Summary of changes

We would like to thank the reviewers for their assessment of our manuscript. We made several modifications to our manuscript to include suggestions from the reviewers and we substantiated our approach in the responses. We refer to our author comment AC C8971 that we previously posted on the interactive discussion from for our responses to anonymous referee 2, Kane E.S., and Kasischke E.S. Point-by-point responses to anonymous referee 3 are given in this document below. The changes that we made in the revision are highlighted in track changes in the attached manuscript files. Because of manuscript length considerations, the changes in the manuscript are in some instances slightly different than presented in AC C8971. We also uploaded revised data files to our ftp server.

These are the main changes to our manuscript:

- We included additional analysis to assess the effect of the spatial resolution of the model and we included this effect in a revised uncertainty analysis (Figure S11)
- We extended our uncertainty analysis with a Monte Carlo analysis that accounts for uncertainties in regression prediction and state-wide extrapolation (Figure 11, sections 3.4, 4.3, and 5.4).
- .We included comparison between annual burned area, carbon emissions and carbon consumption values from AKFED and the Wildland Fire Emissions Information System (WFEIS). We moved the resulting comparison table up to the main manuscript (Table 2).
- We extended the discussion sections on the comparison with previous approaches (section 5.3) and uncertainties (section 5.4) in the revision.
- We updated all aspects of our manuscript that were affected by the revised analyses and wording.

Point-by-point responses to anonymous referee 3

General comments The development of the Alaska Fire Emissions Database has value for advancing our understanding of the methods and datasets of value for these types of emissions products, despite being based on approaches and data sets previously used in other similar studies. The value of the work presented is in exploring in detail the various data layers available for emissions mapping in Alaska and testing their relevance for quantifying fire emissions in boreal Alaska. The overwhelming problem of the manuscript and outputs presented is that the work does not provide significant advances from current state of the art. The claim that the AKFED provides the first publically available data available on emissions for Alaska is not valid, because this has been accomplished in other studies (see next paragraph) and the work presented provides only an assessment in black spruce types. Furthermore, all of the input data used in this study has been developed and used in previous products with varying success. I would say that the value of the work presented in this manuscript is not in providing improved estimates of fire emissions for Alaska, but rather in detailing the data of value for emissions mapping and needs for improvement in several of these inputs. In my opinion, the manuscript needs to be re-focused to state its true value – in providing a comprehensive review of data and methods for Alaska fire emissions mapping and detailing the data inputs of value and their drawbacks. There is neither new data nor approaches presented in this work.

a) While we agree with the reviewer that our effort builds extensively on existing data and findings, we do not agree with the reviewer's assertion that our approach has no new findings. Our approach contributes to the state-of-the-art in several ways. For example, our study presents the first inclusion of a spectral severity index calibrated with field observations in a regional emissions modeling approach. Our analysis on the utility of the dNBR for mapping pyrogenic carbon emissions in black spruce ecosystems may also importantly contribute to a long history of contradictory findings on this topic. While this was comprehensively covered by the review article by French et al. (2008), we feel that misconceptions on this topic may still be abound. We think that our statistical analysis on the utility of the dNBR in a synergistic framework provides a unique perspective on this issue. In addition, we also reported significant correlations between remotely sensed tree cover and depth of burn, and belowground carbon consumption, and included pre-fire tree cover as predictor variable in our model. Our paper is the first to demonstrate these relationships at this scale and this finding may importantly contribute to better spatially explicit pyrogenic carbon emission estimates. Finally, we assert that we are the first to provide regional scale fire progression maps at 450 m resolution with a validated one day accuracy per pixel. This advancement in the combined spatial and temporal resolution of burned area and carbon emission maps is crucial for applications focused on controls on fire growth and trace gas applications. It is true that our progression approach build on previous work and that similar approaches have been presented before (e.g. French et al., 2014; Kasischke & Hoy, 2012; Parks, 2014; Sedano & Randerson, 2014; Veraverbeke et al., 2014), however, to the best of our knowledge, these have not resulted in decadal region wide data layers with a validated one-day accuracy and public availability. We think that the inclusion of these aspects in our synergistic modeling approach not only advances the current state-of-the-art, but also that our publicly available data provide opportunities to further advance several research lines.

The use of field data to complement and assess modeled fuel consumption was completed by Kasischke and his colleagues in several studies (Kasischke and Hoy 2014, Genet et al. Barrett et al.). Exploration of dNBR for consumption in the context of fire emissions has been deeply explored. These past activities were duly noted by the authors, and relevant discussions included, and the critique by Kasischke in the discussion reviews the gaps related to these aspects of your study.

b) We certainly agree that the work of Barrett et al., (2010, 2011), Kasischke and Hoy (2012), Genet et al. (2013) and many other researchers have significantly advanced this field of research. We think that is overstepping to assert that they 'completed' this research topic. As mentioned in our response a, we showed relationships that have not been revealed in any of these previous studies. In addition, to the best of our knowledge, none of these previous efforts have resulted in publicly available daily carbon emission maps for a decadal time period.

However, the employment of FCCS and Consume to estimate state-wide fire emissions was not covered in Kasischke's review and not acknowledged in the manuscript, although these tools have been employed by French et al. (2014) and used in BlueSky emissions approach and products. The manuscript fails to recognize this emissions work, which is reviewed in several papers including French et al. 2011 (supplemental materials) and French et al. 2014:

French, N. H. F., D. McKenzie, T. Erickson, B. Koziol, M. Billmire, K. A. Endsley, N. K. Y. Scheinerman, L. Jenkins, M. E. Miller, R. Ottmar and S. Prichard (2014). Modeling regional-scale fire emissions with the Wildland Fire Emissions Information System. Earth Interactions 18: 1-26 DOI: 10.1175/EI-D-14-0002.1.

The French et al 2014 paper describes WFEIS, an online system that provides open access to tools for fire emissions modeling for Alaska and the Lower 48 states. WFEIS was developed by French's team and colleagues at the US Forest Service FERA lab where FCCS and Consume were developed. WFEIS operates as a kind of "spatial Consume", allowing users to choose data inputs and providing defaults for assessing daily emissions based on the weather conditions present on the day of burning. In addition, pre-calculated estimates of emissions by year are available on the WFEIS web site (an output produced for the NASA CMS program; see http://wfeis.mtri.org/examples – the AK results are on the ftp server – see link below CONUS table of results). The authors should consider citing French et al 2014 and the on-line products, since it provides the only nation-wide (with the exception of Hawaii) method of estimating emissions at moderate spatial resolutions (1 km grid scale), and can serve as an excellent comparison to AKFED results. Because WFEIS uses basic tools for estimations and does not directly employ field-derived information on fuel consumption, it is likely that the approach presented in this manuscript will provide improvements for Consume and the WFEIS approach.

c) We are grateful to the reviewer for pointing us to the French et al. (2014) paper. We had already referred to WFEIS precursor paper (French et al., 2011) in the original manuscript. The French et al. (2014) paper was published shortly before the original submission of our manuscript and we must have just missed it. We referenced French et al. (2014) in our revision. In addition, we agree that a comparison between AKFED and WFEIS is useful, and we integrated this comparison in our paper.

We added the following text to the Results section:

'Annual burned area from AKFED, WFEIS and GFED3s were fairly similar (Table 2). Relative to the AKFED burned area estimates between 2001 and 2010, WFEIS burned area estimates were about 10 % lower, and GFED3s estimates approximately 2 % lower. Annual carbon emissions estimates showed larger differences. WFEIS carbon emissions estimates were approximately 142 % higher than AKFED between 2001 and 2010, and GFED3s carbon emissions estimates were approximately 13 % lower than AKFED. Carbon consumption estimates of WFEIS were approximately 168 % higher than AKFED, whereas GFED3s carbon consumption estimates were approximately 12 % lower than AKFED between

2001 and 2010. No significant correlations were found between year-to-year variations in mean carbon consumption estimates from the different models.'

Table 2. Annual burned area, carbon emisisons, and mean carbon consumption between 2001 and 2010 from the Alaskan Fire Emissions Database (AKFED), the Wildland Fire Emissions Information System (WFEIS), and the Global Fire Emissions Database version 3s (GFED3s). Values were extracted for the domain between 58° and 71.5° N, and 141° and 168° W. We used the MCD64A1 burned area product and the default parameters within the WFEIS emissions calculator (http://wfeis.mtri.org/calculator, last accessed April 3, 2015). We included both emissions from natural and agricultural fuels in WFEIS.

	annual burned area (kha)			annual C emissions (Tg)			mean C consumption (kg/m^2)		
year	AKFED	WFEIS	GFED3s	AKFED	WFEIS	GFED3s	AKFED	WFEIS	GFED3s
2001	61	0	2	1	0	0	1.89	/	2.57
2002	739	595	636	17	46	15	2.27	7.74	2.44
2003	200	188	200	5	10	5	2.74	5.24	2.51
2004	2294	2253	2283	69	167	52	3.03	5.88	2.26
2005	1660	1320	1538	46	102	38	2.76	7.75	2.47
2006	47	68	86	1	3	2	1.76	4.75	2.40
2007	200	130	165	5	8	5	2.63	6.55	2.80
2008	37	24	34	1	2	1	2.37	7.32	1.86
2009	1046	1054	1130	26	77	29	2.51	7.27	2.52
2010	268	283	324	6	16	8	2.25	5.55	2.34
2001-2010	655	592	634	18	43	15	2.72	7.29	2.40

We added the following text in Discussion:

'Decadal-scale comparison between AKFED, WFEIS and GFED3s demonstrated fairly similar burned area estimates, although AKFED and GFED3s were slightly higher than WFEIS (Table 2). The similarity between the burned area from AKFED, WFEIS and GFED3s is not surprising since they operate with similar algorithms. All algorithms look at changes in a spectral index derived from MODIS surface reflectance imagery to map burned area. Burned area in GFED3s and WFEIS were from the MCD64A1 product (Giglio et al., 2009), complemented with small fire contributions outside the MCD64A1 burned area detections for GFED3s (Randerson et al., 2012). AKFED used active fire detections that occurred outside the fire perimeters to include contributions from small fires. The contribution from small fires that were included in GFED3s and AKFED may explain the slightly higher burned area estimates than in WFEIS.

Carbon consumption was not correlated between different models (Table 2). In addition, carbon consumption was slightly lower in GFED3s compared to AKFED, and significantly higher in WFEIS compared to AKFED. This suggests that GFED3s slightly underestimates carbon consumption from boreal fires, although the difference in mean carbon consumption between AKFED and GFED3s is with the range of the region-wide mean uncertainty estimate of 0.50 kg C m^{-2} (Figure 11). The comparison also indicates that region-wide WFEIS estimates are several fold higher than those from AKFED, GFED3s, or Kasischke and Hoy (2012). The high levels of carbon consumption in WFEIS for Alaska are consistent with the study of Billmire et al. (2014) that showed for the contiguous U.S. WFEIS estimates were about double of GFED3 estimates. Differences in the carbon emissions estimates between approaches result from differences in the methods and input data to quantify burned area, fuel type, and carbon consumption. Billmire et al. (2014) found that the difference between WFEIS and GFED3 *carbon emission estimates in the contiguous U.S. was primarily driven by the higher fuel loads assigned in WFEIS. This effect may also explain the discrepancy in Alaska, and further effort is needed to compare the different modelling approaches. These findings also highlight the need for synthesis and intercomparisons of the different data inputs required for emission modelling, including fuel load, combustion completeness, and emission factors. Such efforts are ongoing (van Leeuwen and van der Werf, 2011; van Leeuwen et al., 2014); van Leeuwen et al. (2013) for example assessed the impact of different sets of emission factors on CO mixing ratios. One constraint with large scale models is that their coarse spatial resolution does not allow direct comparison with field measurements. This gap may be filled by regional models like AKFED that are calibrated with field data at a higher spatial resolution and can be scaled to a coarser resolution.'*

One general aspect of the study that needs clarification is the fact that two models are developed – one for depth of burning in the organics and one for carbon consumption; this was not clear nor consistently presented throughout the manuscript. Terminology is not consistent (belowground consumption is used in the Results section while belowground carbon consumption is used elsewhere). The considerations for going from depth of burn to carbon consumed are not well described (the first paragraph of the methods section has the review of this). Please spend more effort explaining the way field data (what data?) is used to get to carbon stock from fuel loading or other metrics. On page 17587 line 5 the field data is reviewed. The first line should explicitly say what field data is used (e.g. "Field data on depth of burn, carbon content of the duff fuel layers, etc). Was the data fuel loadings or fuel consumption; how was it measured? It is my understanding that many methods were employed, and this should be noted. The issue comes into play when trying to understand the results section (Page 17595). Line 16 reports the relationship between depth of burn and variables R2 – 0.25, p,0.001), while line 23 reports belowground consumption ($R2$ = 0.05, $p<0.05$). What is the difference? Are these the same? Is this carbon? Eq. 2 tells me the relationships of both depth of burn and carbon consumed are one and the same. I think there needs to be more clarification of the difference between these two values. What conversions are used from depth of burn to carbon?
In a similar vein, there needs to be a bit more description of the field data collections. More on this, rather than having the reader rely on going to the sources of the data, would be helpful. I assume that the data are collected in one location (the lat/long provided), or are the data shown in Supp Table 2 averages for a distributed "site"? How large are sites? Do they represent the surrounding landscape so you can say that the point of collection or mean value of the site data represents the full area of a pixel? A one to two sentence comment on the field collections will go a long way to allowing the reader to understand the value of the field data. Field data collections for connecting to remote sensing metrics need to be collected in a way to represent the site that is sampled by the pixel. If this is the case, this should be stated, since these data were not necessarily collected for remote sensing validation purposes, it may be they do not represent a pixel. This needs to be understood.

e) We understand that the separate depth of burn and belowground carbon consumption models may cause some confusion. The rationale for this decision is the following. All three sources of field data (Boby et al., 2010; Turetsky et al., 2011; Rogers et al., 2014) include depth of burn measurements. Only the Boby et al. (2010) and Rogers et al. (2014) data have carbon consumption measurements, whereas for the Turetsky et al. (2011) data the depth of burn to carbon conversion depends on relationship between cumulative carbon storage and depth (Supplementary Figure 2). Our paper primarily focuses on carbon consumption, but we think that reporting the depth of burn statistics is useful too since it eliminates one step in the field data preprocessing. We modeled the depth of burn and belowground carbon consumption model using the same relationship (equation 2), but the model was optimized separately (in other words, the regression coefficients are unique for both models). We clarified this in the revision. The depth of burn to belowground carbon consumption of the Turetsky et al. (2011) data may add some additional uncertainty in our model and we discussed this in the revision. We also clarified our terminology and provided additional description of the different field datasets used. We also added discussion on uncertainties of the field measurements.

The relationships found between depth of burn/carbon consumption and individual variables, as well as multiple variables, is very weak in most cases. Also, in previous studies many of the variables were seen to be uncorrelated to the phenomenon of interest. There is a concern that the weak results (R2 = 0.40 and 0.29) indicate that the variables used are not very helpful for quantifying emissions with any reliability. The ability to load many weakly related variables into a regression analysis – some of which have been shown to have no biophysical reason for providing predicative ability – does not mean the model has value. This needs to be strongly defended if the paper is to claim that emissions predictions are valuable for use by practitioners. The other reviewers have provided guidance in on this, so more is not required by me.

f) Some perspective is warranted here. While higher model performances would obviously have been desirable, we think that one should not underrate the achieved performance of our prediction models. Our depth of burn model had a $R^2_{adjusted}$ of 0.40 (p = $8.04 \cdot 10^{-13}$), our belowground carbon consumption model 0.29 (p = $6.24 \cdot 10^{-9}$), our aboveground carbon consumption model 0.53 (p = $3.32 \cdot 10^{-6}$). All models were highly significant. 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. While we acknowledge that there exist applications in which field measurements are highly correlated with geospatial variables, even as individual variables, with R^2 values often higher than 0.6 (for example relevant in this context are the many studies that correlated spectral indices with the Composite Burn Index). However, we aim at estimating carbon consumption from boreal fires. This has since long been known as a challenging topic (e.g. French et al., 2004). The advantage of developing predictive observation-driven models is not only that estimates are based on observed relationships, but also that the uncertainty estimates are driven by the unexplained model variance. This approach eliminates a set of assumptions that otherwise have to be made to derive emissions and that only can be assessed using 'best-guess' uncertainty approaches. In our approach, both the estimate and its uncertainty are directly driven by field observations. Moreover, our revised uncertainty analysis that we integrated in the revision (Figure below, more detail can be found in our response to the other reviewers) demonstrated that the region wide uncertainty of black spruce consumption model alone equaled 0.41 kg C m^{-2} which is less than 20 % of the region wide mean carbon consumption and within the range of uncertainties found in similar uncertainty analyses that were conducted on pyrogenic carbon emission models in Alaska (French et al., 2004; Kasischke and Hoy, 2012). In addition, regionally calibrated models like AKFED may have value for large scale models like WFEIS and GFED. These large scale models often operate at spatial resolutions that do not allow direct comparison with field data. Scaling regionally calibrated models may be instructive to assess potential systematic biases in large scale models (see response c).

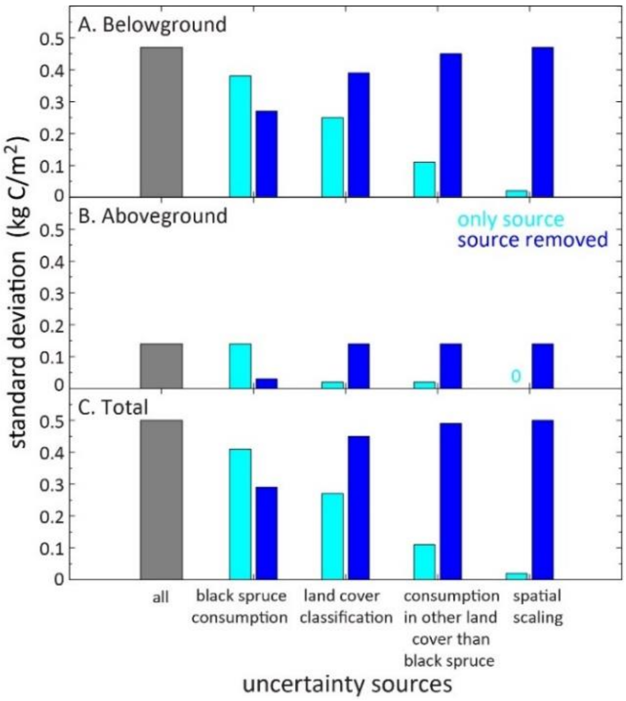

Figure 11: Attribution of uncertainty sources in (A) belowground, (B) aboveground and (C) total carbon consumption estimates. The standard deviation of the consumption estimates from 1000 Monte Carlo simulations was calculated for each scenario.

We stand behind our approach of using relationships between field observations and environmental variables to predict pyrogenic carbon consumption in boreal forest ecosystems, even when the achieved performance may be lower than achieved in other, not directly comparable, applications.

Finally, while "uncertainty" is presented, there is little acknowledgement that the field data used as the metric for developing the emissions model may not fully represent the situation. Field data also have error and uncertainty, and in relying on a regression based assessment for uncertainty, the reliability of the dependent variable is not included. In this case, with the data collected by several teams and with varying methods (and some concern in the community that the data are biased due to the methodology), this factor should be discussed when reviewing the uncertainty of the results.

g) This is a good point and we added this to the discussion of the uncertainties:

'Finally, uncertainties within the set of available field data have not been systematically assessed. These may stem from different methods that were used to estimate depth of burn in the field (combustion rods, adventitious roots technique or unburned-burned site pairing) and assumptions used to convert depth of burn measurements to carbon loss (Rogers et al., 2014). For example, the 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 conversion of the depth of burn observations to belowground carbon consumption for these field plots. While the Rogers et al. (2014) data were collected with the aim of making comparisons with 30 m geospatial layers, some of the other available observations may not have used the same criteria for homogeneity in surrounding areas, and thus may contribute to uncertainties when integrated with other geospatial data.'

Overall, the manuscript is well written and reviews the data used for emissions modeling at regional scales in a comprehensive fashion. A refocus of the purposed of the exercise is required, since the estimation of emissions is derived exclusively from data and methods developed under previous research efforts rather than new work by the authors. The comparison work is the real value of this effort and should be highlighted.

h) While we agree with the reviewer that our effort builds extensively on existing data and findings, we do not agree that our synergistic modeling approach has not revealed new findings. We refer to our previous response a for examples of unique contributions from our work.

Specific comments P17582, line 20: Work by Ottmar and others on Consume should also be cited. Se recent citation: Ottmar, R. D. (2014). Wildland fire emissions, carbon, and climate: Modeling fuel consumption. Forest Ecology and Management 317: 41-50 DOI: 10.1016/j.foreco.2013.06.010.

i) Thank you for pointing us to the Ottmar (2014) paper, which we cited in revision.

P17582 Line 24: ": : : is larger than : : :" – larger in what way? By mass, volume, other?

j) We clarified this in the revision: *'A defining characteristic of fire emissions in the boreal forest is that mass of fuel consumed in the ground layer (comprised of moss, lichens, litter, and organic soils) is larger than the consumption of aboveground biomass (McGuire et al., 2009; Boby et al., 2010; Kasischke and Hoy, 2012)'*

P17583, line 14: Include French et al. 2008 (included in your reference list) instead of Veraverbeke et al, 2010 because French et al 2008 was cited in this earlier work by the author and the French paper is in the context of boreal fire.

k) We cited French et al. (2008) in the revision.

P17588, line 2. The term "time of burning" is used throughout the text, but is also (actually) "day of burning". This term needs to be consistent and to more accurately describe it, "day of burning" is preferred.

l) We consistently used 'day of burning' in the revision.

