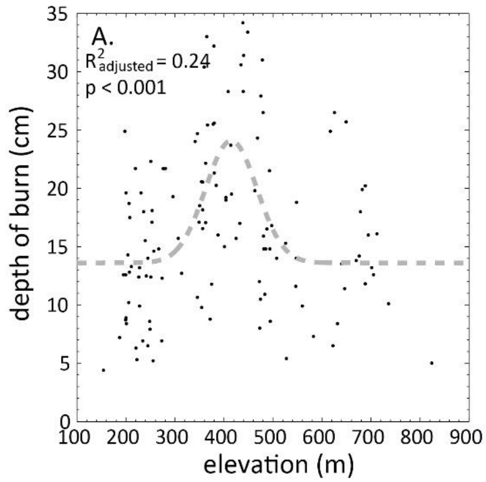
Other than the statement that elevation captures the spatial distribution of cold temperatures that limit the development of soils and black spruce establishment at the higher elevation (altitudinal treeline ecotone), we have not made any assertion that relate to the analysis provided by the reviewer. A potential source of the reviewer's confusion may stem from some of the wording in Table 1, or at p17588l3-5 which we will clarify in the revision.

b) Depth of burning of surface organic layers was not correlated to elevation (r-squared = 0.007).

23) We lack essential information required to allow interpretation of this statistic. It would be helpful to know more about regression type (did the reviewer consider non-linearities?) and statistical significance (p-value).

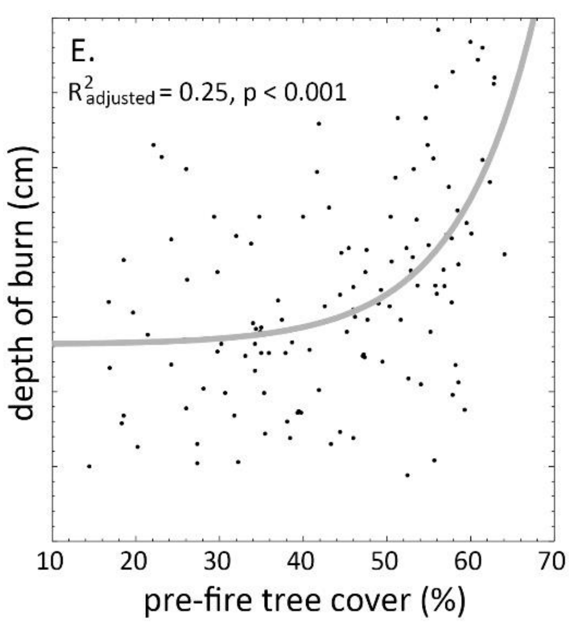
We found a statistically significant nonlinear relationship between depth of burn and elevation (Figure S7A, $p < 0.001$). Solely for the purpose of this response and lacking any additional information on how the reviewer conducted his analysis, we, similar to the reviewer, did not find a linear relationship between elevation and depth of burn ($R^2_{adjusted} \sim 0$, p = 0.39).

Assuming that the reviewer did not consider nonlinearities, this may identify the reason of the discrepancy.



Supplementary figure 7A. Relationship between elevation and depth of burn.

c) Depth of burning was not correlated with stand basal area (of overstory black spruce trees) (r-squared = 0.08)



24) We found a statistically significant nonlinear relationship between depth of burn and tree cover and maintain that this relationship is robust (Figure S7E, $p < 0.001$). Supplementary Figure 7E shows that tree cover is related to depth of burn. We note this tree cover was computed in our analysis using remote sensing observations. We encourage the reviewer to publish his finding, considering non-linearities, that there is no relationship between burn depth and basal area in a future peer-reviewed publication. It does not invalidate our finding that were derived from observations over a different temporal and spatial scale. Further, we think the conceptual underpinnings are robust – more dense stands are likely to cause greater and more uniform heating of the soil organic layer, enabling drying and more complete organic layer combustion.

Supplementary Figure 7E. Relationship between tree cover and depth of burn.

Throughout the introduction, the authors present a narrative to support their use of the dNBR metric to assess variations in fire severity and to estimate fuel consumption in Alaskan boreal forests. The use of dNBR to assess fire severity in the Alaskan boreal forest appears to be supported by a number of peer-reviewed studies where this metric has been used to map fire severity (Duffy et al. 2007; Beck et al. 2011; Jin et al. 2012; Mann et al. 2012). However, I believe from a careful examination of the literature that

involves comparing satellite-based indices to surface measures of field data does not support using dNBR as a metric for assessing severity in black spruce forests.
While there have been several studies that have shown positive correlations between dNBR and surface measures of severity (Allen and Sorbel 2008/Epting and Verbyla 2005 [both these studies used the same data set], Hall et al. 2008; Rogers et al. 2013) other studies showed no correlation between dNBR and field measures of severity (Hoy et al. 2008; Murphy et al. 2008). The number of sites/plots from where positive correlations between dNBR and suface measures were found (14 fires, 472 plots) were similar in number to those where no correlations were found (8 fires, 374 plots). In addition, French et al. (2008) showed that algorithms based on data collected during the lower-area burned fire years (1999 and 2000 and 2002) by Allen and Sorbel did not predict the field measures of fire severity in the studies of Murphy et al. (2008) and Hoy et al. (2008) using dNBR and field data from the large fire years when on which their studies were based. In addition, in spite of the positive correlations between dNBR and CBI found in the multiple studies cited by the authors from outside of the boreal forest region, Kasischke et al. (2008) showed that the field based Composite Burn Index used to assess burn severity in most studies was not correlated to field measures of specific fire severity characteristics in black spruce forests, including depth of burning of the surface organic layer and measures of canopy burn severity. Importantly, the research by the 7 Alaska researchers summarized by French et al. (2008) also included an assessment of the reasons why the dNBR index does not provide a reliable means for assessing fire severity in Alaskan ecosystems. Verbyla et al. (2008) showed that during the growing season, there is significant variation in the solar zenith angle in Alaska, which results in direct variations in the radiance measured by Landsat in several ways. Verbyla et al. showed there was a 20 to 100% variation in NBR of unburned areas based on variations in solar zenith angles. They also demonstrated that variations in slope and aspect also introduce uncertainties into the NBR metric, so that sites that vary by slope and aspect and have the same fire severity will have different dNBRs. This means that even if positive correlations between dNBR and surface measures of severity exist from specific studies, use of satellite data from throughout the year will introduce errors and uncertainties in satellite-estimates of fire severity. In summary, the detailed research presented by the 7 experts in Alaska present 3 lines of evidence that showed that dNBR index is not suitable for estimating fire severity in the forests of this region.

25) This comment illustrates at least three of major points of disagreement with the reviewer: a) lack of recognition of the synergistic role that the dNBR spectral index can have in combination with other environmental variables and field data, b) a different interpretation of the literature on this topic, and c) a lack of willingness to consider different perspectives on this complex issue.

We have discussed a) before. In summary, we reviewed all pertinent literature and came to the conclusion that some authors found support for the use of dNBR and others did not. This point is clearly made in our Introduction and Discussion. An excellent assessment of this debate can be found in the review paper of French et al. (2008), which includes the reviewer as co-author. Based on the literature we decided to investigate the potential of the dNBR in assessing pyrogenic carbon consumption in black spruce ecosystems. This demonstrated that there was a statistically significant ($p < 0.001$) and relatively strong relationship between dNBR and field measurements of depth of burn (Supplementary Figure 7F). The final decision to incorporate dNBR as environmental variable in our model is based on its contribution in synergy with other environmental variables as can be seen in Figure 4. The inclusion of the dNBR in our final model is thus solely based on our mathematical analysis. This difference is fundamental. Note, again, that we DO NOT argue for the use of dNBR alone, but instead that its inclusion into statistical models that account for other important factors via other predictors can be of value.