Page 17591, lines 6-10. The resolution of the MODIS data is confusing. As a remote sensing person I think I understand, but to non-RS readers, it is difficult to understand why the resolution is 500m on line 7 and 463 m on line 9. I think this needs to be revised. I also suggest you use the term "grid scale" rather than resolution. The resolution of a RS system is determined by the system, not the post-processing. In fact, resampling will not improve resolution if resampled to a finer scale, and resolution is determined by more than the pixel spacing.

m) We will clarify our terminology with regards to spatial resolution. We will add a supporting reference (Masuoka et al., 1998) to the statement of MODIS's native nadir resolution of 463 m. All data layers in our analysis have a spatial resolution that is smaller or equal to the 463 m resolution. The resolution in our application is determined by the data layer with the lowest spatial resolution, here dNBR. As explained, the exact spatial resolution of AKFED is 450 m, which is the multiple of 30 closest to 463 m. This resolution facilitated the spatial averaging of 30 m DEM, tree cover, dNBR and land cover data. Given these considerations, we think that it is correct to use resolution rather than grid scale in our paper.

Page 17592, line 10. The FCCS code 931 number is not relevant unless you want to include a review of the codes. I suggest not including it, but saying the 500 m of barren pixels is determined from the FCCS map – that is what you are saying, I think.

n) The FCCS codes for all fuel types that occurred in the AKFED burned area was already included in Supplementary Table 1. We made no changes.

Page 17599, line 21. The statement that elevation was the most important variable to depth of burn is confusing to me. In the Results section it is said to be dNBR and Tree cover. Please explain. Also, Figure 4 gives no evidence that elevation is important on its own. Presentation of these results is confusing and should be clarified.

o) We understand the reviewer's confusion. In our results and discussion analyses it is important to distinguish between relationships with individual variables and contributions of individual variables to the multiplicative model. The reviewer correctly identified dNBR and tree cover as variables with the highest performance as predictor of depth of burn as individual variables. The statement that elevation was the most important variable in the depth of burn model considers the interactions between variables in the multiplicative model as analyzed in Figure 4. We described in the Results (p17596l14-19), that *'To assess the importance of the individual variables in the model we compared all models inputting two or more variables for the depth of burn and belowground consumption models (Fig. 4). For the depth of burn model, elevation was the most important explanatory variable. 2-variables models combining elevation with time of burning and dNBR for example performed better than the 3-variables models that excluded elevation.'* Our discussion of the elevation variable thus correctly reflects the analyses represented in the Results section. To avoid confusion, we further clarified this. We also want to add that depth of burn showed a Gaussian relationship with elevation with a $R^2_{adjusted}$ of 0.24 (Supplementary Figure 7A).

Page 17600, line 26. Change heading to "Date of burning"

p) We changed this in the revision.

Page 17606, lines 9-17. The inclusion of albedo in the discussion on future directions is extraneous to the topic of the manuscript. Albedo changes are relevant for climate forcing, but not to estimating emissions. A mention of albedo as relevant along with other impacts of fire is OK, but this text covers the topic too much and should be removed.

q) We removed this paragraph in revision.

Figure 4: The colors of text is not needed – it confuses and is difficult to read. Also, where is the aboveground model results? If not included, there should be an explanation of why in the caption.

r) We produced the figure with black y-axis labels in revision. We also added in caption that no similar analysis was performed for the aboveground carbon consumption model, since this model only included two variables.

Supplementary Table 2 should provide the values of the data used from the "T" reference rather than relying on the reader to have to translate to consumption with the curve. In other words – provide the number used, not the topographic class.

s) We included the belowground carbon consumption values that we derived for the Turetsky et al. (2011) data in Supplementary Table 2 of the revision.

Typing errors Page 17584, line 25: “and their influence” is repeated.

t) We corrected this in the revision.

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Daily burned area and carbon emissions from boreal fires in Alaska

Manuscript ~~draft~~ revision for Biogeosciences – ~~November~~ April 3~~25~~, ~~2014~~2015

S. Veraverbeke[1], B. M. Rogers[2] and J. T. Randerson[1]

[1]{University of California, Irvine, California}

[2]{Woods Hole Research Center, Falmouth, Massachussetts}

Correspondence to: S. Veraverbeke (sander.veraverbeke@uci.edu)

Abstract

Boreal fires burn into carbon-rich organic soils, thereby releasing large quantities of trace gases and aerosols that influence atmospheric composition and climate. To better understand the factors regulating boreal fire emissions, we developed a statistical model of carbon consumption by fire for Alaska with a spatial resolution of ~~500~~ 450 m and a temporal resolution of one day. We used the model to estimate variability in carbon emissions between 2001 and 2012. Daily burned area was mapped using imagery from the Moderate Resolution Imaging Spectroradiometer combined with perimeters from the Alaska Large Fire Database. Carbon consumption was calibrated using available field measurements from black spruce forests in Alaska. We built two nonlinear multiplicative models to separately predict above- and belowground carbon consumption by fire in response to environmental variables including elevation, day of burning within the fire season, pre-fire tree cover and the differenced normalized burn ratio (dNBR). Higher belowground carbon consumption occurred later in the season and for mid-elevation ~~regions~~forests. Topographic slope and aspect did not improve performance of the belowground carbon consumption model. Aboveground and belowground carbon consumption also increased as a function of tree cover and the dNBR, suggesting a causal link between the processes regulating these two components of carbon consumption. Between 2001 and 2012, the median ~~fuel~~ carbon consumption was ~~2.48~~2.54 kg C m^{-2} ~~and the median pixel-based uncertainty (standard deviation of prediction error) was 0.38 kg C m^{-2}~~. ~~There were considerable amounts of b~~Burning in ~~other~~ land cover types other than black spruce was considerable and was associated with lower levels of carbon consumption ~~in~~ than for pure black spruce stands was generally higher. ~~Fuel~~ Carbon consumption originated primarily from the belowground fraction (median = ~~2.30~~2.32 kg C m^{-2} for all cover types and ~~2.63~~2.67 kg C m^{-2} for pure black spruce stands). Total carbon emissions varied considerably from year to year, with the highest emissions occurring during 2004 (~~67~~ 69 Tg C), 2005 (~~44~~ 46 Tg C), 2009 (~~25~~ 26 Tg C), and 2002 (~~16~~ 17 Tg C) and a mean of ~~14~~ 15 Tg C per year between 2001 and 2012. Mean uncertainty of carbon consumption for the domain, expressed as one SD, was 0.50 kg C m^{-2}. Uncertainties in the multiplicative regression model used to estimate to estimate belowground consumption in black spruce stands and the land cover classification were primary contributors to uncertainty estimates. Our analysis highlights the importance of accounting for the spatial heterogeneity ~~within~~ of fuels and ~~consumption~~ combustion when extrapolating

emissions in space and time, and the need for of additional field campaigns to increase the density of observations as a function of tree cover and other environmental variables influencing consumption. The daily emissions time series from the Alaskan Fire Emissions Database (AKFED) presented here creates new opportunities to study environmental controls on daily fire dynamics, optimize boreal fire emissions in biogeochemical models, and quantify potential feedbacks from changing fire regimes. ~~These data on daily burned area and emissions may be useful for in understanding controls and limits on fire growth, and predicting potential feedbacks of changing fire regimes.~~

1 Introduction

Fire is the most important landscape disturbance in the boreal forest (Chapin et al., 2000; Krawchuk et al., 2006). Increases in the extent and severity of burning in the last several decades have been reported for Alaska and Canada (Gillett et al., 2004; Kasischke and Turetsky, 2006; Kasischke et al., 2010; Turetsky et al., 2011). ~~With accelerated warming predicted for the boreal region during the remainder of the 21st century (Collins et al., 2013), intensification of the fire regime is expected~~Fire regimes are expected to intensify (Amiro et al., 2009; Balshi et al., 2009; Yuan et al., 2012; de Groot et al., 2013) ~~W~~with the predicted accelerated warming ~~predicted~~ for the boreal region during the remainder of the 21st century (Collins et al., 2013)~~,~~, although this may be mediated in part by changing vegetation cover (Krawchuk and Cumming, 2011; Mann et al., 2012; Kelly et al., 2013; Héon et al., 2014)~~. The interactions between the boreal ecosystem, fire and climate are complex.~~ Boreal fires have both positive and negative climate feedbacks (Randerson et al., 2006; Bowman et al., 2009; Oris et al., 2014; Rogers et al., 2015). Cooling is primarily caused ~~the increased~~ increases in surface albedo ~~due to~~from more ~~persistent~~ exposed snow cover during spring in young stands ~~and early successional vegetation in burned areas mainly occurring during the spring and winter months~~ (Jin et al., 2012; Rogers et al., 2013), and the influence of organic carbon aerosols ~~effects~~ on tropospheric radiation (Tosca et al., 2013). ~~The e~~Emission of greenhouse gases and black carbon aerosols (Bowman et al., 2009), and the deposition of black carbon on snow and ice (Flanner et al., 2007) are the dominant warming feedbacks.

The magnitudes of these feedbacks are tightly linked with the severity of the disturbance (Beck et al., 2011a; Turetsky et al., 2011; Jin et al., 2012). Severity is often referred to in a general way describing the amount of environmental damage that fire causes to an ecosystem (Key and Benson, 2006). In the context of mostly stand-replacing ~~boreal~~ fires in boreal North America, severity is expressed as the degree of consumption of belowground organic matter. Differences in ground layer burn depths control the amount of carbon combusted, and impact post-fire succession trajectories and consequent albedo feedbacks (Johnstone and Kasischke, 2005; Johnstone et al., 2010; Jin et al., 2012). Heterogeneity in fuels, fuel conditions, topography and fire weather can result in different post-fire effects over the landscape (Rogers et al., 2015). Resolving the spatial heterogeneity in severity using post-fire remote sensing observations can improve emissions estimates (Michalek et al., 2000; Veraverbeke and Hook, 2013; Rogers et al., 2014) and more accurate carbon emissions estimates could lower the uncertainties in estimating the net climate feedback from boreal fires under the current and future climate (Oris et al., 2014).

Fire emissions are generally calculated as the product of burned area, fuel consumption and emission factors (Seiler and Crutzen, 1980). Fuel consumption represents the amount of biomass consumed by the fire, and gas-specific emission factors describe the amount of gas released per unit of biomass consumed by the fire. Examples of models building on this paradigm at continental or global scales~~this approach~~ include the Wildland Fire Emissions Information System (WFEIS, ~~(~~French et al., (2011, 2014))~~)~~ and the Global Fire Emissions Database version 3 (GFED3, van der Werf et al. (2010)), updated with contributions of small fires (GFED3s, Randerson et al. (2012)). Several similar approaches have been developed specifically for boreal forests (Kasischke et al., 1995; Amiro et al., 2001; Kajii et al., 2002; Kasischke and Bruhwiler, 2002; French et al., 2003; Soja et al., 2004; de Groot et al., 2007; Tan et al., 2007; Kasischke and Hoy, 2012). The quantification of fuel consumption in boreal emission models is often driven by empirical relationships between fire weather variables and combustion completeness that vary by fuel type (Amiro et al., 2001; de Groot et al., 2007; Ottmar, 2014). ~~However, de Groot et al. (2009) found that although these relationships may be relatively strong for experimental fires, they are clearly weaker for wildfires.~~ A defining characteristic of fire emissions in the boreal forest is that ~~the~~ mass of fuel ~~consumption~~ consumed ~~of~~ in the ground layer (comprised of moss, lichens, litter, and organic soils) is larger than the consumption of aboveground biomass (McGuire et al., 2009; Boby et al., 2010; Kasischke and Hoy, 2012). Because of the seasonal thawing of the permafrost, the active layer becomes deeper and drier throughout the fire season and thus more prone to deeper burning (Lapina et al., 2008; Turetsky et al., 2011; Kasischke and Hoy, 2012). 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). The dryness of the forest floor depends both on the time within the season and local drainage conditions (Kane et al., 2007; Turetsky et al., 2011). Kasischke and Hoy (2012) incorporated this expert knowledge to derive emissions from a set of Alaskan fires by accounting for differential impacts of fire seasonality on several topographic classes.

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 (Ottmar, 2014). Quantifying relationships between field data of carbon consumption and pre- 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 field observations and environmental variables may allow for a data-driven approach for uncertainty quantification. ~~A complementary approach to derive different levels of fuel consumption is to use direct post-fire remote sensing observations of severity (Kolden and Abatzoglou, 2012; Veraverbeke and Hook, 2013; Rogers et al., 2014). Severity is often referred to as fire or burn severity (Lentile et al., 2006; Keeley, 2009) and the difference between both terms lays within the temporal dimension of the post-fire environment. By definition fire severity measures the immediate impact of the fire, whereas burn severity incorporates both the immediate fire impact and subsequent recovery effects (Lentile et al., 2006; Veraverbeke et al., 2010).~~ Spectral changes after a fire have shown to be strongly related to field measurements of severity in a wide range of ecosystems (e.g. van Wagtendonk et al., 2004; Cocke et al., 2005; De Santis and Chuvieco, 2007; Veraverbeke and Hook, 2013), including the boreal forest (Epting et al., 2005; Allen and Sorbel, 2008; Hall et al., 2008; Soverel et al., 2010). Severity is often referred to as fire severity or burn severity (Lentile et al., 2006; Keeley, 2009) ~~and~~with the difference in definition between ~~both~~the two terms ~~lays~~associated with~~in~~ the temporal dimension of ~~the post-fire environment~~fire effects. By definition fire severity measures the immediate impact of the fire, whereas burn severity incorporates both the immediate fire impact and subsequent recovery effects (Lentile et al., 2006; French et al., 2008; Veraverbeke et al., 2010). In particular the differenced normalized burn ratio (dNBR) has become accepted as ~~the~~ a standard spectral index to assess severity (López García and Caselles, 1991; Key and Benson, 2006). ~~The~~ dNBR is an index that combines near and short-wave infrared reflectance values obtained before and after a fire (Eidenshink et al., 2007). The spectral regions in dNBR are especially sensitive to the decrease of vegetation productivity and moisture content after the fire. Because of this, dNBR is a good indicator of aboveground biomass consumption, but may be less effective in estimating belowground consumption of boreal fires (French et al., 2008; Hoy et al., 2008; Kasischke et al., 2008). Other studies, however, have reported significant relationships between spectral indices, including dNBR, and belowground consumption measurements from field sites in boreal ecosystems (Hudak et al., 2007; Verbyla and Lord, 2008; Rogers et al., 2014). Rogers et al. (2014) also found a relatively strong correlation between field measurements of aboveground and belowground consumption, which partly explained the observed relationship between dNBR and belowground consumption. Effective use of dNBR and other remote sensing observations requires careful integration with other driver data and ~~Extrapolation of relationships like this needs further~~ calibration with field ~~data~~ observations that span a wide range of ~~fire seasonality and topographic~~environmental conditions.

The day of burning within the fire season covaries with the depth of burning in the ground layer and ~~thus~~ this temporal information ~~on the time of burning within the season~~ may aid prediction of belowground consumption (Turetsky et al., 2011; Kasischke and Hoy, 2012). Convolving burned area detection algorithms with active fire hotspots from the multiple overpasses per day from the Moderate Resolution Imaging Spectroradiometer (MODIS) allows for the development of daily burned area estimates (Parks, 2014; Veraverbeke et al., 2014). Daily burned area products provided evidence that vapor pressure deficit has an important influence on several aspects of fire dynamics including initial spread rate, daily variations in regional burned area, and fire extinction (Sedano and Randerson, 2014). Kasischke and Hoy (2012) developed a daily fire emissions time series to investigate causes of year-to-year variability in carbon consumption for a regional subset of fires during high and low fire years.~~using this approach have already been developed for regional studies in interior Alaska to develop daily fire emission estimates for a limited number of years (Kasischke and Hoy, 2012), and to infer burned area-climate relationships (Sedano and Randerson, 2014)~~.

Daily burned area and emissions estimates may allow ~~several improvements~~for advances in studies ~~focused~~ investigating~~on~~ the composition and transport of ~~fire~~ aerosols and greenhouse gases, fire behavior, ~~and~~ or fire modeling. No fire emissions product calibrated using field observations currently exists for use in studying these processes with continuous spatial and temporal coverage and public availability. Hyer et al. (2007) found that emissions from boreal fires averaged over 30-day intervals resulted in a reduction of 80% of the variance compared to daily and weekly data in a fire aerosol transport simulation. The temporal resolution of emission data is especially important for boreal fires since they often reach most of their burned area in only a couple of days when the spatiotemporal patterns of ignitions and fire weather optimally coincide (Abatzoglou and Kolden, 2011; Sedano and Randerson, 2014). The representation of extreme fire weather periods and their influence ~~and their influence~~ on burned area in models may allow for more accurate predictions of interannual and decadal changes in the fire regime caused by climate warming (Jin et al., 2014). High resolution emission time series may also improve knowledge about differences in composition of aerosols and trace gases originating from flaming and smoldering ~~fires~~ stages of combustion (Yokelson et al., 2013) as well as allowing for better prediction of human health impacts in downwind areas (Yao and Henderson). More fundamentally, daily burned area estimates are critical for quantitatively examining landscape and weather controls on fire spread rates and severity.

In this paper we describe the creation of a high resolution time series of fire emissions appropriate for investigating many of the fine-scale fire dynamics questions described above. We created a continuous daily time series of fire emissions during 2001-2012 with a spatial resolution of 450 m for the state of Alaska. The combined time span, time step, spatial resolution, spatial domain and calibration with field observations of this product makes it suitable for use in many atmospheric studies, and unique from other published estimates. ~~aim~~ To estimate carbon consumption at each location (kg carbon per m^2 burned area), we ~~to develop a~~developed multiplicative regression models that capture some of the variability in field measurements using gridded ~~statistical model of carbon consumption by fire (kg carbon per m^2 burned area) in Alaska based on relationships between field measurements and~~ environmental variables, including post-fire remote sensing observations of severity. ~~Subsequently, we apply the derived model over the state of Alaska for the years 2001-2012 in synergy with a daily burned area product to derive state-wide daily carbon emissions from fire~~. Our approach also includes uncertainty estimates derived from the fit of our model with the field observations, and includes components associated with our scaling approach used to provide region wide spatial coverage. The derived daily burned area and carbon emissions product ~~is~~, referred to as the Alaskan Fire Emissions Database (AKFED), is the first wall-to-wall multi-year database with daily temporal resolution that is calibrated using field observations for Alaska and is publicly available (upon acceptance we will create a link here to data published on ORNL DAAC). In our analysis, we compared our model estimates with other regional and global biomass burning products from WFEIS and GFED3s. We also show that the set of field observations used does not adequately sample burned area in open forests with sparse tree cover. Since these forests tend to have lower levels of carbon consumption, adjusting for this bias yields lower regional means than what would be inferred directly from the existing set of observations.

2 Spatiotemporal domain and data

2.1 Spatiotemporal domain

The spatial domain covers the area between 58° and 71.5° N, and 141° and 168° W. This represents almost the entire mainland of Alaska with exclusion of the southern part of the Alaska Peninsula and Southeast Alaska, west of British Columbia (Figure 1). The temporal domain of the study includes the years 2001-2012. Most Alaskan fires occur in the interior of the state, which consists of a mosaic of vegetation types (Figure S1). Black spruce forest dominates on cold, poorly drained, north-oriented or lowland sites, whereas white spruce and deciduous species (mainly aspen and birch) prevail on warmer, better drained, south-oriented sites without permafrost (Viereck, 1973; Bonan, 1989). Grass- and shrubland ecosystems occur in early successional stands, poorly drained sites, steep slopes and at and above the treeline. The vegetation mosaic in interior Alaska is constantly reshaped by the occurrence of fire and subsequent post-fire succession. Fewer fires occur in the tundra regions in the north and at the western coastal areas of the state, however, the 2007 Anaktuvuk River fire on the North Slope is the largest tundra fire on record (Jones et al., 2009; Mack et al., 2011; Kolden and Rogan, 2013)~~, and the occurrence of tundra fires may increase with global warming (Hu et al., 2010; Rocha et al., 2012)~~.

FIGURE 1 HERE

2.2 Field data

We assembled field data of depth of burn from three different publications (Boby et al., 2010; Turetsky et al., 2011; Rogers et al., 2014). Due to limited data availability for other land cover types than black spruce (five plots in ~~(~~Rogers et al.~~,~~ (2014)), we focused on black spruce plots and we retained all plots burned since 2000 for which cloud-free one year-post fire dNBR observations were available in the Monitoring Trends in Burn Severity (MTBS, Eidenshink et al. (2007)) database, resulting in a total of 126 plots (Table S2). The location of the field plots is given in Figure 1. Boby et al. (2010) and Rogers et al. (2014) provided a direct estimate of the belowground carbon consumption representing 39 plots. Both studies sampled multiple soil cores (11 in Boby et al. (2010), and 6 in Rogers et al. (2014)) in a 2 m by 30 m transect in each plot. These studies estimated pre-fire carbon stocks from control sites that were chosen to match the conditions of the burned sites. These studies used measurements of adventitious roots (Kasischke and Johnstone, 2005; Kasischke et al., 2008) within the soil column in combination with bulk density and carbon concentrations to calculate the pre-fire soil carbon stock. Belowground carbon consumption was defined as the difference between the pre- and post-fire carbon stocks. These plots, except for one ~~of the~~in Boby et al. (2010)~~ plots~~, also included an estimate of aboveground carbon consumption. Boby et al. (2010) and Rogers et al. (2014) both estimated aboveground carbon stock using allometric equations and diameter-at-breast height measurements of individual trees. Both studies multiplied visual estimates of percentage consumption of the aboveground carbon pools to derive aboveground carbon consumption. Turetsky et al. (2011) aggregated depth of burn data from multiple methods including the adventitious roots technique, burned-unburned site pairings, and combustion rods, with varying numbers of measurements per site. ~~Detailed description of the field sites and data acquisition can be found in the respective publications.~~For the Turetsky et al. (2011) plots, belowground carbon consumption was calculated from depth of burn measurements using separate, region-wide mean soil-carbon accumulation curves for lowland, upland, and slopes with ~~South~~ south (S), ~~North~~ north (N), and ~~East~~ east or ~~West~~ west (EW) aspect (Figure S2). We used a digital elevation model (section 2.3.3) resampled to ~~500~~ 450 m resolution for assigning the topographic classes to the field plots. Concave flat (slope ≤ 2%) areas were classified as lowland (L), convex flat areas were as upland (U). Sloped terrain was categorized as N aspect (aspect ≥ 315° or < 45°), S aspect (aspect ≥ 135° and < 225°), and E or W aspect (aspect ≥ 45° and < 135°, or ≥ 225° and < 315°). ~~D~~More detailed description of the field sites and data acquisition can be found in the respective publications. We also note that the sampling approach used by Rogers et al. (2014) was designed to enable comparisons with 30 m geospatial layers. To account for potential georegistration errors their plots were therefore selected within 100 m by 100 m patches that were relatively homogeneous in pre- and post-fire characteristics.