In addition, the two papers that the reviewer identified as examples in which the dNBR did not provide a relationship with ground measures of consumption actually do show statistically significant ($p < 0.05$) and relatively high correlations (Hoy et al., 2008; Murphy et al., 2008). For example, Hoy et al. (2008) found an adjusted R^2 of 0.46 ($p < 0.0001$) between the dNBR and the depth remaining for the Boundary fire, and an adjusted R^2 of 0.29 ($p < 0.05$) for the Porcupine fire (Table 5 in their manuscript). Murphy et al. (2008) found adjusted R^2 values between 0.11 and 064 for extended assessments over 6 different fires ($p < 0.02$ for all fires). By no means do we give these examples to demonstrate that predictive capabilities of the dNBR as stand-alone variable. These examples do, however, demonstrate that interpretation of dNBR's usefulness is subject to context. In our context, we found the remotely-sensed metric to undeniably be of value Interestingly, the reviewer has co-authored multiple papers (e.g. Barrett et al., 2010, 2011; French et al., 2008) that recommend the synergistic use of field, post-fire spectral, and other geospatial data in estimating carbon combusted from boreal fires. We share these views and these papers were a source of inspiration for our work.

Our paper provides four lines of evidence the use of that dNBR is appropriate to use in synergy with field data and other environmental variables to estimate carbon emission in boreal forest ecosystems:

- as an individual variable, dNBR was the top predictor of depth of burn in black spruce forests together with pre-fire tree cover (Figure S7)
- including dNBR in the model resulted in additional explained variance compared to models that excluded dNBR (Figure 4)
- dNBR and tree cover were found to vary at a finer spatial scale than elevation or time of burning (Figure S12), and their inclusion in the model as such likely improved the representation of the spatial heterogeneity in fuel consumption
- dNBR was significantly correlated with fire size and annual burned area ($p < 0.05$), variables previous research identified to be related with pyrogenic carbon consumption

In contrast, the authors of this manuscript argue that dNBR is a suitable index to assess fire severity based on positive correlations between dNBR and CBI found in other regions of the U.S. and by positive correlations found in three separate studies in Alaska. While they use the results from Verbyla and Lord to support their use of dNBR, the field data in this study was collected 23 (years)[sic] following the fire event used for this study.

26) The assertion that we decided to include dNBR in our model solely based on a literature review is incorrect. Again, after reviewing all pertinent literature we came to the conclusion that some authors found support for the use of dNBR and others did not. An excellent assessment of this debate can be found in the review paper of French et al. (2008). Based on the literature we decided to investigate the potential of the dNBR in assessing pyrogenic carbon consumption in black spruce ecosystems. This demonstrated that there was a statistically significant ($p < 0.001$) and relatively strong relationship between dNBR and field measurements of depth of burn (Supplementary Figure 7F). The final decision to incorporate dNBR as environmental variable in our model is based on its contribution in synergy with other environmental variables as can be seen in Figure 4. This inclusion of the dNBR in our final model is thus based on our analysis and not by picking a side in the long-standing debate of dNBR's usefulness, which we argue is largely a result of interpretation and context. This difference is fundamental.

2. Previous studies (Turetsky et al. 2011; Barrett et al. 2011; Genet et al. 2013) have shown that complex topographic variables are more suitable for explaining depth of burning in black spruce forests than use of single topographic measures (such as elevation, slope, aspect). These more complex variables focus on dividing the landscape into discrete landscape units that can be more directly linked to the spatial variations in soil moisture that control depth of burning.

27) Based on findings of previous work on this topic (Barrett et al., 2010, 2011; Turetsky et al., 2011; Genet et al., 2013) we fully integrated variables related to topography and drainage into our research design and analysis during AKFED development. We already reported in the original manuscript that, as individual variables, slope was significantly correlated with both depth of burn and belowground C consumption, and northness was significantly correlated with belowground consumption ($p < 0.05$, Supplementary Figures 7 and 8). As reported in the manuscript, inclusion of slope and northness did not result in additional explained variance when using the multiplicative models.

We are aware that previous work has focused on more complex variables that can be derived from a DEM. We have therefore considered and tested such variables in the construction of 30 m consumption model, but found that they had no relationships as individual variables, neither did they contribute to the final model through interactions with other variables. To illustrate this we show the scatter plots between flow accumulation and curvature at 30 m, and the corresponding depth of burn field measurements (Figure below).

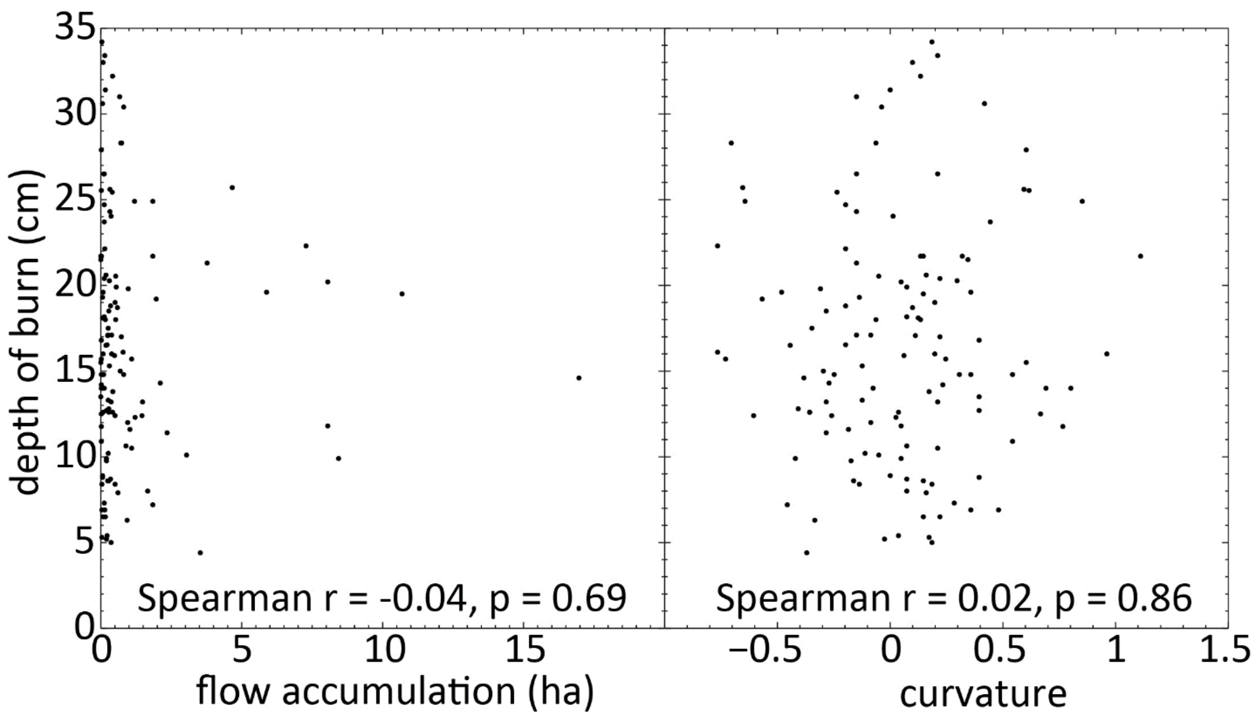


Figure. Scatter plots between depth of burn field measurements and (left) flow accumulation, and (right) curvature extracted from a 30 m DEM.

We agree that it is interesting that our dataset, which covers data from 3 different publications, did not reveal similar topographic controls on consumption compared to previous research. Although these variables did not contribute in our analysis, we do agree that some additional discussion on this topic may be of interest of our readership and we plan on integrating some additional discussion in the revision. We hypothesize that the controls that we identified operate at the regional scale of the state of Alaska, the domain of our study, while local drainage conditions may allow further refinements. This wasn't realized based on the dataset we used, we however do not exclude this possibility, and this again is a call for more data. This comparison with previous work was an interesting point that we already discussed in our manuscript (p17600l8-25):

'Inclusion of the northness and slope variables did not improve our model prediction. This contrasts with the findings of Barrett et al. (2010, 2011) who ranked slope and aspect, and derived drainage indicators, in the top predictors for depth of burn. It contrasts with Turetsky et al. (2011) who found differences in average consumption among different aspect classes. As an individual variable, slope did display some explanatory power (Figure S7B and S8B), but did not contribute to the final model. The contrasting findings of this study compared to Barrett et al. (2010, 2011) and Turetsky et al. (2011) can partly be explained by the scale-dependency of controls on carbon consumption. The model in this study was developed for regional state-wide emission predictions. At this scale, the topographic variable explaining most of the variability in belowground fuel consumption (as a proxy of drainage condition and soil organic layer thickness) was elevation. At a more local scale, for example within one fire, differences in elevation may be smaller, and the variability in drainage conditions and hence belowground fuel consumption may be better captured by including slope and aspect variables. Hollingsworth et al. (2006) found a similar scale-dependency explaining the occurrence and abundance of black spruce types from local to regional scales. Further improvements of the model could include fine scale drainage effects driven by slope and aspect superimposed on the elevation control on consumption.'

Although categorization of continuous variables into a discrete number of classes may help conceptualizations and is sometimes unavoidable (e.g. use of categorical land cover maps) we believe that landscapes should be regarded as much as possible as continuums. Categorization of continuous spatial variability inherently results in a loss of information of spatial heterogeneity. In this case, landscape and drainage conditions can be fully characterized by topographic indices (or by combining different topographic indices). The weak relationships and analyses discussed above demonstrate that in our study such variables (or combination of variables) did not improve model performance, and there is no reason to believe that a class discretization would be helpful here.

3. I do not believe that using a 500 m DEM provides adequate resolution to map variations in topography that are critical drivers of organic layer thickness and depth of burning in Alaskan black spruce forests. For example, in the collection of our field datasets (e.g., Turetsky et al 2011), we frequently located plots along a transect that crossed the threshold between flat uplands and back slopes or between toe and footslopes (which are poorly drained sites and included in our studies as a lowland) and backslopes. The transitions between flat uplands and backslopes as well as flat lowlands and uplands often occurred over 200 to 300 m. Thus, use of a 500 m DEM is likely to result in the misclassification of the topographic positions in the Turetsky et al. data. Using 60 m DEM data, Kasischke and Hoy (2012) also used a flow accumulation model, which allowed further refinement of identification of poorly drained data, which can be challenging in areas with complex terrains, such as interior Alaska.

28) We refer back to our response 27 where we compared field measurements of depth of burn with flow accumulation and curvature derived from a 30 m DEM. No relationship was apparent. Second, we extracted elevation, slope and northness at 30 m level for the comparison with field data and derivation of the multiplicative model (p17592l21-23: 'We aimed to separately predict below- and aboveground carbon consumption based on the relationships between field plot data and environmental variables at 30m (elevation, slope, northness, pre-fire tree cover, time of burning and dNBR)'). Third, a linear regression between the compiled field data from this study with depth-cumulative carbon curves (Supplementary Figure 2) from the topographic classes assigned by Turetsky et al. (2011) as dependent variable (range 0.6-10.4 kg C m^{-2}), and with curves assigned in our study (Supplementary Table 1, range 0.6-10.4 kg C m^{-2}) results in adjusted R^2 of 0.81 with a slope of 0.85 and intercept of 0.50 ($p < 0.001$). Given the close resemblance in carbon combustion from both curve assignment approaches, we do not think that the DEM resolution used here for the conversion of the depth of burn data from Turetsky et al. (2011) had a major impact on our results. We will, however, add a sentence in our discussion section that this may have introduced some additional uncertainty: *'Finally, the cumulative carbon-depth curves used in this study for the Turetsky et al.(2011) data are based on multiple measurements per landscape class and have an inherent uncertainty (Turetsky et al., 2011). In addition, the source and spatial resolution of the DEM may add some additional uncertainty to the depth of burn to belowground carbon consumption conversion for these field plots. Parts of this uncertainty source are likely reflected in the fact that the belowground carbon consumption model resulted in a slightly lower performance than the depth of burn model, and are as such implicitly embedded in the uncertainty estimates from the black spruce model.*'. Fourth, the multiplicative nonlinear regression model for depth of burn was independent of this topographic class assignment and retained the same four variables in the final model.

4. Other variables have been shown to be important in explaining depth of burning could be considered, including size of the fire year, and size of individual fire events during early season fires (Turetsky et al. 2011).

29) These factors are interesting, but in our opinion are emergent properties related to fire weather, fuel composition and continuity, and other factors. We believe it is important to build a 'bottom-up' model using the important local-scale drivers, so that these relationship can be investigated using independent products. We discussed the relationships between fire size and annual burned area, and consumption in our manuscript on lines 17597l14-16 and p17605l4-9

'Mean annual carbon consumption increased slightly with total annual burned area (Figure 8) and mean carbon consumption per fire and fire size were positively correlated (r = 0.22, p < 0.001).'

'We found that large fires years generally have higher consumption estimates (Figure 8). This corroborates findings of Turetsky et al. (2011) and Kasischke and Hoy (2012), although the increase of consumption with higher annual burned area was less than reported in these studies. We also found support for the finding of Duffy et al. (2007) and Beck et al. (2011a) that fire size and consumption level are positively correlated.'

Observed relationships between fire weather severity and fire progression (Sedano and Randerson, 2014) suggest that fire size and total annual burned area may also influence fuel consumption. Our study focuses on a spatially explicit pixel-based model to landscape heterogeneity in fuels and consumption. Fire size and total burned area do not preserve this heterogeneity. We tested if individual fire size and total annual burned area were positively correlated to mean dNBR per fire and per annual burned area. We found that this was indeed true with a Spearman correlation of 0.63 ($p < 0.01$) for fire size and mean dNBR per fire, and a Spearman correlation of 0.73 ($p < 0.05$) for annual burned area and mean dNBR per year. We are grateful to the reviewer for making us looking into this additional analysis and we plan on integrating these new results into the revision. This provides further support for the integration of the dNBR in a synergistic framework for estimating carbon emissions from boreal fires. We plan on adding these findings in the Results section complemented with the following text in Discussion section 5.2.3:

'Building on relationships between fire weather severity and fire progression (e.g. Sedano and Randerson, 2014), previous work has included variables as fire size and total annual burned area as predictor variables in pyrogenic carbon consumption model (Barrett et al., 2010, 2011; Kasischke and Hoy, 2012; Genet et al., 2013). The significant positive correlations between fire size and mean dNBR (Spearman r = 0.63, $p < 0.001$) and annual burned area and mean dNBR (Spearman r = 0.73, $p < 0.05$) provide additional support for the inclusion of the dNBR in a synergistic carbon emissions modeling framework. The advantage of using dNBR for capturing this variability compared to fire size and total annual burned area is that it allows to resolve the spatial variability in fuel consumption, which is impossible from aggregated variables like fire size and annual burned area.'