2.3 Geospatial data

2.3.1 Alaska Large Fire Database (ALFD)

The Alaska Large Fire Database (ALFD) currently contains fire perimeters for the state of Alaska from 1940 ~~till now~~through the present (downloaded from http://afsmaps.blm.gov/imf/imf.jsp?site=firehistory, last accessed ~~November 25~~April 3, ~~2014~~2015). The database receives yearly updates. The reliability of the database ~~increased~~ increases ~~over~~ through time as mapping technologies advanced~~, and~~; since the 1980s, consistent mapping with high quality and few omissions has been achieved (Kasischke et al., 2002, 2011). For our study, we extracted the fire perimeters of the years 2001-2012 from the ALFD (Figure 1).

2.3.2 Active fire data

The Global Monthly Fire Location Product (MCD14ML) contains geographic location and time for each fire pixel detected by MODIS on Terra (launched in December 1999) and Aqua (launched in May 2002). Additional information on brightness temperature, fire radiative power, scan angle and detection confidence is also provided. The product is based on a contextual active fire algorithm that exploits the strong emission in the mid infrared region from fires (Giglio et al., 2003, 2006). We extracted the fire detections from all confidence levels for our domain for the months May-September, the months of the fire season, for all years. MODIS on Terra experienced an extended outage during our study period from June 16 through July 2, 2001 (Giglio et al., 2013).

2.3.3 Environmental variables

Ground layer consumption by fire depends on the amount of available dry fuels, which is determined by thickness, density and moisture content of the organic layer. After an extensive literature review, we selected a set of environmental variables to predict ground layer consumption over the landscape (Table 1). The selected environmental variables were elevation, slope, northness (defined as the cosine of the aspect), tree cover, ~~time~~ day of burning, and dNBR.

TABLE 1 HERE

Topography is a good proxy of site conditions for several reasons. Elevation ~~regulates~~ influences organic layer thickness, carbon density, drainage and permafrost thaw by means of its control on climate. At higher elevations the seasonal permafrost thaw starts later (Kasischke and Johnstone, 2005; Kasischke and Hoy, 2012). Uplands generally have shallower organic layers with a slightly higher carbon density than lowlands (Kane et al., 2005, 2007; Turetsky et al., 2011). Uplands are generally also better drained than lowlands (Barrett et al., 2010; Kasischke and Hoy, 2012). Steep terrain is better drained than flat land, but above a certain threshold steepness limits the establishment of trees resulting in shallower organic layers at steeper sites (Hollingsworth et al., 2006). In crown fire ecosystems, fire severity tends to increase with steepness when the wind direction aligns upslope (Rothermel, 1972; Pimont et al., 2012; Lecina-Diaz et al., 2014), and this may also affect ground layer consumption. N-oriented slopes are wetter and colder than S-faced slopes and have thicker, less dense organic layers (Kane et al., 2007; Turetsky et al., 2011). Here we derived elevation, slope and northness from the Advanced Spaceborne Thermal Emission and Reflection Radiometer Global Digital Elevation Model Version 2 (ASTER GDEM 2, Tachikawa et al. (2011)). The ASTER GDEM 2 is a 30 m elevation model ~~extracted~~ retrieved from ASTER stereo-pair images.

Pre-fire tree cover is closely related to to site productivity and stand age, and thus influences organic layer thickness, density and moisture content (Kasischke and Johnstone, 2005; Beck et al., 2011b; Rogers et al., 2013). Tree cover generally increases with stand age and better drainage conditions (Beck et al., 2011b; Rogers et al., 2013). Tree cover also is directly related to the amount of biomass available for aboveground consumption, which has been shown to correlate reasonably well with belowground consumption within a single fire (Rogers et al., 2014). For the comparison with the field plots, we used 30 m tree cover data from the Landsat-based tree cover continuous field product for the year 2000 (Sexton et al., 2013). For the statewide-extrapolation, tree cover was downloaded from the annual Terra MODIS Vegetation Continuous Fields Collection 5 product at 250 m resolution for the years 2000-2010 (MOD44B, Hansen et al. (2003)). The generation of the MOD44B product was discontinued after 2010, and we therefore used the tree cover layer of the year 2010 as pre-fire tree cover for the year 2012.

The day~~time~~ of burning in the season covaries with the mean depth of the active layer, and thus may be related to the amount of dry ground fuels available for burning (Turetsky et al., 2011; Kasischke and Hoy, 2012). We assigned the day~~time~~ of burning for each pixel based on the MODIS active fire observations. We found that the nearest neighbor variant of the inverse distance weighting technique, in which the pixel is assigned the value of the closest active fire detection excluding scan angles larger than 40°, performed best and with a within-one-day accuracy for most pixels (Figure S3). The resulting progression maps were binned with a daily time step, at local solar time.

We investigated the dNBR as an explanatory variable in our ~~fuel~~ carbon consumption model because extensive literature suggests that it may have some predictive power in boreal forest ecosystems. For the comparison with the field plots, 30 m dNBR data was retrieved from the Landsat-based Monitoring Trends in Burn Severity database (MTBS, Eidenshink et al. (2007)). 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 500 m 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. We only used good data as indicated by the MOD13A1 quality flags. NBR values were calculated as the mean of all available good observations within the five composites. ~~The~~ dNBR was calculated using the one-year pre-and post-fire NBR layers. Within the MTBS database, we also only considered one-year post-fire dNBR information. This minimized potential differences in the interpretation of dNBR values from different post-fire years (Veraverbeke et al., 2010; Rogers et al., 2014).

The above six variables (elevation, slope, northness, tree cover, day~~time~~ of burning and dNBR) were targeted to develop the belowground carbon consumption model. dNBR and tree cover were used as predictors of aboveground carbon consumption.

2.3.4 Land cover data

We used the Fuel Characteristic Classification System (FCCS, Ottmar et al. (2007), Riccardi et al. (2007)) layer of the year 2001 at 30 m to represent land cover in the study area (downloaded from http://landfire.cr.usgs.gov/viewer/, last accessed ~~November~~ April 3~~25~~, 2014). The FCCS is a national effort by the U.S. Forest Service to provide a fuel type classification that is compiled from literature, inventories, photo series and expert opinion (Ottmar et al., 2007; Riccardi et al., 2007). For Alaska, the layer is available for the years 2001 and 2008. Since less than one percent of reburning occurred during the period of our study (2001-2012), we decided to only use the 2001 layer. We aggregated the fuel types into five land cover classes: black spruce, white spruce, deciduous, tundra-grass-shrub and non-vegetated (Table S1, Figure S1). Other than the National Land Cover Database in Alaska (Stehman and Selkowitz, 2010), the FCCS layer discriminates between black and white spruce fuel types. The uncertainty of the FCCS layer in Alaska has not been formally assessed.

3 Methods

AKFED provides daily burned area and carbon emissions for the state of Alaska between 2001 and 2012 at ~~500~~ 450 m resolution. Since unburned islands are not fully accounted for within ~~-~~perimeters (Kasischke and Hoy, 2012; Kolden et al., 2012; Rogers et al., 2014; Sedano and Randerson, 2014), and some small fires are not accounted for outside the perimeters (Randerson et al., 2012), we developed a burned area mapping approach that screened dNBR values within the ALFD perimeters and in the vicinity of active fire pixels outside the perimeters (section 3.1).

The carbon consumption model was formulated for black spruce based on the relationship between the observed carbon consumption at the field locations and the environmental variables. We extracted the pixel values of elevation, slope, northness, pre-fire tree cover and dNBR at 30 m at the location of the field plots. The day~~time~~ of burning was assigned from the nearest active fire observation.

To extrapolate the model in space and time, we used a spatial resolution of ~~approximately~~ ~~500~~450 m. ~~,~~ This is the multiple of 30 m closest to the exact 463 m native resolution of the MOD13A1 product used to derive the dNBR layers (Masuoka et al., 1998). ~~the native resolution~~

~~of the MOD13A1 product used to derive the dNBR layers. The exact spatial resolution of AKFED is 450 m, which is the multiple of 30 m closest to the exact 463 m native resolution of the MOD13A1 product.~~ This spatial resolution facilitated spatial averaging of 30 m DEM, tree cover, dNBR and land cover data~~, and is referred to in this manuscript as 500 m~~. 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~~caused by the Landsat 7 scan line corrector failure.

Elevation, aspect and northness were spatially averaged from the native 30 m resolution of the ASTER GDEM 2 to the ~~500~~ 450 m resolution. Similarly, the MOD44B tree cover product was spatially averaged from its native ~~250 m~~ resolution to the ~~500~~ 450 m resolution. The day~~time~~ of burning was also obtained at this grid resolution. To account for other land cover types than black spruce, the aggregated FCCS product was rescaled to ~~500~~ 450 m in a way that every pixel at ~~500~~ 450 m contained the percentage of black spruce, white spruce, deciduous, tundra-grass-shrub and non-vegetated land (Figure S1). All analyses were performed within the Albers equal area projection for Alaska (central meridian: 154°W, standard parallel 1: 55°N, standard parallel 2: 65°N, latitude of origin: 50°N) with North American Datum 1983 (NAD83). An overview of the workflow is given in Figure 2.

FIGURE 2 HERE

We compared the ~~yearly~~ annual burned area and carbon emissions estimates derived from AKFED with those from ~~-~~WFEISv0.4 (French et al., 2014) and GFED3s (Randerson et al., 2012), two continental to global scale modeling systems. ~~and therefore spatially averaged the AKFED estimates over the 0.25° grid from GFED3s for the period 2001-2010~~. Since WFEIS and GFED3s were not directly calibrated with region specific field data, comparisons with AKFED may be instructive for improving boreal carbon consumption in boreal forest ecosystems. We used the MCD64A1 burned area product (Giglio et al., 2009) within the WFEIS emissions calculator. MCD64A1 was also the burned area layer within GFED3s (Randerson et al., 2012). A small amount of burned area (8 %) associated with fires outside the

MCD64A1 burned areas, are accounted for in Alaska in the GFED3s approach (Randerson et al., 2012). AKFED burned area has conceptual similarities with this latter approach.

3.1 Daily burned area mapping (~~500~~ 450 m)

Annual burned area maps at ~~500~~ 450 m were derived by applying a threshold on the dNBR values of pixels within the perimeters of the ALFD and outside the perimeters but within 1 km of an active fire pixel. If any fraction of the ~~500~~ 450 m pixel was covered by a fire perimeter polygon, then this pixel was considered in the perimeter. Pixels with a dNBR value larger than 0.15 were classified as burned. The dNBR threshold was determined based on the dNBR variability that exists within unburned pseudo-invariant pixels (100% barren pixels at ~~500~~ 450 m, FCCS code 931). We found ~~that~~, as expected, that the mean dNBR was close to zero (0.01). The standard deviation of the distribution equaled 0.15. By selecting this value as our threshold for the burned area mapping, we aimed to minimize commission errors, however, we recognize that this may have incurred a small omission error for pixels that were only partially burned and/or burned with low severity. The threshold value we used was the same as the one applied by Sedano and Randerson (2014) who used a similar burned area mapping approach within ALFD perimeters. All burned pixels were assigned a day~~time~~ of burning from the detection time of the nearest active fire observation excluding observations with view zenith angles higher than 40° (Figure S3).

3.2 Carbon consumption model (30 m)

We aimed to separately predict below- and aboveground carbon consumption based on the relationships between field plot data and environmental variables at 30 m (elevation, slope, northness, pre-fire tree cover, day~~time~~ of burning and dNBR). We focused on modeling carbon consumption, however, we also reported the results of the depth of burn model because of this variable is widely measured and analysed in the literature (e.g. Barrett et al., 2010, 2011; Turetsky et al., 2011; Genet et al., 2013). We investigated two modeling techniques to formulate a carbon prediction model. The first technique was multiplicative nonlinear regression. This technique is based directly on the interpretation of empirical relationships that may exist between the environmental variables and the carbon consumption field data. ~~This technique~~Multiplicative nonlinear regression has demonstrated to be effective in a similar application to predict fire occurrence and size in Southern California (Jin et al., 2014). The second technique was gradient boosting of regression trees. We applied this technique because previous work indicated that it may have value in predicting depth of burning in boreal black spruce forests (Barrett et al., 2010, 2011). Gradient boosting is a machine learning technique, which produces a prediction model in the form of an ensemble of, in our case, multiple regression trees. We parameterized the gradient boosting of regression trees with the requirement that each leaf ~~of~~ included at least 10% of the data per leaf and using 50 weak learner trees. Both multiplicative nonlinear regression and gradient boosting of regression trees allow for nonlinear relationships between the dependent and independent variables, and interactions between the independent variables. We opted to use the multiplicative nonlinear regression model for our study because we found it to considerably outperform the gradient boosting model in predicting observations that were not used to train the models (Figure S4).

3.3 Daily carbon emissions, 2001-2012 (~~500~~ 450 m)

Once ~~the carbon consumption prediction model was~~ optimized, we extrapolated th~~is~~e carbon consumption model over the spatiotemporal domain of the study at ~~500~~ 450 m resolution. To do so, we first quantified the linear relationship between Landsat and MODIS dNBR and tree cover (Figure S5). The resulting regression equations were applied to the MODIS-derived dNBR and tree cover layers to allow direct application in the carbon consumption model that was optimized using Landsat data.

Due to data paucity of carbon consumption observations in other land cover types than black spruce, we ~~were only able to formulate a prediction model for black spruce forest~~developed separate consumption models for these ecosystems that drew upon the data-driven approach for black spruce. Deciduous and white spruce stands generally have higher aboveground and lower belowground fuel loads (Kasischke and Hoy, 2012; Rogers et al., 2014). We assumed that ~~fuel~~ carbon consumption in these land cover types was controlled by the same variables as from the black spruce consumption model. However, we multiplied the estimates derived from our black spruce-based equations by consumption ratios for above- and belowground deciduous and white spruce stands that were developed using the Consume 3.0 fuel consumption model (Ottmar et al., 2006; Prichard et al., 2006) (Figure S6). Consumption estimates derived from the black spruce model were multiplied with the consumption ratios proportional to the land cover fractions within each pixel. For the state-wide extrapolation over pixels classified as tundra-grass-shrub and non-vegetated, we used the model derived for black spruce. The mean tree cover value of all 30 m tundra-grass-shrub and non-vegetated pixels within the ALFD perimeters between 2001 and 2012 was 11% (standard deviation = sd = 14%).

We also quantified the influence of applying the nonlinear multiplicative model (developed at 30 m resolution) using data with a spatial resolution of 450 m to enable state-wide coverage. For this analysis, we 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 (derived using the nearest neighbor approach), and the 30 m land cover map. We then estimated carbon consumption at 30 m and averaged the resulting carbon consumption over 450 m pixels for those 450 m pixels that had complete 30 m dNBR and tree cover coverage. 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.

3.4 Uncertainty

We adopted a Monte Carlo approach to quantify uncertainties in AKFED. We identified four main sources of uncertainty. The first source originates from the unexplained variance in the black spruce consumption model. The uncertainty estimate from the black spruce consumption model was derived quantitatively from the regression model and varied from pixel to pixel as a function of the input variables. The other sources of uncertainty were related to assumptions and data required to extrapolate the model over Alaska. These included uncertainties in the spatial scaling of a model developed with 30 m data at 450 m resolution, the land cover classification, and assumptions made for deriving carbon consumption for other land cover types than black spruce. Uncertainties derived from the spatial scaling were quantitatively estimated using the approach described in section 3.3. For the land cover classification, because of a lack of quantitative information associated with the classification uncertainty, we assumed a best-guess standard deviation uncertainty of 20% of pixel-based the black spruce fraction. We also assigned a best-guess uncertainty (one sd) of 20 % of the value range for the factors developed to estimate carbon consumption in other land cover types than black spruce (Figure S6). We ran 1000 simulations at each pixel that burned between 2001 and 2012 in which we randomly adjusted the regression model estimates, the land cover fractions, and scaling relationships using the uncertainty information described above. We conducted three separate Monte Carlo simulation analyses for belowground, aboveground and total carbon consumption.

~~A pixel-based uncertainty was included in the extrapolation, here reported as the standard deviation of the prediction error. The uncertainty in the total consumption was calculated from the uncertainties in the below- and aboveground consumption predictions:~~

$$uncertainty_{total} = \sqrt{uncertainty^2_{belowground} + uncertainty^2_{aboveground}}. \qquad (1)$$

4 Results

4.1 Carbon consumption model

The relationship between the depth of burn and the individual environmental variables was strongest for dNBR and tree cover ($R^2_{adjusted}$ = 0.25, p < 0.001), with both relationships modeled using exponential response functions (Figure S7). Depth of burn responded with a relatively strong Gaussian relationship to elevation ($R^2_{adjusted}$ = 0.24, p < 0.001), with the deepest burning occurring in the mid-elevation range between 300 and 600 m. A weak relationship was found for slope ($R^2_{adjusted}$ = 0.05, p < 0.05), and no relationship was observed for day~~time~~ of burning or northness. The strongest individual predictors for belowground carbon consumption were day~~time~~ of burning ($R^2_{adjusted}$ = 0.09, p < 0.001), slope ($R^2_{adjusted}$ = 0.08, p < 0.01) and dNBR ($R^2_{adjusted}$ = 0.06, p < 0.01). Northness ($R^2_{adjusted}$ = 0.04, p < 0.05), elevation ($R^2_{adjusted}$ = 0.04, p < 0.05), and tree cover ($R^2_{adjusted}$ = 0.03, p < 0.05) had a weaker influence (Figure S8). The aboveground carbon consumption demonstrated stronger, also exponential, relationships with pre-fire tree cover ($R^2_{adjusted}$ = 0.53, p < 0.001) and dNBR ($R^2_{adjusted}$ = 0.23, p < 0.001) variables (Figure S9).

The optimized multiplicative nonlinear model for the depth of burn and belowground carbon consumption in black spruce forest based on the field and 30 m data was formulated as:

$$depth_{30m}\ or\ C_{belowground,30m} = c_1 + c_2 \cdot e^{c_3 \cdot dNBR} \cdot e^{C_4 \cdot tc} e^{c_5 \cdot DOY} \cdot e^{\frac{-(elev - c_6)^2}{2 \cdot c_7}} \qquad (~~2~~1)$$

where $c_{1,\ldots,7}$ are the optimized coefficients, dNBR is the differenced normalized burn ratio, tc is the pre-fire tree cover, DOY is the day of the year and elev is the elevation. Two separate models were developed for depth of burn and belowground carbon consumption using equation 1. ~~This model~~The depth of burn model yielded a $R^2_{adjusted}$ of 0.40 ~~and~~ with a ~~Root Mean Square Error (RMSE)~~median absolute residual of ~~5.44~~3.65 cm ($p < 0.001$) ~~for depth of burn~~ (Figure 3A). For belowground carbon consumption, the model and a $R^2_{adjusted}$ of 0.29 ~~and a RMSE~~with a median absolute residual of 1.~~99~~ 18 kg C m^{-2} ($p < 0.001$) for belowground carbon consumption (Figure 3C). Inclusion of slope and northness did not improve the performance of the two models.

The aboveground carbon consumption in black spruce forest was modeled as a multiplicative exponential model of the 30 m dNBR and pre-fire tree cover variables:

$$C_{aboveground,30m} = c_1 + c_2 \cdot e^{c_3 \cdot dNBR} \cdot e^{C_4 \cdot tc} \qquad (\cancel{3}2)$$

where $c_{1,\ldots,4}$ are the optimized coefficients. This model had a $R^2_{adjusted}$ of 0.53 ~~and a RMSE~~with a median absolute residual of 0.~~26~~ 12 kg C m^{-2} ($p < 0.001$) (Figure 3E), ~~the same as~~with a performance similar to ~~-~~the individual relationship between the aboveground carbon consumption and pre-fire tree cover. In the mostly stand-replacing fires that occur in black spruce forest, dNBR did not contribute to the aboveground model. However, we decided to include dNBR to allow for variations in the severity of burning in other land cover types than black spruce, for example in deciduous stands which often burn less severely and frequently (Viereck, 1973; Cumming, 2001). We found no trends in the residuals of any of the models (Figure 3B, D and F). The environmental variables used in the carbon consumption models are ~~plotted~~ shown for the spatiotemporal domain in Figure S10.

FIGURE 3 HERE

Applying the black spruce model at 450 m resolution introduced little systematic bias from the coarser spatial resolution (Figure S11). Using the consumption ratios derived for white spruce and deciduous cover (Figure S6) and slope and intercept from the 30 m to 450 m scaling analysis (Figure S11), below- and aboveground carbon consumption at ~~500~~ 450 m resolution were calculated as:

$$C_{belowground,\cancel{50}450m} = -0.005 + 1.015 \cdot (fr_{bs} + 0.66 \cdot fr_{ws} + 0.31 \cdot fr_{dec}) \cdot C_{belowground,30m} \qquad (\cancel{4}3)$$

$$C_{aboveground,\cancel{50}450m} = 0.023 + 1.077 \cdot (fr_{bs} + 1.56 \cdot fr_{ws} + 1.75 \cdot fr_{dec}) \cdot C_{aboveground,30m} \qquad (\cancel{5}4)$$

where fr_{bs} is the fraction of black spruce within the ~~50~~450 m pixel, fr_{ws} is the fraction of white spruce and fr_{dec} is the fraction of deciduous. The black spruce model was also applied to residual tundra-grass-shrub and non-vegetated parts of each pixel. Before application ~~in~~ of equations ~~4~~ 3 and ~~5~~4, the dNBR and tree cover from MODIS were first converted into their Landsat equivalent values using the equations from Figure S5. The total carbon consumption was calculated as the sum of the below- and aboveground carbon consumption.