5. Turetsky et al. (2011) showed that interactions between factors are important in explaining depth of burning in black spruce forests. In particular, variations in depth of burning associated with seasonal thickening of the active layer varied significantly as a function of landscape position. I do not think the modeling approach used by the authors provides for capturing important interactions that control depth of burning.

30) We fully agree that interaction between different variables is important to estimate carbon consumption from boreal forest ecosystems. It is unclear why the reviewer believes that our multiplicative regression approach is unable to capture interaction between different variables since this is one of the key characteristics of multiplicative regression models. This was explicitly spelled out on p17593l10-12. Close examination of Figure 4A for example shows that the interaction between time of burning and elevation was particularly important in the depth of burn model. Together they were able to explain 32% of the variance in depth of burn, clearly more than they did as individual variables (24% for elevation, Figure 7A, and 0% for time of burning, Figure 7B). These findings were already integrated in the manuscript, for example on p17601l1-2.

6. In developing their new approach for estimating depth of burning/ground fuel consumption, the authors do not discuss the suitability of their data set for this purpose. In particular, does the dataset that they developed from their own research and from other studies provide a sampling of the landscape and climatic conditions that are known to control depth of burning in black spruce forests? While one might assume that using the Turetsky et al. (2011) and Boby et al. (2010) (which represents 2/3 of the data used in the study) provides an adequate sample for fire conditions that existed for 2004 (since Turetsky et al. developed a sampling scheme to collect data across different landscape units during early and late season fires), it is very unlikely that the other 40 points used in this study that were collected in fires that burned in other fire years provides enough information to capture

the variation in factors controlling depth of burning across topographic positions, variations associated with seasonal thawing of permafrost, and variations in burning associated with different climate conditions. For example, Turetsky et al. (2011) showed that fire year size was correlated to depth of burn, most likely because fire year size is correlated with the degree of climate-controlled surface drying of organic layers (e.g., dryer conditions that occur during large fire years lead to drier surface organic layers). The 40 points that were from sites sampled in years outside of 2004 provide a very small sample for year with a range of fire sizes (19 points from 2003 – 226,000 ha burned; 17 points from 2010 – 454,000 ha; 2 points from 2002 – 862,000 ha; and 2 points from 2005 – 1,760,000 ha).

31) As described above (response 20), we used all available data during the MODIS era that met the requirements for post-fire dNBR observations. More data needs to be collected to resolve some these interactions, and we will make this point more clearly in our revised draft. We please also want to refer back to our response 29 where we demonstrated that the dNBR partly captures the variability that others have intended with spatially aggregated variables like fire size and annual burned are. The advantage of the dNBR is obvious here, because, in contrast with aggregated variables, the dNBR preserves spatial heterogeneity.

c. Uncertainties associated with the C emission estimates

In equation (1) in Section 3.3, the authors present the algorithm used to estimate total uncertainty for their carbon emission estimates and is based on using the above and below ground consumption predictions developed for this study. Based on the RMS uncertainties presented in Figure 3, this equation results in an uncertainty of 2.01 kg C/sq m. However, in the paper, the authors report an uncertainty of only 0.38 kg C/sq m. My question is how did they calculate the uncertainty value presented in the manuscript? The approach they use appears to be based on the standard error for all the output pixels generated by their model, but they do not present a clear explanation of how Figure 9 was created.

32) We already addressed parts of this comment in our response 21, we will repeat where necessary for easy reference. We have modified our error estimates from the regression approach to make them conform to their non-parametric distribution. We are thankful to the reviewer for giving us the chance to correct this. We will express our regression model error as the median absolute residual in the revision. We will replace the RMSE number in Figure 3 with the median absolute residuals for the depth of burn model (3.65 cm), belowground carbon model (1.18 kg C m^{-2}) and aboveground carbon model (0.12 kg C m^{-2}). Even when these values are corrected for the non-parametric distribution of the residual it is still incorrect to directly relate these residuals to statewide average consumption since we demonstrated that the field dataset used in this study is not fully representative for the state wide burning conditions between 2001 and 2012. Given this observation, there is no reason to believe that the distribution of residuals from the field data would be representative for the distribution of statewide uncertainty estimates between 2001 and 2012.

The reported median uncertainty value of 0.38 kg C m^{-2} in the original manuscript was indeed the statewide pixel-based uncertainty for all burned pixel between 2001 and 2012 following equation in the manuscript. All methods were clearly described in the text. However, we plan on integrating more analysis and discussion on uncertainty in the revision and the black regression model uncertainty will be one of several uncertainty sources. We will further describe our revised uncertainty section response 33.

In addition, the approach presented in Eq. (1) and in Figure 9 does not account for numerous other sources that will contribute uncertainties to the carbon consumption values associated with their overall methodology, including:

(a) uncertainties associated with the calculations of carbon consumption by the Consume model that were used for other vegetation types; (b) uncertainties associated with the scaling the Consume calculations of carbon consumption based on using estimates from their model for black spruce vegetation; (c) the uncertainties in the baseline vegetation cover map (which are discussed but not quantified); (c) uncertainties associated with using 500 m products, especially in topographic information;(d) the uncertainties introduced by using 500 m resolution products for estimation of carbon consumption, where the algorithm themselves are based on using 30 m resolution products; (e) not including dead wood debris in their estimates of total carbon emissions, which Kasischke and Hoy (2012) show represent 5 to 7% of all emissions; and (d) uncertainties associated with the representativeness of the database used to develop the C consumption algorithms. At the very least, the authors need to provide a discussion on the various sources of uncertainties that are present in their estimates of carbon consumption.

33) We are grateful to the reviewer for suggesting a thorough regional uncertainty analysis and we plan on integrating additional analysis and discussion on this topic in the revision. This will address all the reviewer's concerns. We identified four main sources of uncertainty (see new table below). The first source is the result of the unexplained variance in the black spruce consumption model. The other sources of uncertainty were related to assumptions and data required to extrapolate the model over Alaska. These included uncertainties of the land cover classification, in assumptions made for deriving carbon consumption for other land cover types than black spruce, and from spatial scaling of a model developed with 30 m data at 450 m resolution. We ran a Monte Carlo analyses for different scenarios to quantify region wide uncertainty and the relative importance of uncertainty sources. We will add new uncertainty sections in the Methods and Results, and more discussion on uncertainty.

We will add the following section in the Methods:

'3.4 Uncertainty

We adopted a Monte Carlo approach to assess uncertainties in AKFED. We identified four main sources of uncertainty (Table 2). The first source is the result of the unexplained variance in the black spruce consumption model. The other sources of uncertainty were related to assumptions and data required to extrapolate the model over Alaska. These included uncertainties in the land cover classification, assumptions made for deriving carbon consumption for other land cover types than black spruce, and spatial scaling of a model developed with 30 m data at 450 m resolution. The uncertainty of the black spruce model and spatial scaling was quantified with statistical methods. Due to data paucity we assigned 'best-guess' uncertainties to the land cover classification and scaling factors developed to estimate consumption in other land cover types than black spruce (Figure S6). We ran 1000 simulations in which we randomly added normally distributed uncertainties to the input values. We separated between uncertainties in belowground, aboveground and total carbon consumption. For each run and each uncertainty source, we assumed a uniform spatial distribution of the uncertainty in the simulation.'