To assess the importance of the individual variables, ~~in the model~~ we compared all possible multiplicative regression models ~~inputting~~ with two or more input variables for the depth of burn and belowground carbon consumption ~~models~~ (Figure 4). For the depth of burn model, elevation was the most important explanatory variable. For example, 2-variables models combining elevation with day~~time~~ of burning and dNBR ~~for example~~ performed better than the 3-variables models that excluded elevation. For the belowground carbon consumption model, the day~~time~~ of burning variable was crucial. All 2-variables models combining day~~time~~ of burning with any of the other variables performed better than the 3-variables models that excluded day~~time~~ of burning.

FIGURE 4 HERE

4.2 Daily burned area and carbon emissions, 2001-2012

The total carbon emissions and uncertainty for the spatiotemporal domain are shown in Figures 5 and 6. Daily carbon emissions over the entire spatial domain were primarily driven by daily burned area (Figure 6), however, there was ~~considerably~~ considerable spatial variability in carbon consumption (Figure 5~~A~~). Annual burned area in Alaska from AKFED ranged between ~~35~~ 37 and ~~2268~~ 2295 kha per year between the years 2001 and 2012, resulting in a carbon emission range between 1 and ~~67~~ 69 Tg per year (Figure 7A). 1% of the burned area was mapped from active fire detections outside the perimeters, whereas 18% of the pixels within the ALFD perimeters were mapped as unburned after dNBR screening ~~(to remove edge effects due to low resolution bias burned pixels within 900 m of the perimeter edge were considered in the perimeter, and unburned pixels in the perimeter within 900 m of the perimeter edge were considered outside the perimeter in these statistics)~~. 2004 (~~2268kha~~2295 kha), 2005 (~~1642kha~~1669 kha), 2009 (~~1030kha~~1046 kha) and 2002 (~~723kha~~739 kha) were the largest fire years. More than 50% of the burned area between 2001 and 2012 burned in 53 single days

(Figure 6). Most of the burning occurred in July and August (Figure 7B). The seasonal pattern of carbon emissions generally followed the same seasonal pattern as the burned area. However, carbon consumption increased by a small amount later in the season. 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~~24, $p < 0.001$). Mean dNBR per fire was correlated with fire size (Spearman r = 0.63, $p < 0.001$) and dNBR averaged over the fire season was correlated with annual burned area (Spearman r = 0.73, $p < 0.05$). Most of the burned area occurred in black spruce and white spruce ecosystems (61%), followed by tundra-grass-shrub ecosystems (23%), deciduous forests (14%), and non-vegetated areas (2%), with an overall mean tree cover of 32%.

FIGURE 5 HERE

FIGURE 6 HERE

FIGURE 7 HERE

FIGURE 8 HERE

The median total carbon consumption in AKFED for all burned pixels between 2001 and 2012 was 2.~~48~~54 kg m^{-2}, with the majority originating from belowground losses (median = 2.32 kg C m^{-2}) (Figure 9A). The median aboveground carbon consumption was 0.~~14~~18 kg C m^{-2} ~~(median = 2.3 kg C m^{-2}) (Figure 9A)~~. ~~The median pixel-based uncertainty of the total consumption was 0.38 kg C m^{-2} and originated largely from the uncertainty in belowground consumption (median = 0.35 kg C m^{-2}) (Figure 9B). The median uncertainty in aboveground carbon consumption was 0.11 kg C m^{-2}.~~ The median belowground carbon consumption was higher ~~was higher~~ in burned pixels that had a vegetation cover of 100% black spruce (median = 2.6~~3~~7 kg C m^{-2}) (Figure ~~10~~9B). However, belowground carbon consumption estimates for black spruce were lower than those observed in the field data median = 3.1 kg C m^{-2}). The field data also had a higher median elevation, tree cover and dNBR compared to the distribution of the burned area between 2001 and 2012 (Figure ~~S~~1~~1~~0).

FIGURE 9 HERE

FIGURE 10 HERE

~~Yearly burned area and carbon emissions from AKFED and GFED3s were similar in all years except 2001 (Table S3) when MODIS experienced an outage (Giglio et al., 2013). A strong linear relationship existed between the annual spatial distribution of AKFED and GFED3s 0.25° burned area between 2001 and 2010 (r = 0.95, intercept = 0.04 and slope = 0.98). The similarity between the burned area from AKFED and GFED3s is not surprising since they operate with similar algorithms. Both algorithms look at changes in a spectral index derived from MODIS surface reflectance imagery within a spatial context that is known to have high burned area probability. GFED3s therefore exclusively relies on the MODIS active fire data, while AKFED made combined use of the perimeters of the ALFD and MODIS active fire data outside the perimeters. Carbon emissions were also closely related between the two products (r = 0.87, intercept = 0 and slope = 0.79), as well as mean consumption (2.48 kg C m^{-2} for AKFED versus 2.57 kg C m^{-2} for GFED3s). Statistics of individual years generally followed these trends, except for the year 2001. AKFED and GFED3s exhibited no significant spatial correlation for carbon consumption (r = -0.04, p = 0.13). The difference between the consumption estimates from GFED3s and AKFED is likely a consequence of the different parametrization of belowground consumption in the two products. GFED3s estimates organic layer consumption in boreal soils directly as a function of soil moisture (van der Werf et al., 2010). AKFED uses elevation and time of burning to estimate soil moisture, and is complemented with pre-fire tree cover and post-fire dNBR data. The difference in spatial resolution between AKFED (500 m) and GFED3s (0.25°) may also explain part of the discrepancy.~~

Annual burned area from AKFED, WFEIS and GFED3s were fairly similar (Table 2). Relative to the AKFED burned area estimates between 2001 and 2010, WFEIS burned area estimates were about 10 % lower, and GFED3s estimates approximately 2 % lower. Annual carbon emissions estimates showed larger differences. WFEIS carbon emissions estimates were approximately 142 % higher than AKFED between 2001 and 2010, and GFED3s carbon emissions estimates were approximately 13 % lower than AKFED. Carbon consumption estimates of WFEIS were approximately 168 % higher than AKFED, whereas GFED3s carbon consumption estimates were approximately 12 % lower than AKFED between 2001 and 2010. No significant correlations were found between year-to-year variations in mean carbon consumption estimates from the different models.

4.3 Uncertainties

Uncertainty in total carbon consumption originated primarily from the belowground fraction (Figure 11). 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 carbon consumption in other land cover types than black spruce and spatial scaling introduced smaller uncertainties.

FIGURE 11 HERE

5 Discussion

5.1 Burned area

Our results corroborate previous work highlighting the importance of unburned islands, which amounted to 18% of the fire perimeters. This value is close to the estimates of 14 %, 15 %~~and~~, 17 %~~%~~, and 20 % reported by Kolden et al. (2012), Sedano and Randerson (2014)~~ and~~, Rogers et al. (2014) and ~~(~~Kasischke and Hoy~~,~~ (2012) for fires in interior Alaska. Burned area and emissions peaked in July and August and extended later in the fire season than what has been previously reported for burning before the 2000s (Kasischke et al., 2002) (Figure 7B). This tendency towards late-season burning was found for the four largest fire years that occurred during the study period (2002, 2004, 2005 and 2009) (Figure 6) and can be attributed to the late-season occurrence of weather conditions favorable to fire spread during these large fire years (Hu et al., 2010; Sedano and Randerson, 2014). ~~Some of these late-season fires have occurred outside the fire-sensitive region of interior Alaska which is dominated by black spruce forest. The large Anaktuvuk River fire of 2007 on the North Slope is a well-known example of this (Hu et al., 2010; Mack et al., 2011; Rocha et al., 2012). This suggests that late-season fires may increasingly occur in sparsely vegetated areas like tundra that, despite low aboveground biomass, contain large belowground carbon stocks.~~

5.2 Environmental variables controlling carbon consumption

5.2.1 Elevation

Elevation was the most important variable in the multiplicative depth of burn model and contributed to the skill of the belowground carbon consumption model (Figure 4). Barrett et al. (2010, 2011) and Turetsky et al. (2011) demonstrated the explanatory power of topographic variables for belowground carbon consumption in black spruce forests. Kasischke and Hoy (2012) ~~elaborated~~ drew upon ~~on their~~these findings and assigned ~~curves~~ seasonal trajectories of carbon consumption ~~that linearly increased with time of burning throughout the fire season~~ to three different topographic classes. The predictive power of elevation for belowground carbon consumption is likely explained by two effects. Elevation captures the spatial distribution of cold temperatures that limit the development of soils and black spruce establishment at the higher elevations (Figure S7A). Elevation also captures the fuel moisture controls resulting in generally wetter fuels at lower elevations. This moisture control is dynamic through the fire season and this is captured in our model by interactions between elevation and day~~time~~ of burning (Figure 4). 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 carbon 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. Here we developed our mulitplicative regression model treating all data points within and across different burns with equal weighting. ~~The model in this study was developed for regional state-wide emission predictions. At~~ With this assumption~~scale~~, the topographic variable explaining most of the variability in belowground ~~fuel~~ carbon 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~~ carbon 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 in future work could include fine scale drainage effects driven by slope and aspect. More field observations are needed to robustly separate these different topographic effects. ~~superimposed on the elevation control on consumption.~~

5.2.2 ~~Time~~ Day of burning

~~Time~~ Day of burning within the fire season was the most important variable in the belowground carbon consumption model (Figure 4). ~~Time~~ Day of burning is used as a proxy for seasonal drying of the soil organic layer (Turetsky et al., 2011; Kasischke and Hoy, 2012; Genet et al., 2013). This, however, also depends on elevation as lower elevations will thaw and dry earlier than higher elevations. Because of typically drier conditions of the belowground fuel later in the season, late-season fires tend to have higher carbon consumption rates (Figures 6, 7B, S8D). We found the magnitude of this seasonal change to be smaller than previously reported by Turetsky et al. (2011) and implemented by Kasischke and Hoy (2012). ~~A potential improvement we tested is the replacement of the time of burning with actual fire weather indices that quantify the drying of the ground layer like the drought and duff moisture codes (Van Wagner, 1987). We calculated these indices from daily air temperature, relative humidity, precipitation and wind speeds at 32 km resolution from the North American Regional Reanalyis (NARR, Mesinger et al. (2006), downloaded from http://www.esrl.noaa.gov/psd/data/gridded/data.narr.html, last accessed November 25, 2014) and assigned the daily value, as determined by time of burning estimates, of the weather indices from the nearest grid cell to the field plot locations. At the spatial resolution used in our analysis the weather indices did not improve the carbon consumption model. Although strongly related during experimental fires, the relationship between fire weather and belowground fuel consumption has generally been weak for wildfires (de Groot et al., 2009). This may potentially be the result of the common approach of assigning fire weather index values from the nearest ground weather station, which may not fully represent the actual weather conditions at the place of burning, or the use of gridded meteorological data at a coarser spatial resolution. Weather data with higher spatial resolution, for example derived from downscaling coarse resolution data like NARR, may provide a valuable pathway to re-assess the relationships between field-observed consumption of the organic layer in wildfires and fire weather conditions (Abatzoglou~~

~~and Kolden, 2011; Waddington et al., 2012). Weather indices may also capture the climatological and fuel moisture controls that are currently imposed in the model by elevation (section 5.2.1)~~. Replacement of ~~time~~ day of burning and elevation with weather indices in future work may enable broadening the geographical scope of the current regional carbon consumption model to other regions of boreal North America. This could include components from the Canadian fire weather index system, ~~-~~(Van Wagner, 1987), such as the drought code, possibly with modifications that account for differences in topographic conditions (Waddington et al., 2012).

5.2.3 Burn severity (dNBR)

The utility of dNBR in the boreal region has been subject to much debate (French et al., 2008). We found a relatively strong relationship between dNBR and aboveground carbon consumption (Figure S9A). The criticism on the use of dNBR, however, has focused on its ability to predict belowground carbon consumption (French et al., 2008; Hoy et al., 2008). Some authors have found relatively strong correlations between field measures of belowground consumption and dNBR (Hudak et al., 2007; Verbyla and Lord, 2008; Rogers et al., 2014). Barrett et al. (2011) also ranked dNBR in the top third predictors of a set of 35 spectral and non-spectral environmental variables. French et al. (2008) concluded that the use satellite-based assessments of burn severity, including dNBR, in the boreal region "need to be used judiciously and assessed for appropriateness based on the users' needs". We found here that, 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). We also found that including dNBR in the model resulted in additional explained variance compared to models that excluded dNBR (Figure 4). In addition, dNBR and tree cover were found to vary at a finer spatial scale than elevation or ~~time~~ day of burning (Figure S12), and their inclusion in the model as such likely improved the representation of the spatial heterogeneity in ~~fuel~~ carbon consumption. 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 $r = 0.73$, $p < 0.05$) provided additional support for the inclusion of the dNBR as a synergistic variable in our carbon emissions modeling framework. The advantage of using dNBR for capturing this variability compared to fire size or total annual burned area is that it enables independent assessment of carbon losses at each pixel. It also provides a more mechanistic underpinning for exploring relationships that emerge at the fire-wide or regional level, including the relationships described above between fire size and carbon consumption.

The relatively high correlations between depth of burn, and dNBR and tree cover suggest that crown fires in high density black spruce plots ~~also~~ may ~~cause~~ contribute to 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~~ day of burning. For a ~~certain~~ given 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~~ day 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, our results suggest the synergistic use of the dNBR with other environmental variables is essential ~~for improving~~improves 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.

5.2.4 Tree cover

This is the first study to evaluate the potential of tree cover as a predictor of ~~fuel~~ carbon consumption in black spruce forests. The relatively strong relationship ~~with~~ between tree cover and aboveground carbon consumption is intuitive as black spruce forest mostly experience stand-replacing crown fires and tree cover is directly related to the amount of available biomass and the probability that the crown fire can spread from tree to tree. Its utility for predicting belowground carbon consumption is less obvious and more indirect. We included tree cover in our analysis since we hypothesized that it would be a good proxy of stand age and site productivity which directly relates to drainage conditions, and thickness and density of the organic layer (Kasischke and Johnstone, 2005; Beck et al., 2011b; Rogers et al., 2013). High intensity crown fires in dense black spruce plots also may provide more radiant heating (and drying) of the ground layer, enabling deeper burns. Significant relationships between tree cover and depth of burn (Figure S7E), and tree cover and belowground carbon consumption (Figure S8E) provided support for these mechanisms. ~~Both dNBR and tree cover relationships with depth of burn observations were consistent with this effect.~~

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

Here we compare our estimates of carbon emissions and carbon consumption with those from ~~(~~Kasischke and Hoy~~,~~ (2012) and ~~(~~Tan et al.~~,~~ (2007) for the subset of years reported in these publications. For 2004, we estimated a total emission of 69 Tg pyrogenic carbon in our domain. This 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 reported by ~~(~~Tan et al.~~,~~ (2007). AKFED and Kasischke and Hoy (2012) also yielded similar estimates for the small fire years 2006 and 2008. The two models had diverging predictions for 2007, however, with the domain-wide AKFED estimate of 5 Tg C substantially higher than the estimate of approximately 2 Tg C by Kasischke and Hoy (2012). The discrepancy can be explained in part by the inclusion of the large Anaktuvuk tundra fire within the AKFED domain, whereas the analysis by Kasischke and Hoy (2012) only considered fires in the boreal interior of Alaska.

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 from Kasischke and Hoy (2012). The close agreement between AKFED and the ~~(~~Kasischke and Hoy~~,~~ (2012) for burned area is be expected since they use similar input data. Both approaches, for example, use fire perimeter data in combination with spectral screening to estimate burned area.

Carbon consumption estimates for the large fire year 2004 were fairly similar among estimates from ~~(~~Kasischke and Hoy~~,~~ (2012) (3.0 kg C m^{-2}), ~~(~~Tan et al., (2007) (3.1 kg C m^{-2}) and AKFED (3.0 kg C m^{-2}). Both AKFED and Kasischke and Hoy (2012) estimated lower consumption values for the small fire years 2006, 2007 and 2008, although the estimates from Kasischke and Hoy (2012) (1.5-1.9 kg C m^{-2}) were lower than AKFED (1.8-2.6 kg C m^{-2}) ~~carbon consumption~~. Kasischke and Hoy (2012) used observations derived conceptually from observations reported by Turetsky et al. (2011) that indicated that ground layer consumption increased with fire season progression. We derived a similar relationship with day of burning using a different set of data and statistical approach (Figure 6 and 7B). We found that, in our application, the nonlinear multiplicative regression model outperformed other statistical methods for extrapolating carbon consumption in space and time (Figure S4). Our depth of burn model achieved an $R^2_{adjusted}$ of 0.40, which is similar to the explained variance of 50 % 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 by topographic class. We aimed at preserving the within-fire variability by using spatially varying dNBR and tree cover observations as model drivers (Figure S11). The representation of these higher resolution dynamics in fuel and consumption variability may partly explain our slightly lower model performance.

We further compared AKFED burned area, carbon consumption and emissions estimates with estimates from two larger scale models, WFEIS and GFED3s. ~~(~~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 – similar to the multi-model mean. Our carbon emissions estimate for this fire was slightly higher than estimates from WFEIS (5.3-5.7 Tg C) and field assessment 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 differences in burned area, with the field assessment of E. Kasischke in French et al. (2011) reporting a total that was about 10 % lower than AKFED. GFED3 reported 207 ha and 4.64 Tg C emissions for this fire.

Decadal-scale comparison between AKFED, WFEIS and GFED3s demonstrated fairly similar burned area estimates, although AKFED and GFED3s were slightly higher than WFEIS (Table~~s~~ 2). The similarity between the burned area from AKFED, WFEIS and GFED3s is not surprising since they operate with similar algorithms. All algorithms look at changes in a spectral index derived from MODIS surface reflectance imagery to map burned area. Burned area in GFED3s and WFEIS were from the MCD64A1 product (Giglio et al., 2009), complemented with small fire contributions outside the MCD64A1 burned area detections for GFED3s (Randerson et al., 2012). AKFED used active fire detections that occurred outside the fire perimeters to include contributions from small fires. The contribution from small fires that were included in GFED3s and AKFED may explain the slightly higher burned area estimates than in WFEIS.

Carbon consumption was not correlated between different models (Table 2). In addition, carbon consumption was slightly lower in GFED3s compared to AKFED, and significantly higher in WFEIS compared to AKFED. This suggests that GFED3s slightly underestimates carbon consumption from boreal fires, although the difference in mean carbon consumption between AKFED and GFED3s is with the range of the region-wide mean uncertainty estimate of 0.50 kg C m^{-2} (Figure 11). The comparison also indicates that region-wide WFEIS estimates are several fold higher than those from AKFED, GFED3s, or Kasischke and Hoy (2012). The high levels of carbon consumption in WFEIS for Alaska are consistent with the study of Billmire et al. (2014) that showed for the contiguous U.S. WFEIS estimates were about double of GFED3 estimates. Differences in the carbon emissions estimates between approaches result from differences in the methods and input data to quantify burned area, fuel type, and carbon consumption. ~~(~~Billmire et al.~~,~~ (2014) found that the difference between WFEIS and GFED3 carbon emission estimates in the contiguous U.S. was primarily driven by the higher fuel loads assigned in WFEIS. This effect may also explain the discrepancy in Alaska, and further effort is needed to compare the different modelling approaches. These findings also highlight the need for synthesis and intercomparisons of the different data inputs required for emission modelling, including fuel load, combustion completeness, and emission factors. Such efforts are ongoing (van Leeuwen and van der Werf, 2011; van Leeuwen et al., 2014); ~~(~~van Leeuwen et al.~~,~~ (2013) for example assessed the impact of different sets of emission factors on CO mixing ratios. One constraint with large scale models is that their coarse spatial resolution does not allow direct comparison with field measurements. This gap may be filled by regional models like AKFED that are calibrated with field data at a higher spatial resolution and can be scaled to a coarser resolution.

~~5.3~~5.4 ~~Representativeness of the field data and u~~Uncertainties

The domain wide mean uncertainty for carbon consumption was slightly lower than 20 % of the mean, and similar to fire-wide uncertainty reported by ~~(~~Rogers et al.~~,~~ (2014). Our approach integrated observed and best-guess uncertainty estimates for different aspects of our modeling system, including components originating from comparisons of our model with field observations and other components associated with spatial scaling. Other studies reporting 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 report uncertainty levels in the range of 5 to 30 %, expressed as the coefficient of variation (standard deviation/mean). For AKFED, the most important source of uncertainty originated from the belowground carbon consumption model for black spruce (Figure 11). This results is consistent with findings from ~~(~~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.

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 and other aspects of our burned area algorithm, the assumption of the same controls on pyrogenic carbon consumption in non-black spruce ecosystems, consumption of woody debris, and uncertainties in field measurements. In places where uncertainties in burned area mapping are large, 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 ALFD perimeters (1 % of total burned area) and excluding unburned islands within the fire perimeters (18 % of perimeter area). We believe that this approach for mapping burned area was relatively robust and minimized uncertainties from this source.

A more significant uncertainty in estimating region-wide fire emissions comes from a paucity of field observations in ecosystems other than black spruce. Here we assumed that the same environmental variables that controlled carbon consumption in black spruce ecosystems also operated for white spruce and deciduous forest, and grassland and shrub land. This assumption may not entirely be valid but cannot be verified until more field data becomes available for these cover types. Another important source of uncertainty originates from consumption of coarse woody debris. Consumption of coarse woody debris is difficult to quantify and was not explicitly accounted for in our approach. 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). Thus, our model estimates may have a small low bias as a consequence of our lack of explicitly accounting for this pool. Field measurements of fuel loads of woody debris in unburned stands in function of stand age and their combustion in relation to fire weather conditions may allow for improved models of pyrogenic carbon consumption in boreal forest ecosystems.

Finally, uncertainties within the set of available field data have not been systematically assessed. These may stem from different methods that were used to estimate depth of burn in the field (combustion rods, adventitious roots technique or unburned-burned site pairing) and assumptions used to convert depth of burn measurements to carbon loss (Rogers et al., 2014). For example, the 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 conversion of the depth of burn observations to belowground carbon consumption for these field plots. While the Rogers et al. (2014) data were collected with the aim of making comparisons with 30 m geospatial layers, some of the other available observations may not have used the same criteria for homogeneity in surrounding areas, and thus may contribute to uncertainties when integrated with other geospatial data.

~~The state-wide median belowground consumption estimate of 2.3 kg C m~~$^{-2}$ ~~of this study is lower than the median values of the field data used in this study (Figure 10). Most available field data focus on black spruce ecosystems. While this 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%. Although deciduous and white spruce trees may have higher amounts of available aboveground fuel (Kasischke and Hoy, 2012; Rogers et al., 2014), it is well known that the~~

~~belowground consumption of fuels dominates in boreal ecosystems and that the largest fire-affected belowground carbon stocks are stored in black spruce ecosystems (McGuire et al., 2009; Kasischke and Hoy, 2012). The burning in other land cover types than black spruce thus partly explains the relatively low state-wide median belowground consumption estimate of 2.3 kg C m^{-2}. We here used the FCCS classification to characterize land cover. We found this layer indicative for the vegetation patterns in the region. However, we found that 60 out of the 126 black spruce plots from the field dataset (section 2.2) were misclassified as white spruce (29), tundra-grass-shrub (14), deciduous (12) and non-vegetated (5). 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). The median belowground consumption estimate increased to 2.63 kg C m^{-2} in pure black spruce stands (Figure 10). This value was still clearly lower than the median of 3.1 kg C m^{-2} from the field data used in this study. The field data were, relative to the state-wide distribution, disproportionally sampled in mid-elevation areas with high tree cover and high dNBR (Figure 11S). This suggests that currently available field measurements of carbon consumption in black spruce forest are biased towards areas that tend to have higher levels of fuel consumption. Part of this bias can also be explained by the fact that most of the field plots used in this study were sampled in fires from the large and severe fire year 2004 (85 out of the 126 plots). 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. In our study the belowground fraction of the total carbon consumption was higher than those from the field plots used.~~

5.5 Representativeness of the field data

The state wide median belowground carbon consumption estimate of 2.32 kg C m^{-2} of this study is lower than the median values of the field data used in this study (Figure 9). The median belowground carbon consumption estimate increased to 2.67 kg C m^{-2} when only pure black spruce stands were considered (Figure 9B). This value was still considerably lower than the median of 3.10 kg C m^{-2} from the field data used in this study. The field data were, relative to the state wide distribution, disproportionally sampled in mid-elevation areas with high tree cover and high dNBR (Figure 10). This suggests that the field measurements of carbon consumption in black spruce forest here were biased towards areas that tend to have higher levels of carbon consumption. Part of this bias may be a consequence of many data being collected from burns during large and severe fire year 2004 (85 out of the 126 plots). We found that large fires years generally have higher carbon consumption estimates (Figure 8). This corroborates findings of Turetsky et al. (2011) and Kasischke and Hoy (2012), although the relative increase of carbon consumption with higher annual burned area from AKFED 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 carbon consumption level are positively correlated.

Several aspects of our 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 increasing the number of observations in black spruce ecosystems using pre-fire tree cover, post-fire dNBR, topographic conditions, and fire seasonality in the sampling design in an effort to better represent the distribution of burning conditions (Figure 10). Second, considerable uncertainty within AKFED originated from assumptions made to estimate carbon consumption in white spruce, deciduous, grassland, and shrub land ecosystems. Very little data on pyrogenic carbon consumption is currently available for these ecosystems and explicit targeting these ecosystems is needed to reduce uncertainties in future work. For white spruce and deciduous ecosystems we developed scaling factors using Consume 3.0 (Figure S6). For grassland and shrub land ecosystems 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 carbon consumption (Figure 7E) and this may justify the use of the model for non-treed ecosystems until consumption data within these ecosystems becomes available. Mack et al. (2011) estimated a mean carbon loss of 2.02 kg C m^{-2} with a standard error of 0.44 kg C m^{-2} for the Anaktuvuk River fire. In comparison, our model estimated a mean carbon consumption of 2.56 kg C m^{-2} with a mean pixel-based uncertainty of 0.54 kg C m^{-2} for this event.

Even with an abundance of high quality plot data along key axes of environmental variability, regional extrapolation requires accurate maps of land cover. 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 carbon 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 ecosystems that burn less regularly, more field measurements are still required to better constrain pyrogenic carbon consumption in boreal forest ecosystems.

~~Our model provided a per-pixel uncertainty estimate, expressed as the standard deviation from the prediction error (Figure 9B). Median uncertainty was 0.38 kg C m^{-2}, mostly originating from the belowground fraction (median 0.35 kg C m^{-2}) and equaling approximately 15% of the modeled consumption values on a per-pixel basis. These values are slightly lower than the per-~~

~~pixel uncertainties from model prediction estimated by Rogers et al. (2014), who demonstrated that these per-pixel uncertainties largely average out when scaled over larger areas. Most other studies that have modeled landscape level carbon emissions from Alaskan fires have relied on scenarios in which uncertainties of different variables 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).~~

~~5.4~~5.6 Future ~~directions~~applications

Databases of burned area, severity and emissions with high spatial and temporal resolution like AKFED are a necessity to advance several related fields in biogeosciences. They allow for a more thorough evaluation of models used to relate weather, fuels and topography to fire spread rates that were originally derived using laboratory measurements (Rothermel, 1972; Beer, 1991). Spatially explicit burned area data with high temporal resolution will also allow for quantitative assessments of constraints on fire progression due to fuel discontinuities and fire weather ~~conditions~~ (Krawchuk et al., 2006). Knowledge of these constraints on fire spread may prove valuable when predicting future fire regimes that will result from changes in fire weather, vegetation dynamics and inherent landscape heterogeneity.

~~At least two aspects of the boreal fire regime in Alaska have already changed over the last half century (Kasischke et al., 2010). There has been an increase in the burned area, driven by a few excessively large fire years, and a shift towards more severe late-season burning. Both changes, however, also provoke additional increases in the surface albedo through deciduous dominance in the early stages of succession and this effect lasts for many decades (Randerson et al., 2006; Johnstone et al., 2010; Barrett et al., 2011; Beck et al., 2011a). Jin et al. (2012) showed that the observed albedo increase scaled with the severity of burning, while Randerson et al. (2006) demonstrated that boreal forest fires can have a slight cooling effect on the climate. The net effect of boreal fires on radiative forcing will have to come from an analysis that integrates the warming, mainly from greenhouse gas emissions, and cooling, mainly from albedo increases, effects over multiple decades with consideration for the spatial heterogeneity in fuels and their consumption.~~

Fire emission databases with high temporal and spatial resolution also may enable improvements in our understanding of fire aerosol composition and decrease the large uncertainties that currently exist in fire emission factors of different gas species by ~~comparing~~ enabling more accurate comparisons ~~them to~~with *in situ* measurements. Fire emissions estimates and atmospheric transport models ~~therefore~~ need to be convolved at high spatial and temporal resolution to capture interactions between emissions, transport, chemical transformation, and deposition of aerosol and trace gas species. In addition, fires in the boreal region are episodic and most of the burned area and emissions occur in a relatively short amount of time. High resolution time series are therefore of paramount importance ~~as input to transport models and~~ to infer and forecast possible health effects in populated areas exposed to smoke plumes (Hyer et al., 2007).

6 Conclusions

By integrating field and remote sensing variables at multiple scales, we developed a database of burned area and carbon emission by fire at ~~500~~ 450 m spatial resolution and daily temporal resolution for the state of Alaska between 2001 and 2012. We found that, although most of the fires burned in black spruce forest, considerable burned area in~~burned~~ white spruce forest, deciduous forest, and grassland~~-~~ ~~and~~and shrub land ecosystems ~~that displayed~~contributed to lower region-wide carbon consumption estimates. This partly explained why the median carbon consumption of 2.~~48~~54 kg C m^{-2} over the spatiotemporal domain was lower than that typically observed in black spruce ~~plots~~ecosystems. However, even solely considering~~when only~~ pure black spruce pixels, ~~were considered the~~ median carbon consumption was still lower than most field observations. This suggests that the ~~currently~~ available field data that were used in this study ~~are biased~~may have a bias toward high carbon consumption. We thus recommend ~~sites and we recommend~~ caution in extrapolating these values over large areas without taking into account spatial heterogeneity in tree cover and other variables influencing fuels and ~~consumption~~ combustion over the landscape. More comprehensive field databases of carbon consumption in black spruce and other ecosystems (e.g. white spruce, deciduous and tundra ecosystems) are required to better constrain region wide carbon emissions and lower uncertainties. Further improvements in land cover characterization are also required to remove potential biases that may originate from uncertainties in this layer.

Our carbon consumption model was driven by four environmental variables: elevation, ~~time~~ day of burning, differenced normalized burn ratio (dNBR) and pre-fire tree cover. At the regional level of our study, elevation controlled fuel moisture conditions and soil organic layer thickness. ~~Time~~ Day of burning within the fire season, in combination with elevation, was used to estimate the seasonal thawing of the permafrost and subsequent ~~availability of dry~~moisture content of organic soil layers. dNBR and tree cover explained additional model variance, and allowed to capture fine scale variability in carbon~~superimposed spatial detail on the~~ consumption~~ estimates that was unavailable from the other layers~~. While the use of dNBR as stand-alone indicator of belowground carbon consumption by fire in boreal ecosystems may have limitations, our model ~~predictions~~ system benefited from its use in synergy with other environmental variables. Higher dNBR values were significantly related to deeper burning in soil organic carbon layers. ~~showed a clear trend towards deeper burning. Tree cover was found to be an excellent proxy of stand age and site productivity and related soil organic layer thickness and density.~~ The observed relationships between belowground carbon consumption, ~~and~~ dNBR and tree cover, suggest aboveground fuel consumption and heat release in ~~a mechanism where high density black spruce plots provide an easier heat transfer of fire from~~may influence the drying of surface fuels~~canopy to the ground layer~~, and vice versa, ~~resulting~~ thus contributing to~~in~~ higher levels of carbon consumption~~s~~.

The Alaskan Fire Emissions Database (AKFED) is publicly available from sites.google.com/a/uci.edu/sander-veraverbeke/akfed and will be updated regularly. This data could further contribute to the knowledge on spatiotemporal patterns, controls and limits on fire progression, air pollution and exposure, and aerosol composition of boreal fires.

Author contributions

SV designed the study, performed the analyses and wrote the manuscript with inputs from BMR and JTR at all stages.

Acknowledgements

This work was funded by the National Aeronautics and Space Administration Carbon in Arctic Reservoirs Vulnerability Experiment (CARVE) and NNX11AF96G project. We would like to thank the authors from the Boby et al. (2010), Rogers et al. (2014) and Turetsky et al. (2011) papers for making their field data publicly available. We are ~~also~~ grateful to several colleagues of the University of California, Irvine for discussions on the work. We are thankful to four reviewers, including E. Kasischke and E. Kane, for constructive comments that considerably improved the discussions version of this manuscript.

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Table 1. Environmental variables selected to predict ground layer consumption by fire in black spruce forest. The pre-fire tree cover and dNBR layers were also used to predict the aboveground carbon consumption.

variable	rationale	data
elevation (m)	Elevation ~~regulates~~ influences soil organic layer thickness, carbon density, drainage conditions and seasonal timing of permafrost thaw (Kane et al., 2005, 2007; Kasischke and Johnstone, 2005; Barrett et al., 2010; Kasischke and Hoy, 2012)	ASTER GDEM 2 (Tachikawa et al., 2011)
slope (°)	Slope regulates drainage conditions, organic layer thickness and fire behavior. Sloped terrain is generally better drained than flat terrain (Barrett et al., 2011). Steepness of the terrain regulates tree establishment (Hollingsworth et al., 2006) and fire spread rates and severity (Rothermel, 1972).	derived from ASTER GDEM 2
northness – cosine of aspect	Northness regulates drainage conditions, organic layer thickness and carbon density. Wetness increases with northness, and solar insolation decreases with increasing northness. North-oriented slopes are wetter and colder than South-faced slopes and have thicker, less dense organic layers (Kane et al., 2007; Turetsky et al., 2011).	derived from ASTER GDEM 2
pre-fire tree cover (%)	Pre-fire tree cover determines the available biomass for aboveground consumption. Aboveground consumption relates to belowground consumption (Rogers et al., 2014). Pre-fire tree cover is also a proxy of stand age, and thus of the thickness, density and wetness of the soil organic layer (Kasischke and Johnstone, 2005; Beck et al., 2011b; Rogers et al., 2013).	tree cover continuous fields 30 m: Sexton et al. (2013) 250 m: Hansen et al. (2003)
~~time~~ day of burning ~~(day of the year)~~	~~Time~~ Day of burning influences the dryness of the soil organic layer during the season (Turetsky et al., 2011; Kasischke and Hoy, 2012)	derived from MODIS active fire data
dNBR	dNBR assesses pre-/post-fire changes in near and shortwave infrared reflectance, which relate to changes in vegetation abundance, charcoal deposition and soil exposure (López García and Caselles, 1991; van Wagtendonk et al., 2004; Key and Benson, 2006)	30 m: MTBS (Eidenshink et al., 2007) 500 m: derived from MODIS surface reflectance

ASTER GDEM 2: Advanced Spaceborne Thermal Emission and Reflection Radiometer Global Digital Elevation Model Version 2 (downloaded from http://reverb.echo.nasa.gov, last accessed ~~November 25~~April 3, ~~2014~~2015)

dNBR: differenced Normalized Burn Ratio

MODIS: Moderate Resolution Imaging Spectroradiometer

MTBS: Monitoring Trends in Burn Severity (downloaded from http://www.mtbs.gov/, last accessed ~~November 25, 2014~~April 3, 2015)

Tree cover data downloaded from http://glcf.umd.edu/data/landsatTreecover/ (30 m), and http://reverb.echo.nasa.gov (500 m), MODIS surface reflectance data from http://reverb.echo.nasa.gov, MODIS active fire data from ftp://fuoco.geog.umd.edu/modis (all last accessed on ~~November 25, 2014~~April 3, 2015)

Table 2. Annual burned area, carbon emisisons, and mean carbon consumption between 2001 and 2010 from the Alaskan Fire Emissions Database (AKFED), the Wildland Fire Emissions Information System (WFEIS), and the Global Fire Emissions Database version 3s (GFED3s). Values were extracted for the domain between 58° and 71.5° N, and 141° and 168° W. We used the MCD64A1 burned area product and the default parameters within the WFEIS emissions calculator (http://wfeis.mtri.org/calculator, last accessed April 3, 2015). We included both emissions from natural and agricultural fuels.

	annual burned area (kha)			annual C emissions (Tg)			mean C consumption (kg/m^2)		
year	AKFED	WFEIS	GFED3s	AKFED	WFEIS	GFED3s	AKFED	WFEIS	GFED3s
2001	61	0	2	1	0	0	1.89	/	2.57
2002	739	595	636	17	46	15	2.27	7.74	2.44
2003	200	188	200	5	10	5	2.74	5.24	2.51
2004	2294	2253	2283	69	167	52	3.03	5.88	2.26
2005	1660	1320	1538	46	102	38	2.76	7.75	2.47
2006	47	68	86	1	3	2	1.76	4.75	2.40
2007	200	130	165	5	8	5	2.63	6.55	2.80
2008	37	24	34	1	2	1	2.37	7.32	1.86
2009	1046	1054	1130	26	77	29	2.51	7.27	2.52
2010	268	283	324	6	16	8	2.25	5.55	2.34
2001-2010	655	592	634	18	43	15	2.72	7.29	2.40

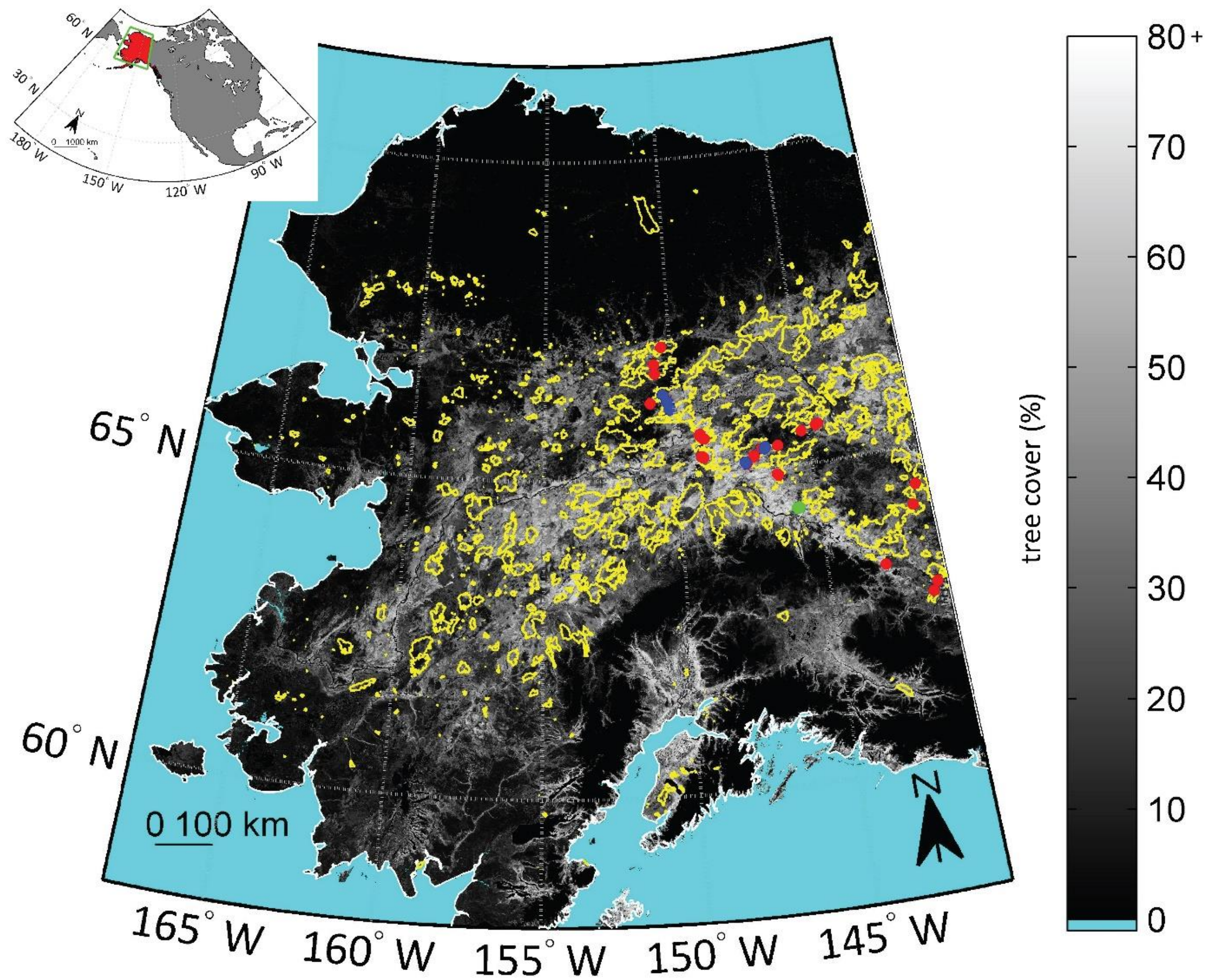
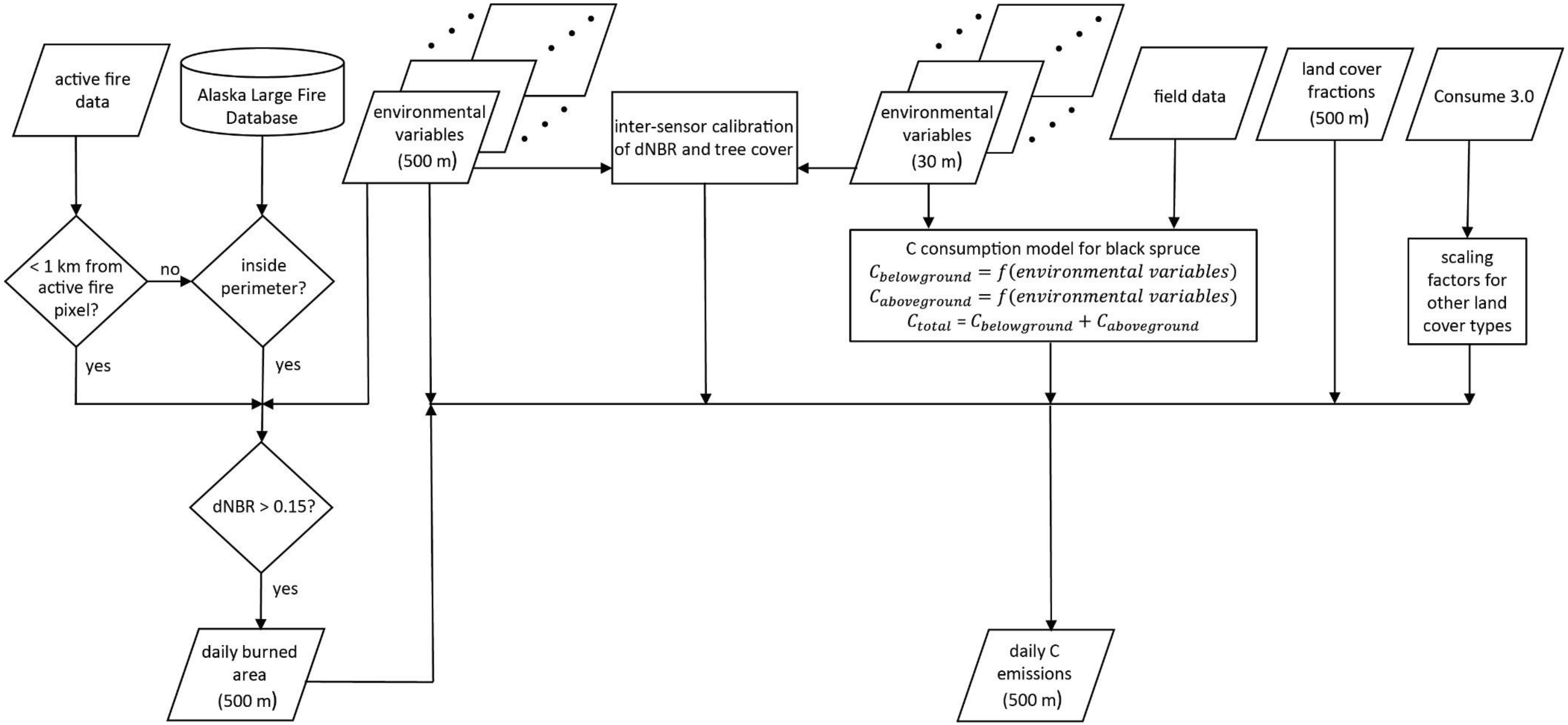