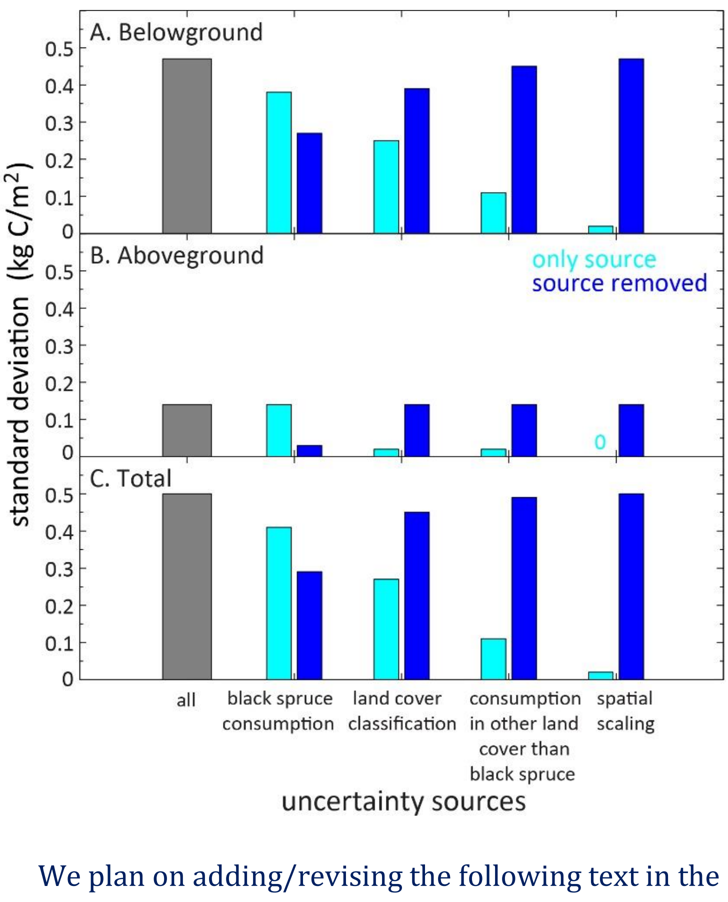
Table 2. Sources and quantification of uncertainty included in the Monte Carlo analysis

source	*standard deviation*
black spruce consumption	*prediction error from regression models (equations 1 and 2)*
land cover classification	*20 % of per-pixel fractional black spruce cover ('best-guess')*
consumption in other land cover than black spruce	*20 % of scaling factors developed for white spruce and deciduous cover (Figure S6) ('best guess')*
spatial scaling	*error in slope and intercept of regression between 30 m and 450 m consumption estimates (Figure S11)*

We plan on adding the following text to the Results:

'*4.3 Uncertainty*

All model means of the different Monte Carlo simulations were within 0.05 kg C m^{-2} of region wide AKFED means between 2001 and 2012 and we therefore focused the uncertainty analysis on the variability within simulations, expressed as the multi-run standard deviation. Uncertainty in total carbon consumption originated primarily from the belowground fraction (Figure 10). The region wide standard deviation of the 1000 simulations that included all uncertainty sources was 0.50 kg C m^{-2} for total carbon consumption. Region wide below- and aboveground uncertainties from all sources were 0.47 kg C m^{-2} and 0.14 kg C m^{-2}. The black spruce model was the main source of uncertainty, followed by the land cover classification. The scaling factors developed to derive consumption in other land cover types than black spruce and spatial scaling introduced smaller uncertainties.'



New Figure to be integrated in the revision. Attribution of uncertainty sources in (A) belowground, (B) aboveground and (C) total carbon consumption estimates. The standard deviation of the consumption estimates from 1000 Monte Carlo simulations was calculated for each scenario.

We plan on adding/revising the following text in the Discussion section:

'The domain wide uncertainty was slightly lower than 20 % of the region wide mean, which was similar to the fire-wide uncertainty estimate from Rogers et al. (2014). Other studies that have modeled region wide carbon emissions and uncertainties from Alaskan fires have relied on scenarios in which uncertainties of different sources were assigned based on expert knowledge (French et al., 2004; Kasischke and Hoy, 2012). These studies found uncertainties in the range of 5 to 30%, expressed as the coefficient of variation (standard deviation/mean). The most important source of uncertainty in AKFED originated from uncertainties in the belowground carbon consumption estimates from the black spruce model (Figure 10). This corroborates with findings of French et al. (2004) and Kasischke and Hoy (2012) who both identified ground layer consumption as a major source of uncertainty within boreal forest ecosystems. We here quantified this uncertainty source based on the unexplained variance of the carbon consumption model that we developed (Figure 3). This approach provided a quantitative region wide uncertainty assessment for pyrogenic carbon consumption in black spruce ecosystems that was directly driven by observations. Due to a lack of data, we relied on best-guess uncertainty estimates for the land cover classification and consumption estimates in other ecosystems than black spruce. While black spruce forest is the ecosystem most affected by fire in Alaska, other land cover types like white spruce, deciduous, shrub or grass cover also burn (Kolden and Abatzoglou, 2012). We estimated a conifer fraction burned of 61% (39% black spruce and 22% white spruce), a tundra-grass-shrub fraction of 23%, and a deciduous fraction of 14%. The land cover layer and consumption scaling factors for other land covers than black spruce were both necessary steps to allow region wide extrapolation of the pyrogenic carbon consumption model. The land cover layer was used to partition consumption between different land cover types. Due to the data paucity in other land covers than black spruce, we developed scaling factors for consumption in other land cover types based on generalized relationships. Unfortunately, no formal state wide uncertainty assessment has been carried for the FCCS fuel type layer in Alaska, neither can the uncertainty of the scaling factors developed from Consume 3.0 be formally assessed. Best-guess scenarios for these uncertainty sources demonstrated that the uncertainty in the land cover classification, and to a lesser degree the scaling factors for other cover types than black spruce, contributed in a non-negligible way to the region wide uncertainty. We also found that the uncertainty introduced by using a nonlinear 30 m model at 450 m resolution was small. The uncertainty analysis gave insight in the uncertainties and their relative importance of the black spruce model and the assumptions and data required to extrapolate the model over large areas. Our analysis and previous studies (French et al., 2004; Jain, 2007; van der Werf et al., 2010; Kasischke and Hoy, 2012), however, assumed that the uncertainty of each input variable is spatially uniform within each model run. This assumption may not be entirely valid. Uncertainty in for example the black spruce model, the land cover classification and spatial scaling may well have spatial variability. This would not affect pixel-based uncertainty estimates, however, it would affect region wide uncertainty estimates as some of the uncertainties may partly average out over large areas. This was demonstrated by Rogers et al. (2014) who demonstrated that pixel-based uncertainties partly average out over a fire perimeter when assuming spatially random uncertainty in the prediction error of a carbon consumption model. Quantifying the spatial distribution of uncertainty is complex and may not be possible with current data. The assumption of spatially uniform uncertainty represents the 'worst-case' scenario and may therefore overestimate region wide uncertainty. Similarly, the assumption of a spatially random uncertainty distribution, however, would likely underestimate region wide uncertainty.

While we identified and quantified four main sources and their relative importance within AKFED, other sources of uncertainty were not included in our analysis. These include the dNBR threshold used for burned area mapping, the assumption of the same controls on pyrogenic *consumption in non-black spruce ecosystems, consumption of woody debris, and the cumulative carbon storage curves used to convert depth of burn into belowground carbon consumption for the Turetsky et al. (2011) plots. When uncertainties in burned area mapping are large, then this variable can be the most important source of uncertainty (French et al., 2004; van der Werf et al., 2010; Kasischke and Hoy, 2012). We used three independent datasets (ALFD perimeters, and MODIS surface reflectance and thermal anomalies) to map burned area, including burned area outside fire perimeters (1 % of total burned area) and excluding unburned islands within the fire perimeters (18 % of perimeter area). We believe that this approach minimized uncertainties from this source. We recognize, however, that the dNBR threshold of 0.15 introduced some uncertainty and likely resulted in the omission of some partially burned and/or low severity pixels, but minimized the occurrence of commission errors. The carbon consequences of omitting burned pixels with a dNBR lower than 0.15 are likely small. Due to the lack of field data to construct empirical models for other land covers than black spruce, we assumed that the same environmental variables that controlled carbon consumption in black spruce ecosystems also operate for white spruce, deciduous species, grassland and shrub land. This assumption may not entirely be valid but cannot be verified until field data becomes available for these cover types. Consumption of woody debris is hard to quantify. Carbon consumption in this pool is small compared to the consumption of the soil organic layers, but can amount up to 5 to 7 % of the total consumption (Kasischke and Hoy, 2012). Field measurements of fuel loads of woody debris in unburned stands in function of stand age and their consumption in relation to fire weather conditions may allow further optimization of pyrogenic carbon consumption models in boreal forest ecosystems. Finally, the cumulative carbon-depth curves used in this study for the Turetsky et al.(2011) data are based on multiple measurements per landscape class and have an inherent uncertainty (Turetsky et al., 2011). In addition, the source and spatial resolution of the DEM may add some additional uncertainty to the depth of burn to belowground carbon consumption conversion for these field plots. Parts of this uncertainty source are likely reflected in the fact that the belowground carbon consumption model resulted in a slightly lower performance than the depth of burn model, and are as such implicitly embedded in the uncertainty estimates from the black spruce model.*

Several aspects of the uncertainty analysis call for a more comprehensive field dataset to better constrain observation-driven empirical models of pyrogenic carbon consumption in boreal ecosystems. First, additional field efforts could focus on gathering more field data of consumption in black spruce ecosystems. In their sampling design, such field data collections could for example consider layers of pre-fire tree cover and post-fire dNBR in an effort to better represent the distribution of burning conditions (Figure 10), in addition to topographic conditions and fire seasonality. Second, considerable uncertainty within AKFED stemmed from assumptions made to estimate consumption in white spruce, deciduous, grassland, and shrub land ecosystems. Very little data on pyrogenic consumption is currently available for these ecosystems. For white spruce and deciduous ecosystems we developed scaling factors using Consume 3.0 (Figure S6). For grasslands and shrub lands we used the black spruce model because tree cover is one of our predictor variables and our model was calibrated for a range of tree cover between 14 and 64 %. Lower tree cover resulted in lower consumption (Figure 7E) and this may justify the use of the model for non-treed ecosystems until consumption data within these ecosystems becomes available. The initiation of field databases within white spruce, deciduous, grassland, and shrub land ecosystems may allow for the development of similar observation-driven models as developed here for black spruce to further partition consumption models per ecosystem type. These field data collections in other ecosystems than black spruce may consider the same environmental variables as identified here for black spruce, however, other factors may be important as well. Third, regional extrapolation of carbon *consumption model from different ecosystems depends on the underlying land cover classification. To date, the FCCS classification is the only classification that for example distinguishes between black spruce and white spruce in Alaska. No formal accuracy assessment of this layer has been conducted, however, we found that, at its native 30 m resolution, 60 out of the 126 black spruce plots from the field dataset (section 2.2) were misclassified;29 as white spruce, 14 as tundra-grass-shrub, 12 as deciduous, and 5 as non-vegetated. We also found that of eight white spruce-aspen plots from Rogers et al. (2014), seven were classified as black spruce and one as shrub-grass-tundra. The sample size of the land cover ground truth data available was too small to robustly quantify potential over- or underrepresentation of land cover types in the FCCS layer. An improved land cover characterization, including quantitative uncertainty estimates, is thus essential for reducing region-wide uncertainties. An underrepresentation of the black spruce cover in the FCCS would result in lower state wide average consumption estimates and vice versa. While some land cover types, such as spruce and deciduous cover, are likely well separable from remote sensing based on spectral and phenological characteristics, more detailed distinctions, for example between black and white spruce, may be more challenging but not impossible with the combined use of structural and optical attributes (e.g. Goetz et al., 2010). More than a decade after the call from French et al. (2004) for more field data, including from ecosystems that burn less regularly, more field measurements are still required to better constrain pyrogenic carbon consumption in boreal forest ecosystems. The upcoming multi-year Arctic-boreal vulnerability experiment (ABoVE, http://above.nasa.gov/, last accessed March 3, 2015) funded by the National Aeronautics and Space Administration may provide opportunities to fill gaps in existing field datasets.*

Another future improvement could be to operate AKFED at 30 m resolution. This would result in much more spatial detail. The tree cover and dNBR layers currently constrained the development of a 30 m product. The tree cover product at 30 m is now only available for a limited amount of years and this would degrade the annual update of tree cover (up through 2010) that we currently included in AKFED. For the 30 m dNBR, we explored the potential of currently available products like WELD (Roy et al., 2010) and MTBS (Eidenshink et al., 2007), but found that even with these products, it would have been impossible to have consistent post-fire observations for every single burned pixel. We therefore pragmatically decided to use MODIS imagery which facilitated elimination of cloud- and smoke-affected observations thanks to its daily revisit time resulting in useful remote sensing observations for the whole spatio-temporal domain. Further development of WELD and the Google Earth Engine (https://earthengine.google.org/, last accessed March 3, 2015), which also provides access to the Landsat record, could eventually lead to an operational model at 30 m resolution. Further updates of the model may also profit from the availability of active fire data from the Visible Infrared Imaging Radiometer Suite at 375 m which may improve the time of burning estimates.'

d. Other issues

Clarification of methods

Why was it necessary to generate a 30 m DEM for this study, when existing DEM data already exist at 60 m resolution? I would understand creating a 30 m DEM if the authors conducted their analyses at this resolution. But in this study, the authors degraded the 30 m DEM product they developed to 500 m.

34) We clearly explained why we built the model using 30 m Landsat data, and why we extrapolated our model in space using MODIS data on p17591l11-16:

'The decision to extrapolate the model at this resolution was driven by data availability. We aimed at complete spatial coverage. Even with current efforts such as MTBS and the Web-Enabled Landsat Data (WELD, Roy et al. (2010)), initial exploration of these datasets indicated that complete Landsat dNBR coverage for every burned pixel was still partly constrained by clouds, smoke, snow and gaps due to the Landsat 7 scan line corrector failure.'

In section 3.3, more detail is needed on how biomass consumption for other fuel types was estimated, in particular, how they scaled the belowground measurements. First, the actual data used for Consume was based on collection during burning conditions that existed in smaller fire years or during early season fires in a large fire year (see, e.g., http://depts.washington.edu/nwfire/dps/). As such, the conditions used to develop the Consume model for Alaska do not match the range of conditions that existed for many of the fires that occurred during the 2000s, in particular, late season fires during large fire years.

Second, scaling fuel consumption in deciduous and white spruce forests forest floors based on deep burning in late season fires does not make sense for these forest types, which do not contain permafrost.