Figure 1. Fires that occurred in the study area between 2001 and 2012 (yellow perimeters) from the Alaska Large Fire Database. The background tree cover map is the Moderate Resolution Imaging Spectroradiometer Vegetation Continuous Fields product (MOD44B, Hansen et al. (2003)) for the year 2000. The colored dots represent the location of field plots from Turetsky et al. (2011) (red), Boby et al. (2010) (blue) and Rogers et al. (2014) (green). Note that at the scale of the map, some field plot locations overlap due to their close proximity to each other.


active fire data
Alaska Large Fire Database
environmental variables (500 m)
inter-sensor calibration of dNBR and tree cover
environmental variables (30 m)
field data
land cover fractions (500 m)
Consume 3.0
< 1 km from active fire pixel?
no
inside perimeter?
yes
yes
C consumption model for black spruce
$C_{belowground} = f(environmental\ variables)$
$C_{aboveground} = f(environmental\ variables)$
$C_{total} = C_{belowground} + C_{aboveground}$
scaling factors for other land cover types
dNBR > 0.15?
yes
daily burned area (500 m)
daily C emissions (500 m)

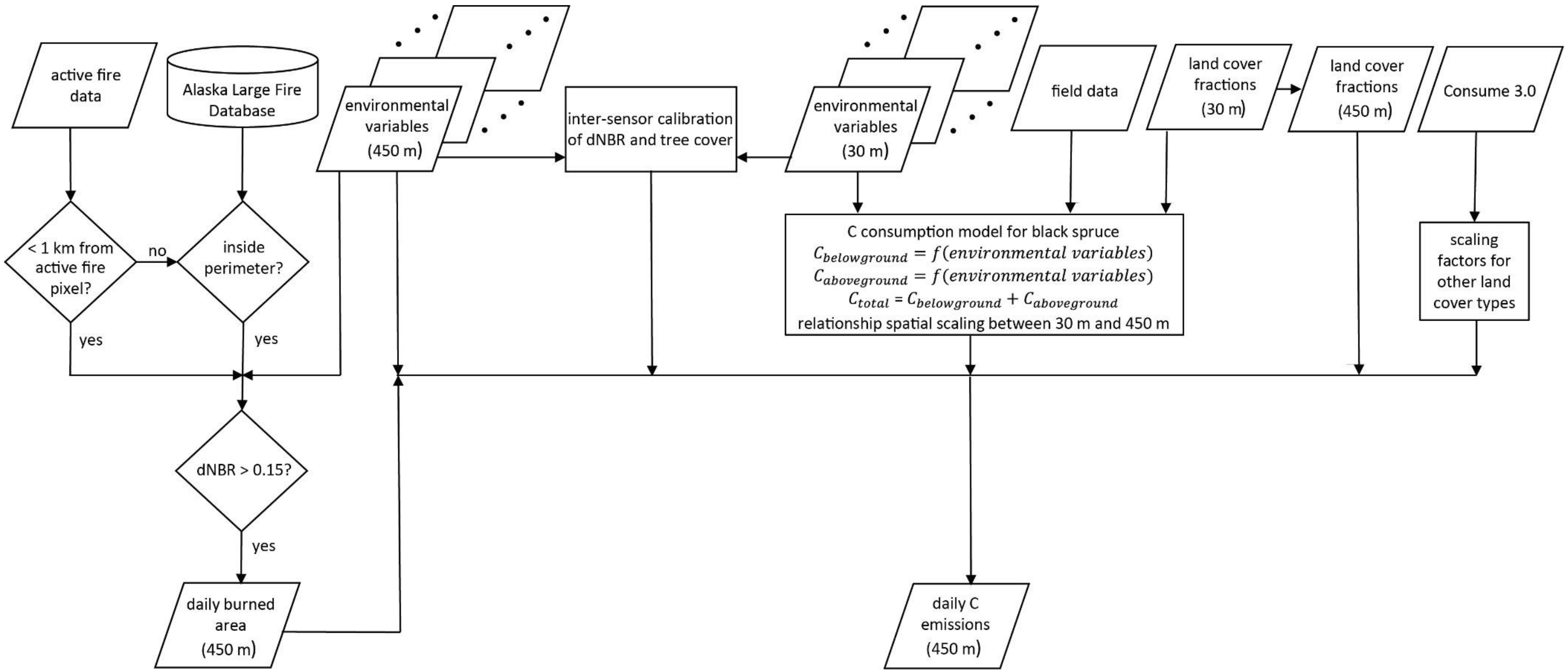
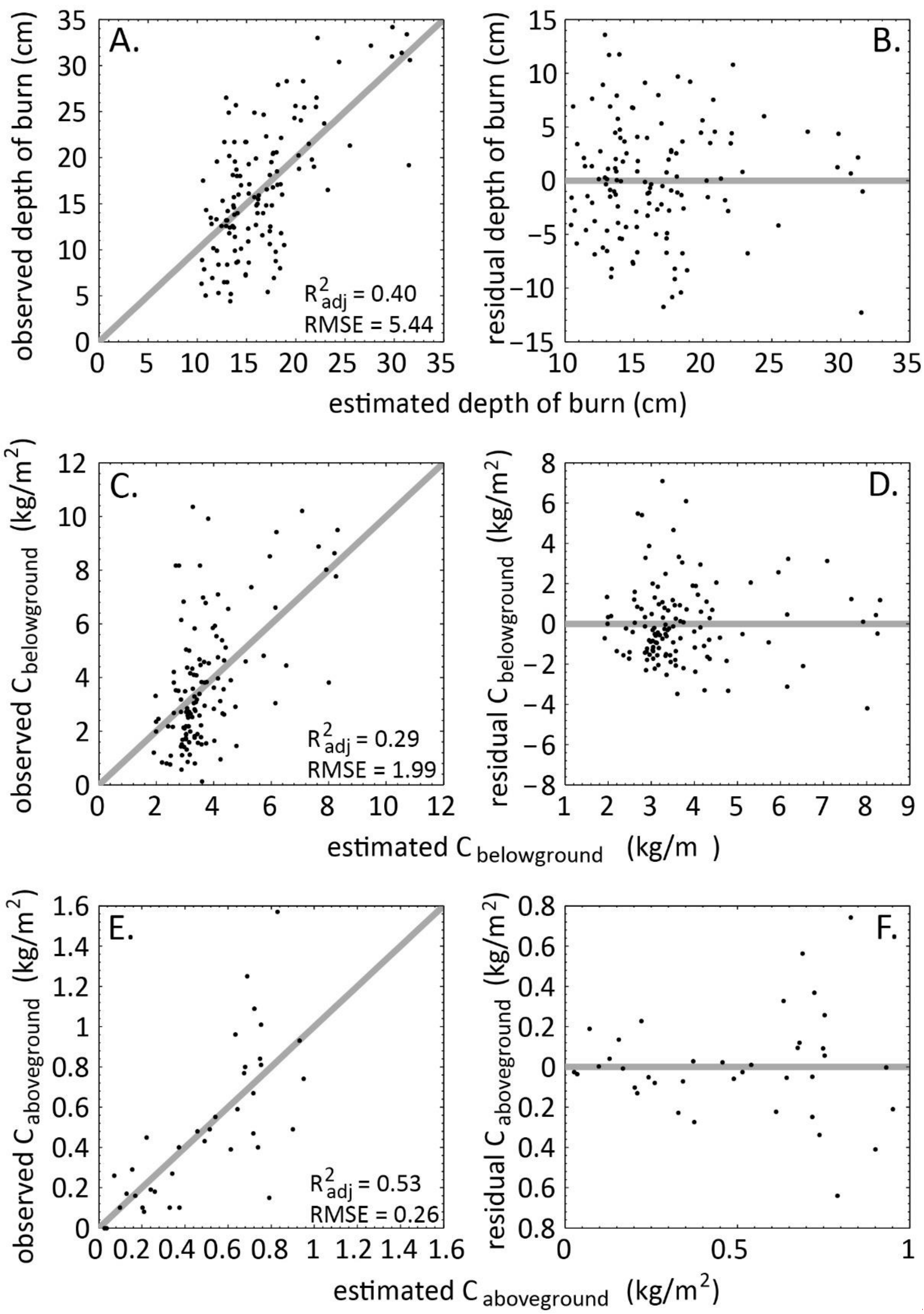


Figure 2. Workflow used to obtain daily burned area and carbon emissions in the Alaskan Fire Emissions Database (AKFED). (dNBR: differenced normalized burn ratio)


A.
B.
C.
D.
E.
F.
observed depth of burn (cm)
residual depth of burn (cm)
estimated depth of burn (cm)
R^2_{adj} = 0.40
RMSE = 5.44
observed $C_{belowground}$ (kg/m^2)
residual $C_{belowground}$ (kg/m^2)
estimated $C_{belowground}$ (kg/m)
R^2_{adj} = 0.29
RMSE = 1.99
observed $C_{aboveground}$ (kg/m^2)
residual $C_{aboveground}$ (kg/m^2)
estimated $C_{aboveground}$ (kg/m^2)
R^2_{adj} = 0.53
RMSE = 0.26

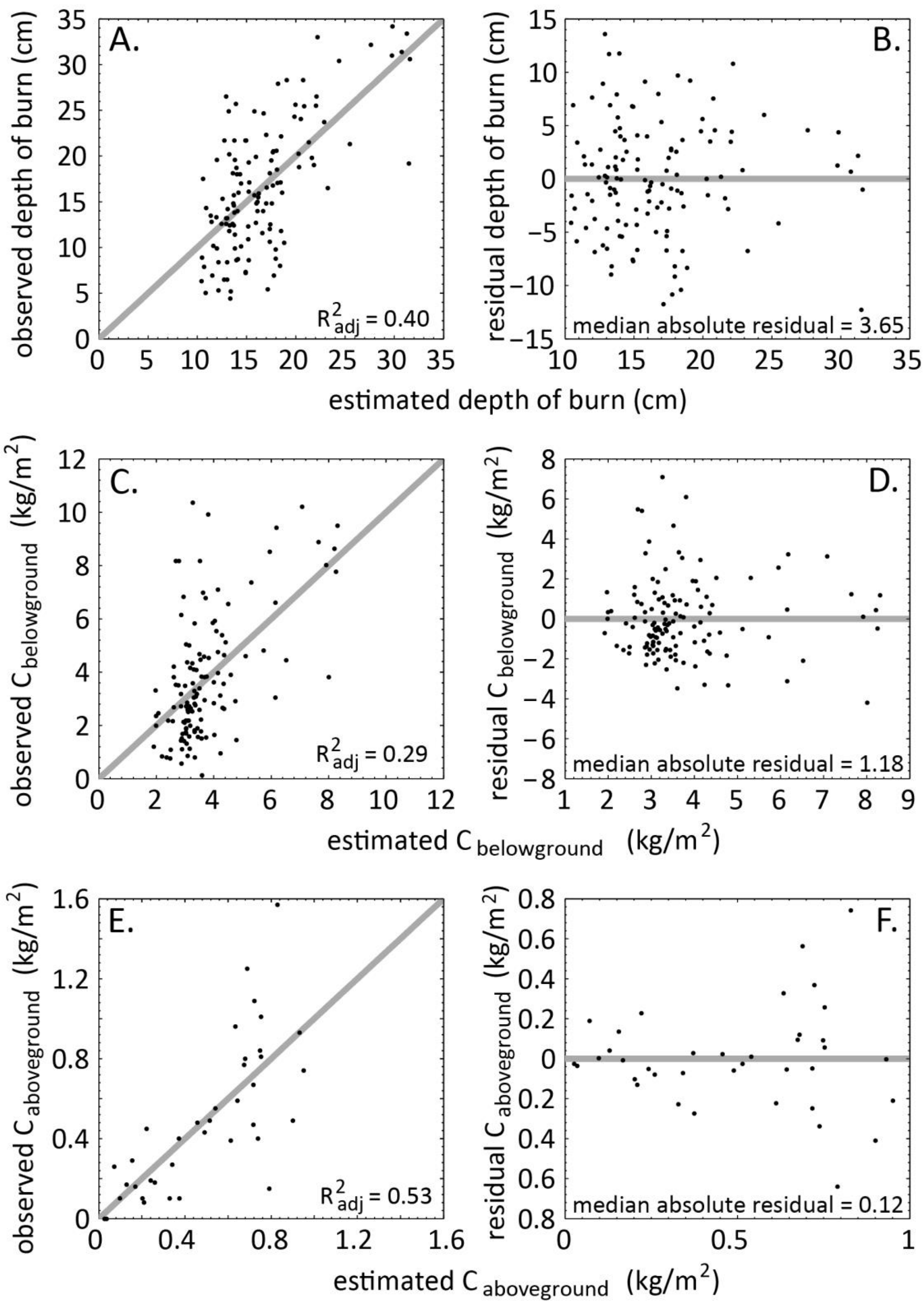
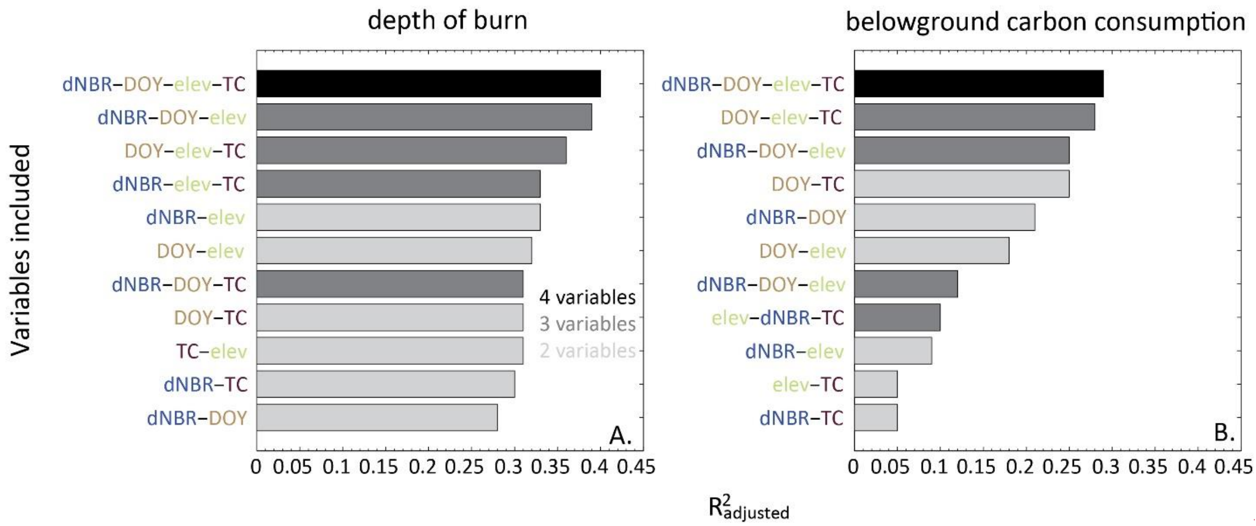


Figure 3. Scatter plots between the observed and estimated (A) depth of burn, (C) belowground and (E) aboveground carbon consumption from the multiplicative nonlinear model, and corresponding regression residuals (B, D and F). The grey line represents the 1:1 line in the left panels, and the y = 0 line in the right panels. All models were significant at $p < 0.001$. ~~(RMSE: root mean square error)~~



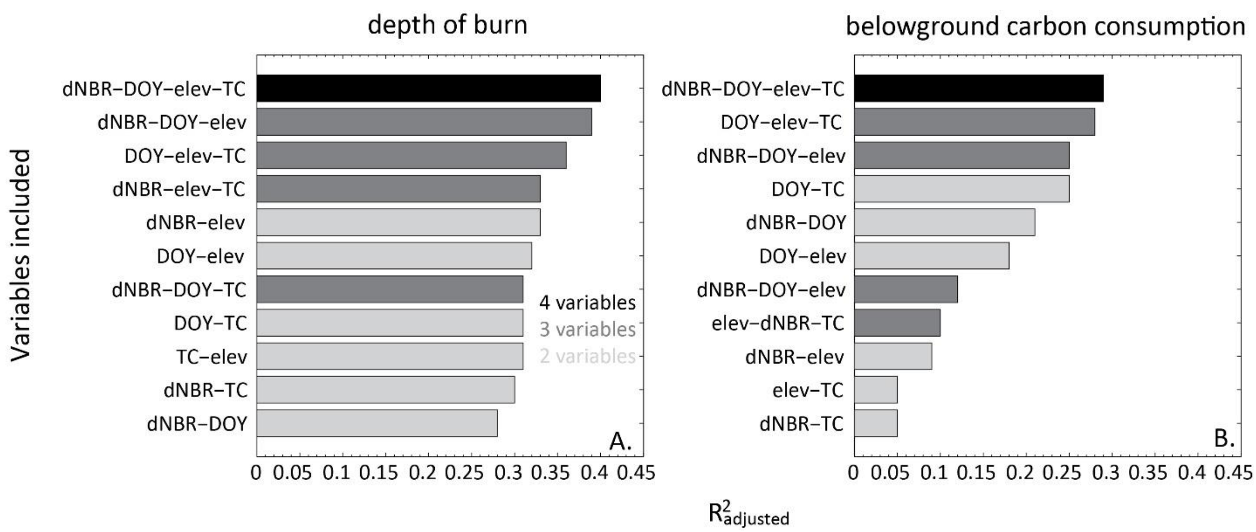


Figure 4. Relative importance of variables assessed from the nonlinear multiplicative models using all different combinations of two or more variables for (A) depth of burn and (B) belowground carbon consumption. Since only two variables were included in the aboveground carbon consumption model, no similar analysis was performed for aboveground carbon consumption. (dNBR: differenced normalized burn ratio, DOY: day of the year, tc: tree cover, elev: elevation)