In addition, the information presented in Supplementary Fig. 6, ground fuel consumption in white spruce forests is about 2/3 of ground fuel consumption in black spruce forests, while ground fuel consumption in deciduous forests is about 1/3 of that in black spruce forests. Based on data present in the USFS fuel layers for Alaska (http://depts.washington.edu/nwfire/dps/), the max fuel levels for deciduous forests is on the order of 1.2 to 1.5 kg/sq m, while the fuel levels for white spruce forests has a maximum level between 2.2 to 2.5 kg/sq m. According to the approach described by the authors, the max fuel consumption for black spruce ground layer is 8 kg/sq m, which results in a max for deciduous of 2.4 kg / sq m and 5.3 kg / sq m for white spruce, both of which are substantially higher than fuels available for burning in these forest types.

Finally, in shrub and grass vegetation types, the foliage and small branches are much less flammable than the foliage in black spruce, and there is likely a much lower level of aboveground fuels in these fuel types than in black spruce forests; thus, using the fuel consumption values for above ground black spruce does not make sense. There is no evidence presented that all shrub and grass lands occur on sites with permafrost. In many instances, these vegetation types are likely the result of regrowing forests following fires. Thus, assuming that the ground-layer fuel consumption in this forest types is the same as in black spruce forests is not justified.

35) Many aspects this comment are addressed with our expanded uncertainty analysis and discussion, and we refer to response 33 for an in-depth discussion. We already extensively discussed in the original paper the assumptions made in the paper for other fuel types black spruce are required due to the limited availability of field data in other fuel types. Nearly all available field measurements of pyrogenic carbon consumption are in black spruce ecosystems and very few data cover white spruce, deciduous, and shrub- and grassland ecosystems. We will clarify this even more in the revision.

Consume 3.0 was solely used to develop general relationships between the expected above– and belowground consumption levels for black spruce, and white spruce and deciduous tree (Supplementary Figure 6). Close examination of the Consume 3.0 data (Table below) and published field measurements of Rogers et al. (2014) (Figure below) within white spruce and aspen sites shows that aboveground fuel loads are generally higher, and belowground lower. For the easy reference of the reviewer we summarized the above- and belowground loads and consumption values that we extracted from Consume 3.0 (Ottmar et al., 2006) for black spruce, white spruce and deciduous stands in the table below. Note that we reported the consumption values for the 'Dry' scenario described in the caption Figure S6. Interestingly, these values are quite a bit different than the ones the reviewer provides. For example, data from Consume 3.0 shows aboveground carbon loads of 4.72 kg C m^{-2} for white spruce and 3.79 kg C m^{-2} for deciduous, compared to the maximum values of 2.5 and 1.5 kg C m^{-2} provided by the reviewer. Comparison with field measurements from Rogers et al. (2014) shows that the numbers extracted from Consume 3.0 are more realistic than the ones provided by the reviewer.

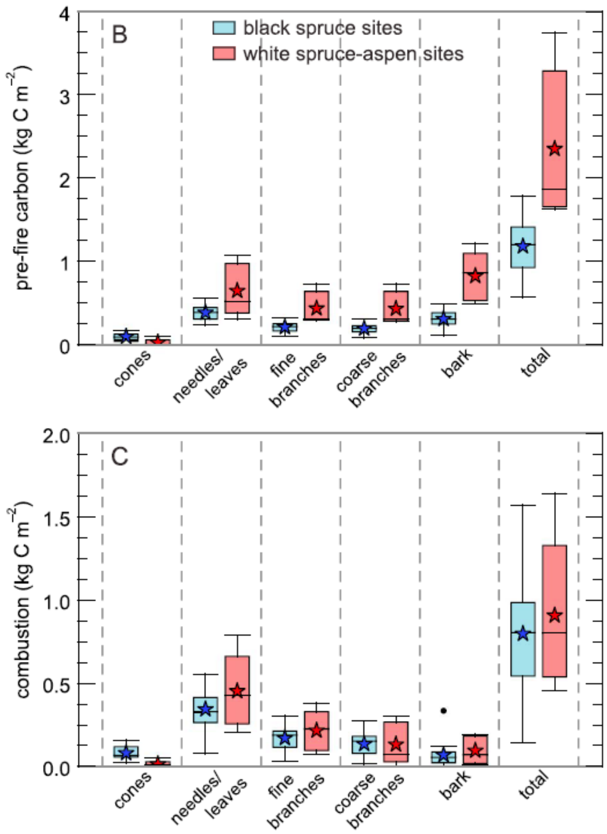


Figure. Pre-fire carbon loads and combustion in black spruce and mixed white-spruce-aspen sites measured in the 2010 Gilles Creek fire perimeter, AK (Rogers et al., 2014).

Table. Above- and belowground carbon loads and consumption for black spruce, white spruce and deciduous ecosystem as derived from Consume 3.0 (Ottmar et al., 2006)

Fuel type	Black spruce	White spruce	Deciduous
FCCS code	87	101	93
aboveground carbon load (kg/m2)	2.23	4.72	3.79
belowground carbon load (kg/m2)	7.26	5.54	4.23
aboveground carbon consumption (kg/m2)	1.06	1.65	1.85
belowground carbon consumption (kg/m2)	2.17	1.44	0.69

The reviewer's critique on applying on our black spruce model on grass- and shrubland shows a lack of understanding of our paper. First, we want to repeat that field data availability is limited to black spruce ecosystems. However, our black spruce plots range in tree cover between 14 and

64. We firmly believe that for fire emissions modeling, we need to move beyond class discretization (e.g. black spruce class versus shrubland class) since these inherently result in information loss. The transition from grass- and shrubland to black spruce forest does follows a continuum of tree cover. As can be inferred from Figures 8E and 9A, lower tree cover results in lower below-and aboveground consumption, and this is exactly what one expects for grass- and shrubland ecosystems. Few estimates of carbon consumption in tundra fires are available, however, we compare our estimates with published estimates for the 2007 Anaktuvuk river fire (Mack et al., 2011) in the revision.

In summary, given the limited availability of field data for other land cover types than black spruce, we made assumptions to allow extrapolation of our model over white spruce, deciduous, and grass- and shrubland ecosystems. These assumptions were based on available data and published material. Uncertainties related to these assumptions will be integrated in our expanded uncertainty analysis and discussion. We do agree with the reviewer that more field measurements in these land cover types are critical to further calibrate and validate our model in these ecosystems and this call for more data will be integrated in our revised manuscript (see also response 33.

3. Section 2.3.4 – Why use LANDFIRE land cover rather than NLCD. In terms of mapping mature black spruce, the Landfire data set has a much lower accuracy than the North American Land Cover dataset, whose accuracy has been assessed for Alaska (Selkowitz DJ, Stehman SV (2010) A spatially stratified, multi-stage cluster sampling design for assessing accuracy of the Alaska (USA) National Land Cover Database (NLCD). International Journal of Remote Sensing, 31, 1877–1896). We determined this by using field plots where we collected depth of burning in black spruce forests during the 2003-2005 wildfires in Alaska. The authors should check this. Thus, another source of uncertainty in their study

36) The Fuel Characteristic Classification System layer is the only available land cover layer for Alaska that discriminates between black spruce and white spruce (see for example our Supplementary Table 1 and Supplementary Figure 1). This is critical given the different below- and aboveground consumption characteristics of both cover types (see response 35). We already discussed the uncertainties in this layer and potential consequences for AKFED in great length (section 5.3 in the original manuscript) and we quantitatively integrated uncertainties of the FCCS layer in our expanded uncertainty analysis (response 33). The NLCD land cover layer does not distinguish between different coniferous tree species. This layer would need an assumption toward the attribution and spatial distribution of black and white spruce within the coniferous class. Such an assumption may even be more uncertain than the uncertainties associated with FCCS layer.