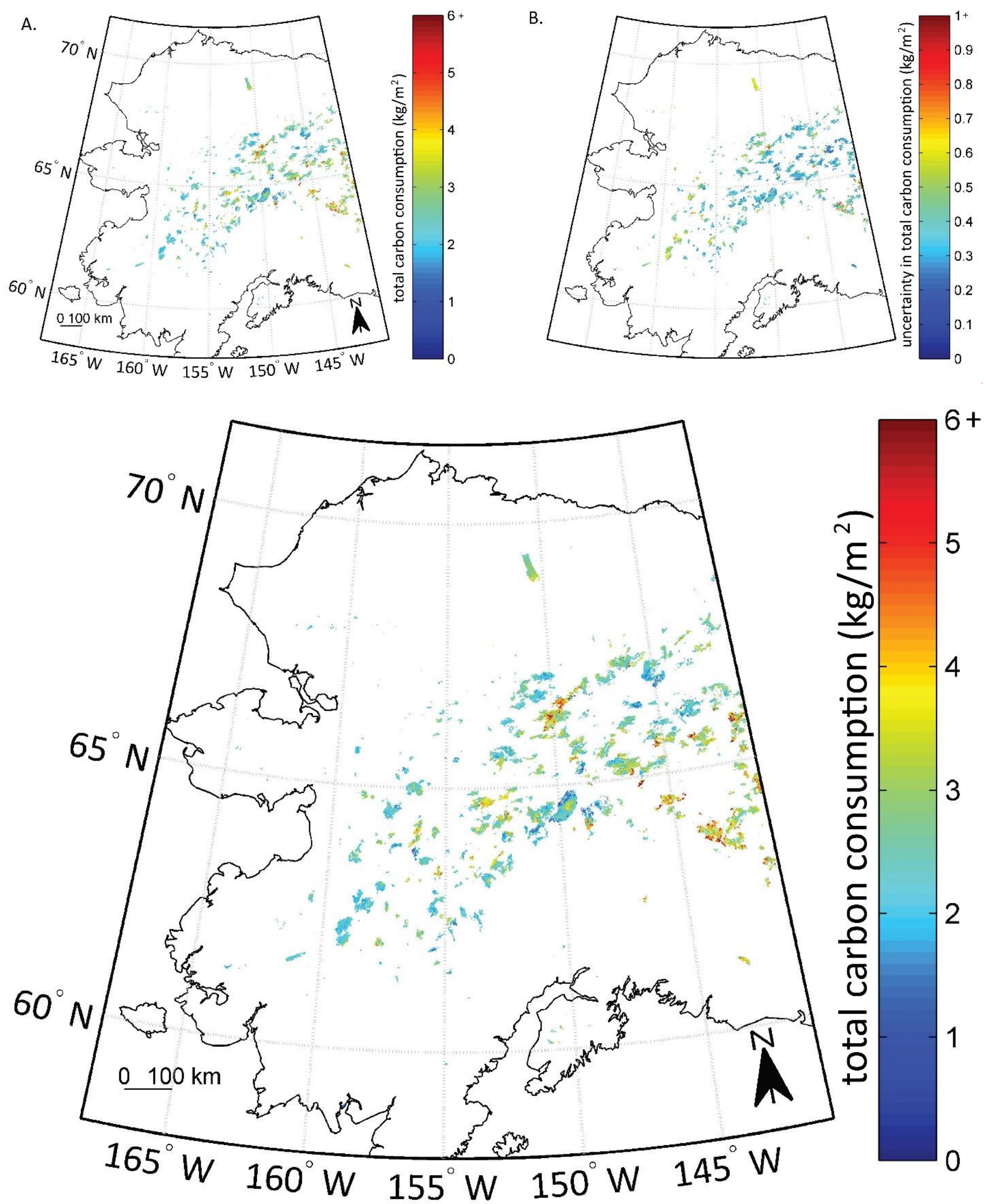
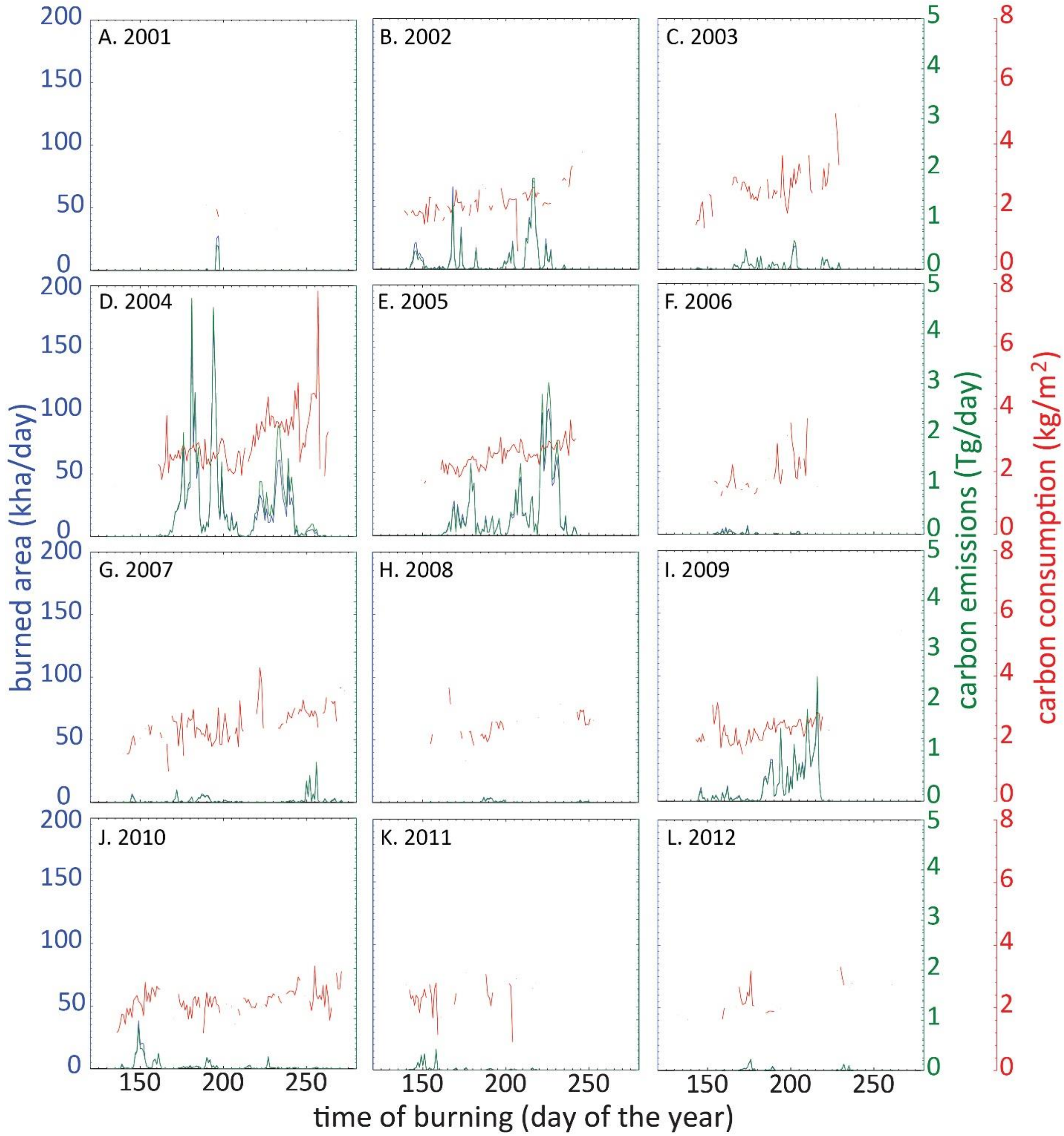


Figure 5. ~~(A)~~ Total pyrogenic carbon consumption map ~~by fire and (B) uncertainty, expressed as the standard deviation of the prediction error,~~estimated from the Alaskan Fire Emissions Database between 2001 and 2012.~~ for the spatiotemporal domain~~.


A. 2001
B. 2002
C. 2003
D. 2004
E. 2005
F. 2006
G. 2007
H. 2008
I. 2009
J. 2010
K. 2011
L. 2012
burned area (kha/day)
carbon emissions (Tg/day)
carbon consumption (kg/m^2)
time of burning (day of the year)
0
50
100
150
200
0
1
2
3
4
5
0
2
4
6
8
150
200
250

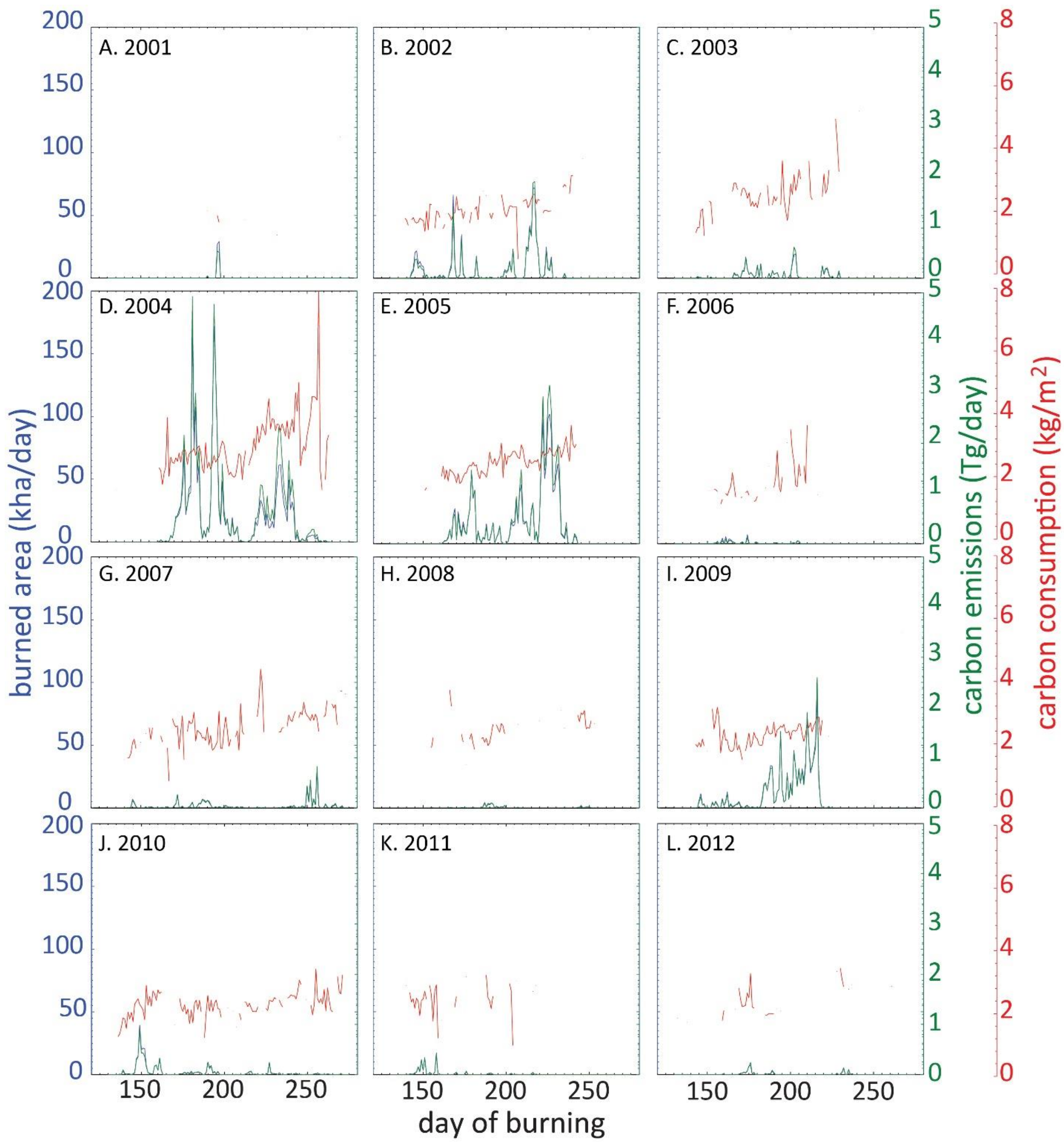
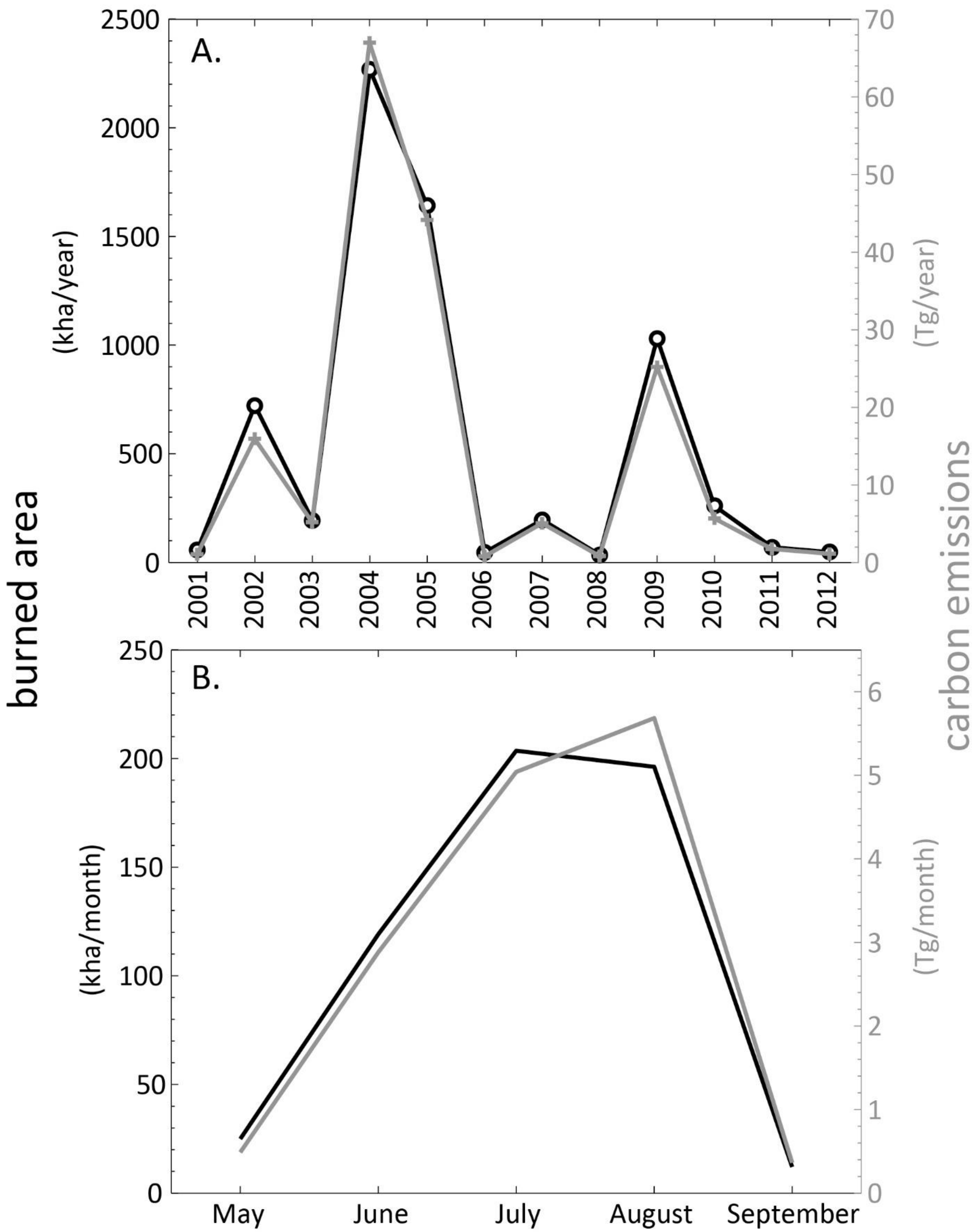


Figure 6. Daily burned area, carbon consumption and emissions ~~from Alaska~~ derived from the Alaskan Fire Emissions Database for the years 2001-2012.


A.
B.
burned area
carbon emissions
(kha/year)
(Tg/year)
(kha/month)
(Tg/month)
2500
2000
1500
1000
500
0
70
60
50
40
30
20
10
0
2001
2002
2003
2004
2005
2006
2007
2008
2009
2010
2011
2012
250
200
150
100
50
0
6
5
4
3
2
1
0
May
June
July
August
September

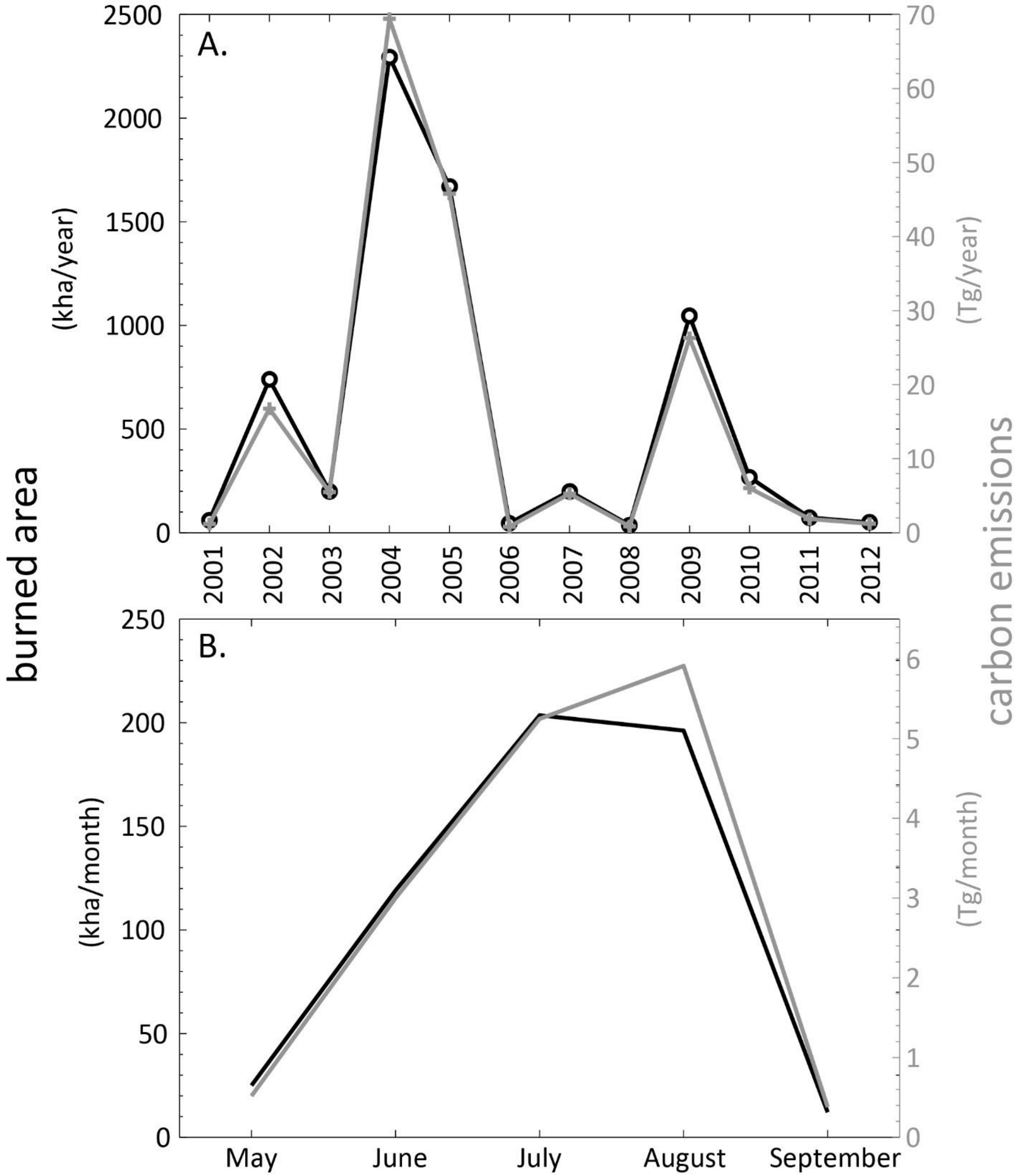
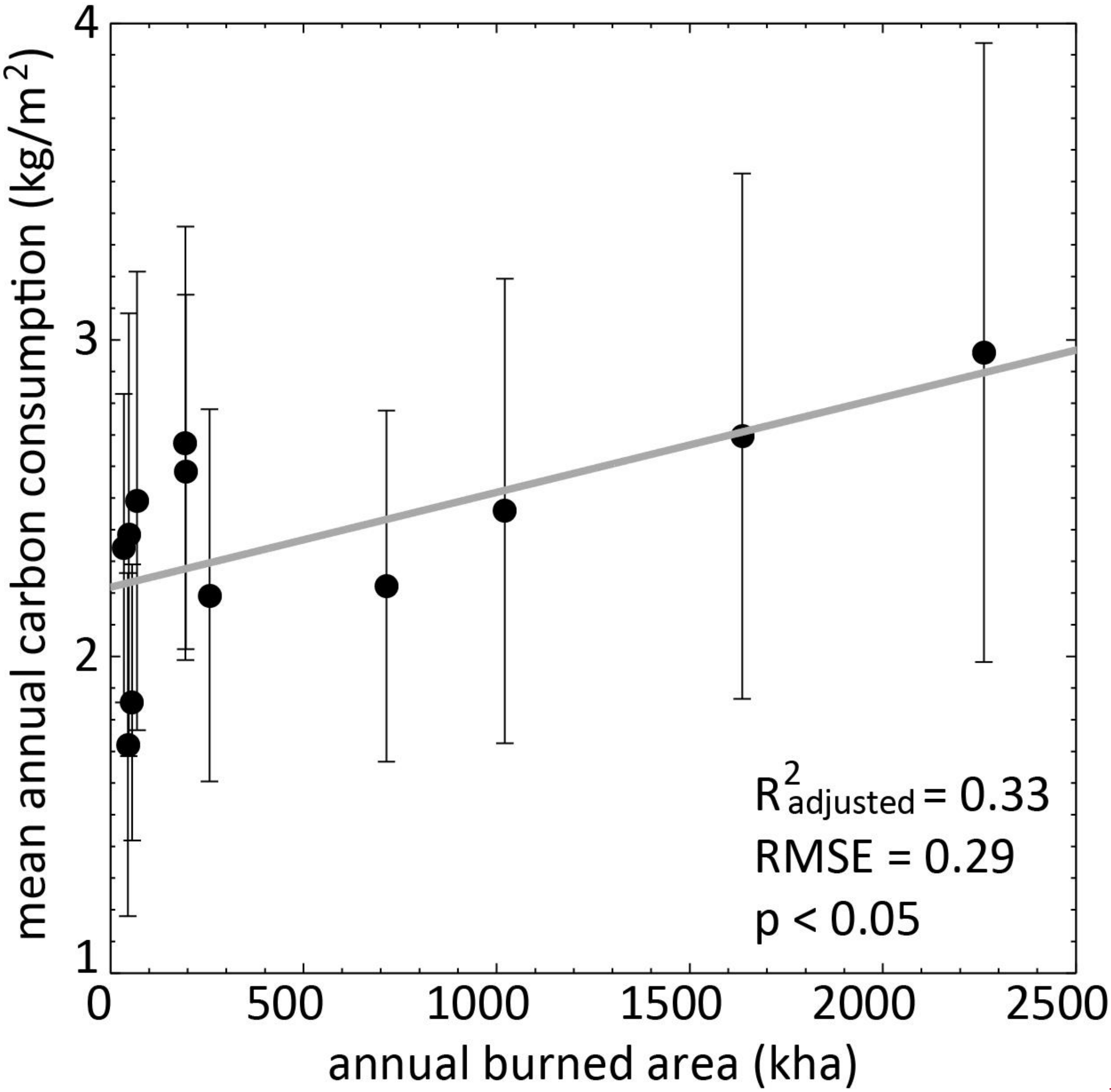


Figure 7. (A) Inter- and (B) intra-annual variability in burned area and carbon emissions in Alaska. In (B), the mean monthly burned area and carbon emissions between 2001 and 2012 ~~is~~ were plotted.


mean annual carbon consumption (kg/m2)
4
3
2
1
0
500
1000
1500
2000
2500
annual burned area (kha)
R2adjusted = 0.33
RMSE = 0.29
p < 0.05