Other Comments

Page 581 – line 10. The references are incomplete, as they only cite papers that are based on models that use climate as the driver of changes to fire regimes. They should also cite research that shows changes in vegetation cover associated with changes to climate and the fire regime will have negative feedbacks to future burned area (Mann et al. 2012; Kelly et al. 2013)

37) We plan on adding these references to the introduction.

Page 581 – line 21: Jin et al. and Beck et al. are two examples of studies that use dNBR for assessing fire severity, when in fact, there is no strong evidence that dNBR is a viable metric for doing so. In addition, Beck et al.'s method for identifying late season fires that result in deep burning, severe was flawed, in that the cut-off date for separating early vs. late season fires was early June.

38) We refer to our previous responses (e.g. 15, 25, 26) with regards to the use of the dNBR in combination with field measurements and other environmental variables, including our point of disagreement a at the beginning of the response to referee Kasischke.

Page 582 – line 3 – Rather than citing their own research, the authors should the research where this approach was first used – Michalek et al. 2000

39) We will cite the paper of Michalek et al. (2000) in the revision.

Page 582, line 27: I would not use modeling studies to support the observation made in this sentence, but rather field-based studies such as Johnstone and Kasischke 2005 and Turetsky et al.

40) Turetsky et al. (2011) was already cited here and we will add reference to Johnstone and Kasischke (2005) in the revision.

Page 584, line 13: Rather than referring to the most recent papers that support observations made in this sentence, the authors should preferably include the papers where the technique was first introduced, in this case Kasischke and Hoy 2012

41) We already referred to Kasischke and Hoy (2012) at the end of the identified sentence. We want to note though that Parks (2014) and Veraverbeke et al. (2014) quantitatively calibrated and validated the fire progression method based on MODIS active fire data. We here elaborated on this approach and optimized the fire progression retrieval for our application (Supplementary Figure 3). Sedano and Randerson (2014) used fixed setting in their interpolation techniques and the description of the method applied in Kasischke and Hoy (2012) is incomplete. No statements can be made with regards to the temporal accuracy of their fire progression data.

Page 582, line 20 – You need to be more specific here – the observations of de Groot et al. (2009) referred only to consumption of ground layer biomass in black spruce forests, and these observations in this paper are not in reference to other fuel types and categories. Except for ecosystems with deep organic layers, the models developed by researchers at the Canadian Forest Service perform quite well for forested area.

42) We disagree. Close examination of the de Groot et al. (2009) paper shows that their analysis included black spruce, white spruce, jack pine, lodgepole pine and deciduous ecosystems (For example Table 1 in their manuscript).

Page 582, lines 25-30. I would stick to papers where direct observations of the effects of late season burning have been made, such as Turetsky et al. and Kasischke and Johnstone 2005. The other papers cited here deal with estimating the impacts of late season burning on emissions.

43) This is the exact same comment as the reviewer made earlier. Please read our response 40.

Page 583, lines 1 to 5. The references are not appropriate. Kajii et al. actually show a decrease in total biomass consumption between Aug and Sep, and thus do not support the point of this sentence. Soja et al. provide a range of depth of burning for different ecosystems, but do not specifically cite late season deepening of the active layer as being the driver of deeper burning fires.

44) We disagree with the reviewer. These references support this sentence 'Based on this rationale, several authors have developed scenarios in which they assign ground fuel consumption values based on the seasonality of the burn (Kajii et al., 2002; Kasischke and Bruhwiler, 2002; Soja et al., 2004)'. Please check for example Table 2 in Kajii et al. (2002) and Figure 1 and Table 4 in Soja et al. (2004).

Page 583, line 28-30: While these studies showed correlations between NBR and depth consumption, these studies were all conducted in sites where deep burning of the surface organic layer did not occur. This should be noted.

45) This is implicitly embedded in p17584l3-5: 'Extrapolation of relationships like this needs further calibration with field data that span a wide range of fire seasonality and topographic conditions.'

Page 584, line 15: Note that Kasischke and Hoy used MODIS Hotspot data to develop daily fire progression maps, which were combined with burned area maps derived from Landsat dNBR products to create daily burned area products. This is a fundamentally different approach than used in this study, and provides much finer spatial information (by an order of magnitude) on patterns of burning than can be derived from using 500 m MODIS burned area maps, the approach used in this study.

46) We refer to our earlier response 41 for the differences in fire progression approach, and to another earlier response 34 on our decision to operate the model at 450 m. We note that we have provided continuous 2001-2012 emissions estimates in our analysis – an advance that has not yet been replicated using other approaches.

Page 585, lines 19-23: This sentence presents an overly simplistic model of the distribution of black spruce in Alaska. Recent studies have shown that black spruce is widely-distributed than just on north aspect slopes and in lowlands. The data from Turetsky et al. provide evidence that mature black spruce is distributed across all aspects on backslopes.

47) Please note that we use the words 'dominate' and 'prevail' in this sentence. These words do not exclude distributions that are slightly different or complementary to this generalized description. Please also note the context of this sentence in section '2.1 Spatiotemporal domain'. The purpose of this sentence is to give the reader a general idea of the spatial distribution of the major ecosystems in Alaska. An in-depth discussion on this is beyond the scope of this manuscript and the reader is referred to the cited references of Bonan (1989) and Viereck (1973) for more information.

Page 589, line 21-22: This statement is not true. AKFED does not estimate soil moisture from elevation and time of burning, but correlates burn depth and carbon consumption to these variables.

48) The identified sentences ('For the statewide extrapolation, we calculated the NBR from MODIS surface reflectance data in the near infrared (NIR, centered at 858 nm) and short-wave infrared (SWIR, centered at 2130 nm) bands: NBR = (NIR - SWIR) = (NIR + SWIR). We used the surface reflectance data contained in the 16 day Terra MODIS Vegetation Indices 16 day Collection 5 product at 500m resolution for the years 2000–2013 (MOD13A1, Huete et al., 2002). To account for cloudy observations in single MODIS composites, we created summer NBR composites using the five 16 day composites between days of the year 177 and 256.') refer to our MODIS data collection and we don't understand how the reviewer's comment relates to this.

Page 599, line 5: Also, Kasischke and Hoy reported that 20% of the areas within the perimeters of the fires they studied.

49) We will add this number and reference to the sentence in the revision.

Page 599, line 15-20: This may not be true based on Jones et al. (2013) who identified several large tundra fires that had previously occurred on the North Slope (JOURNAL OF GEOPHYSICAL RESEARCH: BIOGEOSCIENCES, VOL. 118, 1–11, doi:10.1002/jgrg.20113, 2013)

50) To avoid confusion and since our study does not focus on tundra fires, we will remove these two sentences on tundra fires in the revision.

Page 601, line 9 to 25: This material should go into the methods and be reported in the results section

51) We understand the reviewer's comment and we have considered this in earlier draft. However, our manuscript is already lengthy with for example 12 supplementary figures. Adding more results may confuse the reader. The results also don't really add anything to the presented approach. They do, however, present interesting avenues for future research and we find them therefore well suited in the Discussion section.

Page 605, line 8-9. Since neither Duffy et al. nor Beck et al. actually used field data to quantify fire severity, this sentence does not make sense.

52) We respectfully disagree with the reviewer. In our paper we have tried to relate our findings to all pertinent literature.

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