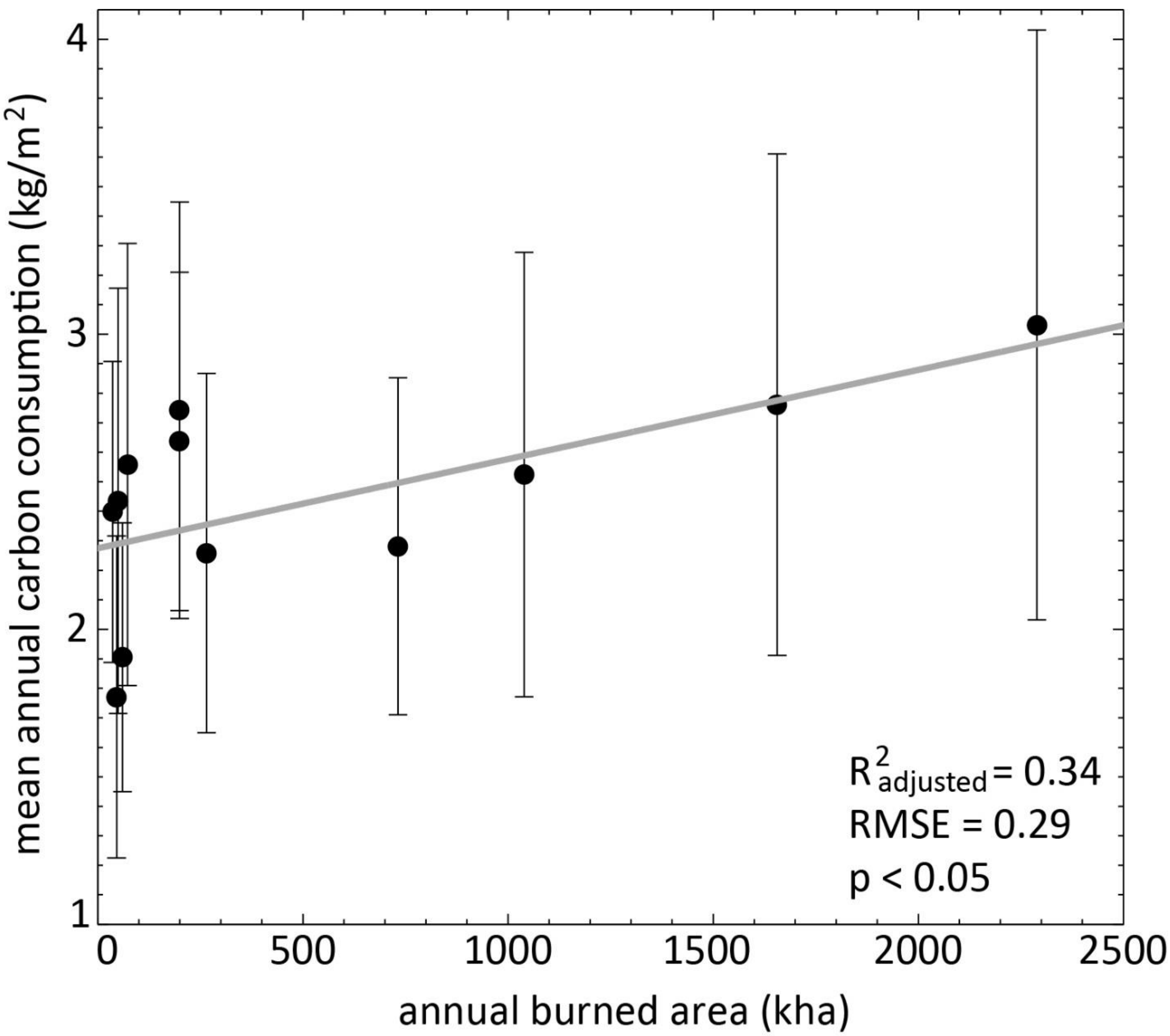
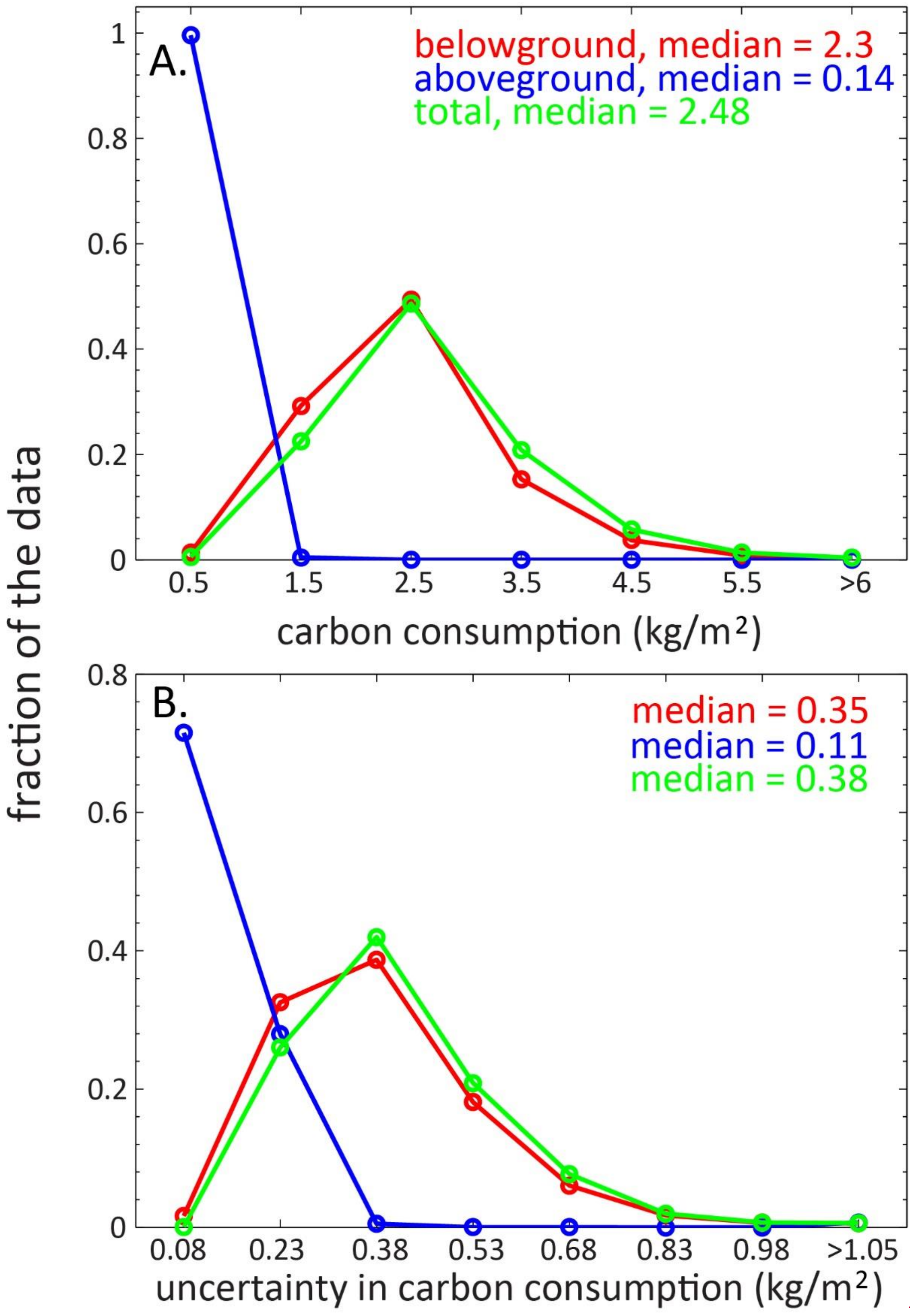


Figure 8. Relationship between annual burned area and mean annual carbon consumption. The error bars represent one standard deviation.


A.
belowground, median = 2.3
aboveground, median = 0.14
total, median = 2.48
fraction of the data
0
0.2
0.4
0.6
0.8
1
0.5
1.5
2.5
3.5
4.5
5.5
>6
carbon consumption (kg/m²)
B.
median = 0.35
median = 0.11
median = 0.38
0
0.2
0.4
0.6
0.8
0.08
0.23
0.38
0.53
0.68
0.83
0.98
>1.05
uncertainty in carbon consumption (kg/m²)

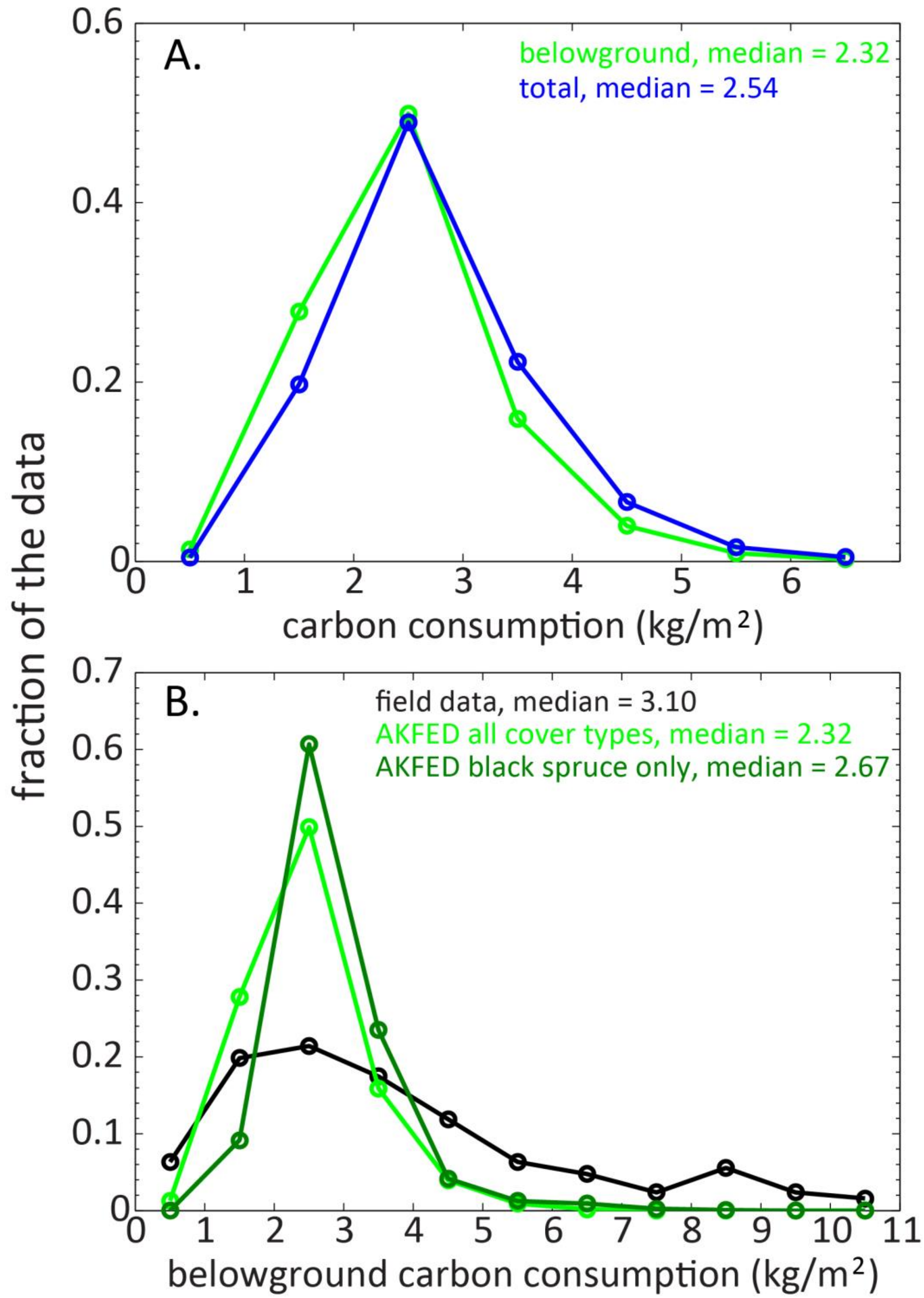
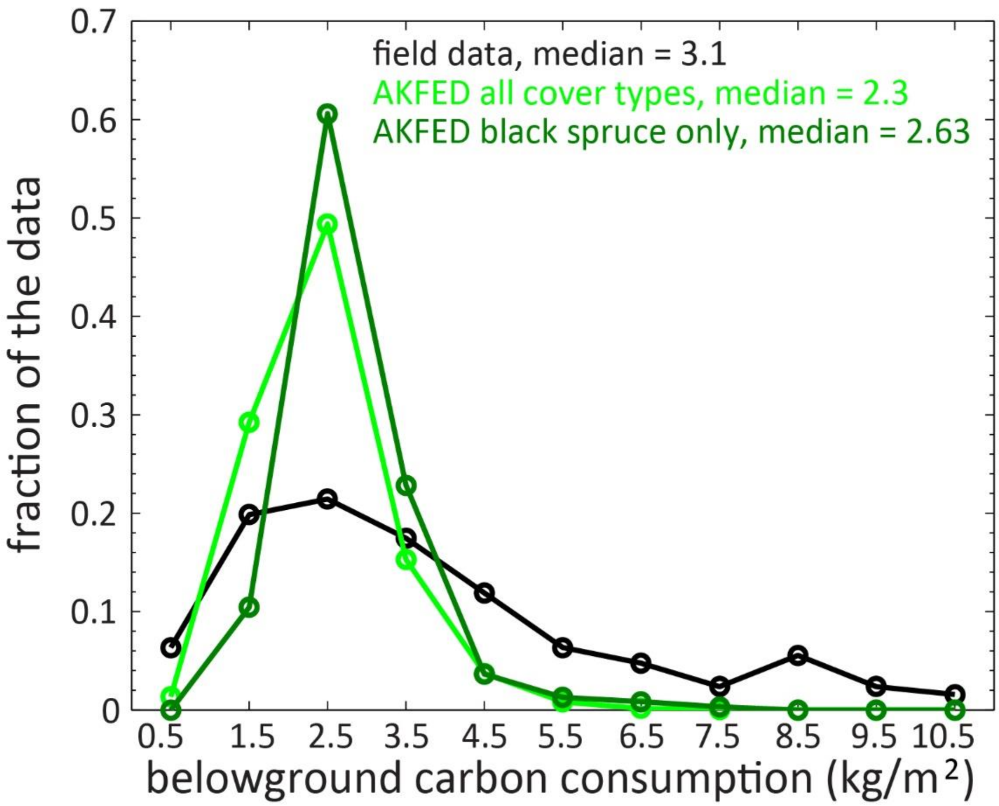


Figure 9. Distribution of (A) belowground, aboveground and total carbon consumption from the Alaskan Fire Emissions Database (AKFED) between 2001 and 2012, and (B) belowground carbon consumption of field data and AKFED ~~pixel-based uncertainties in carbon consumption from the Alaskan Fire Emissions Database between 2001 and 2012~~. ~~The x-axes are labeled with the center of the binning intervals.~~ Data is plotted in the middle of interval boundaries on the x-axis.



~~Figure 10. Distribution of belowground carbon consumption of field data and the Alaskan Fire Emissions Database (AKFED) between 2001 and 2012. The x-axes are labeled with the center of the binning intervals.~~

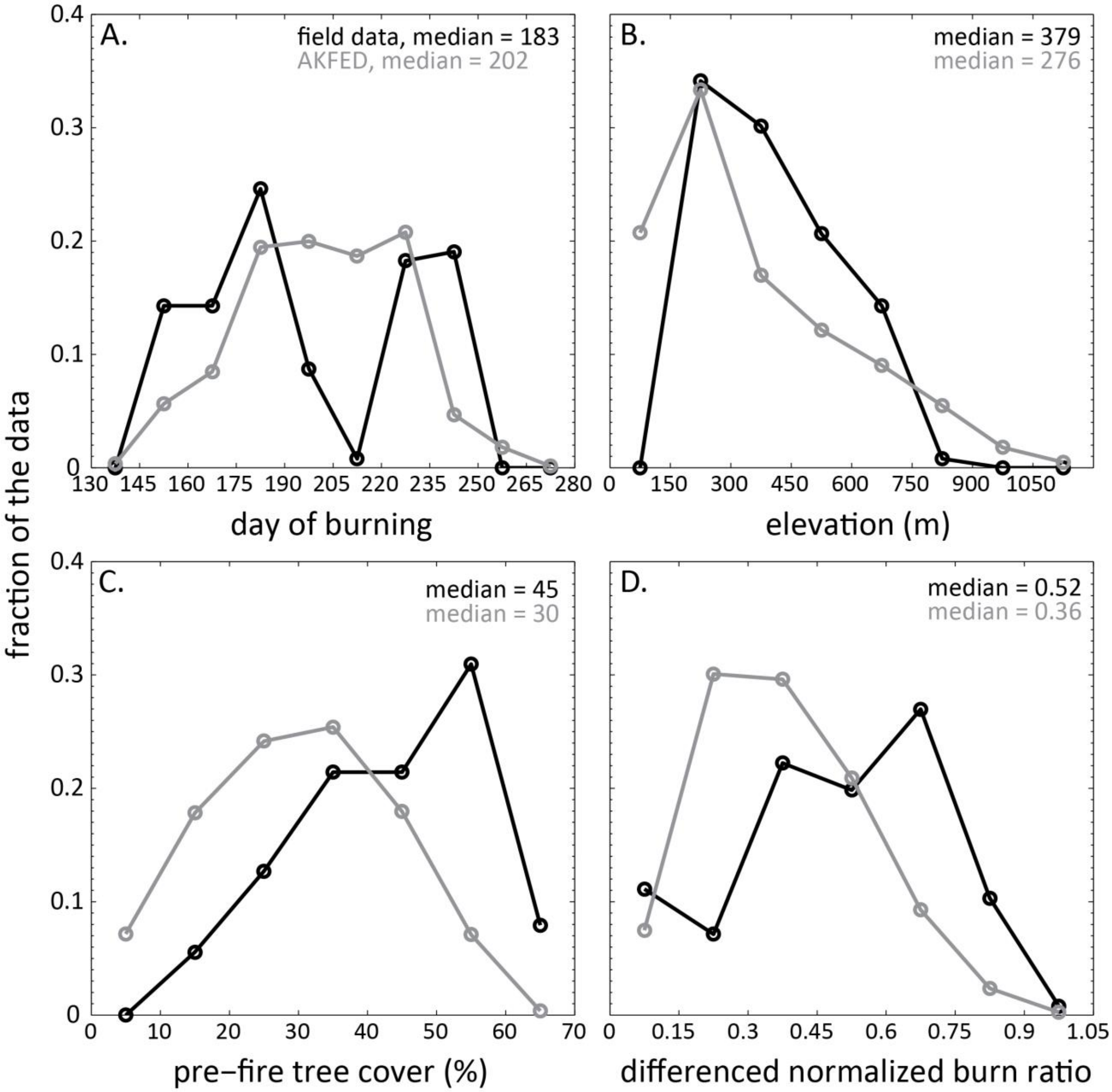


Figure ~~11~~10. Distribution of (A) ~~time~~ day of burning, (B) elevation, (C) pre-fire tree cover, (D) differenced normalized burn ratio of field observations (n = 126) ~~data~~ and ~~the~~ region wide Alaskan Fire Emissions Database (AKFED) between 2001 and 2012. The tree cover and differenced normalized burn ratio derived from the Moderate Resolution Imaging Spectroradiometer were converted to their Landsat-like values using the equations in Figure S5. Data is plotted in the middle of interval boundaries on the x-axis.~~The x-axes are labeled with the center of the binning intervals~~.

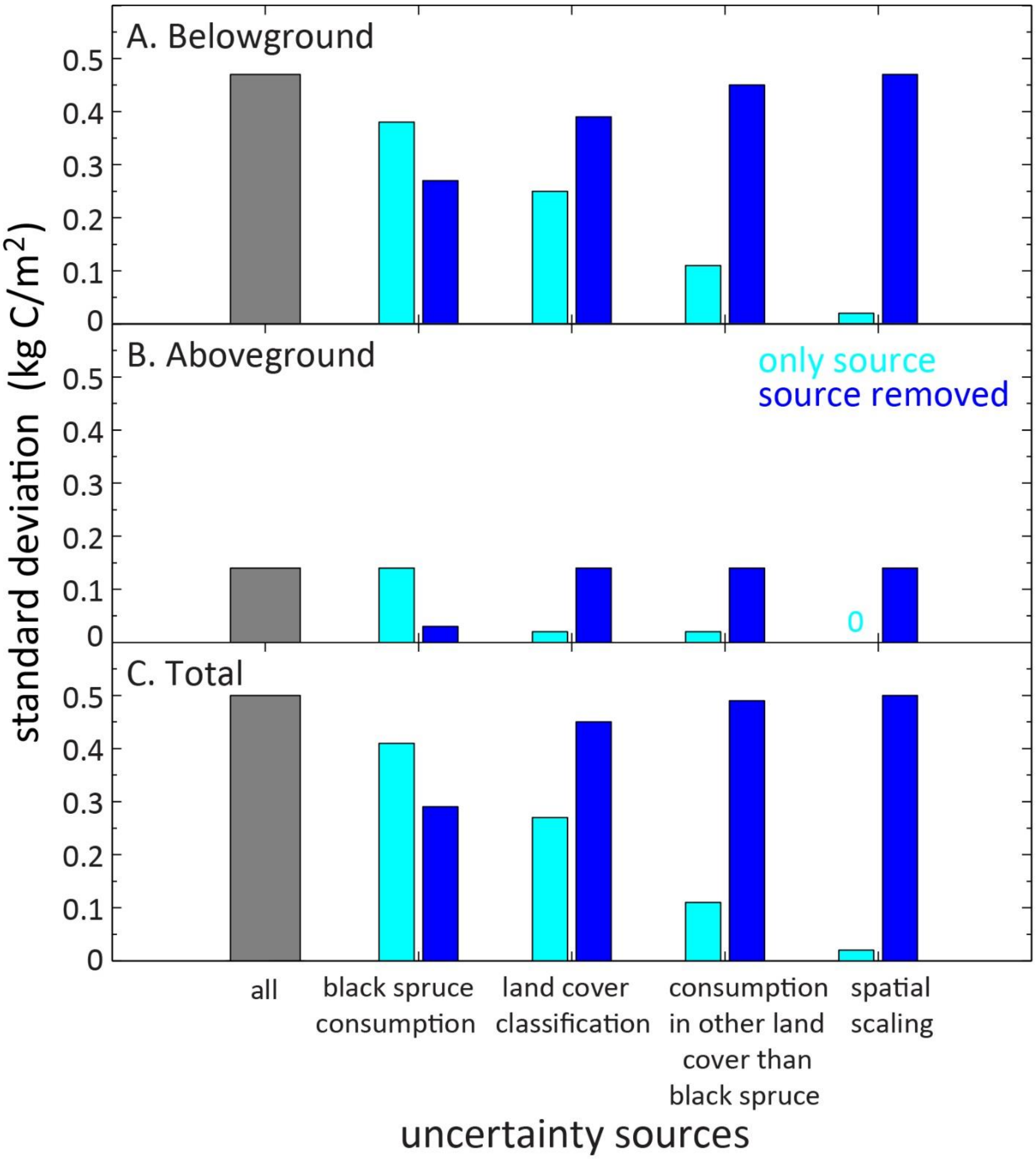


Figure 11. Attribution of uncertainty sources in (A) belowground, (B) aboveground and (C) total carbon consumption estimates. The standard deviation of the consumption estimates from 1000 Monte Carlo simulations was calculated for each scenario.