

1           **Variability in Biomass Burning Emissions Weakens**  
2           **Aerosol Forcing due to Nonlinear Aerosol-Cloud**  
3           **Interactions**

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7           **Key Points:**

- 8           • The radiative forcing due to aerosols is overestimated if emissions are temporally-
- 9           smoothed
- 10          • The differences in radiative forcing are driven by differences in the cloud radia-
- 11          tive effect
- 12          • Differences in the cloud radiative effect are due to nonlinear aerosol-cloud inter-
- 13          actions

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## 14 **Abstract**

15 The magnitude of the aerosol forcing remains among the largest unknowns when assessing  
16 climate sensitivity over the historical period. Here, we describe a previously unconsidered  
17 source of uncertainty in aerosol forcing: the temporal variability of aerosol emissions. We  
18 show that time-variability in biomass burning (BB) emissions weakens the time-averaged  
19 total aerosol forcing, particularly in the Northern Hemisphere mid- to high-latitudes. BB  
20 emissions variability produces weaker (less negative) mean effective radiative forcing (ERF)  
21 compared to scenarios with no interannual variability in emissions. Satellite-estimated BB  
22 emissions (and associated variability) results in a June–September absolute ERF (relative  
23 to zero BB emissions) of  $-7.7 \text{ W}\cdot\text{m}^{-2}$  from  $50\text{--}70^\circ\text{N}$ , compared to  $-10.4 \text{ W}\cdot\text{m}^{-2}$  when no  
24 emissions variability is used in the Community Earth System Model version 2 (CESM2).  
25 This difference in forcing is attributable to nonlinear aerosol-cloud interactions. Aerosol  
26 forcing will be overestimated (i.e. more negative) if emissions are temporally-smoothed.

## 27 **Plain Language Summary**

28 Aerosols and their interaction with the climate system remain one of the largest  
29 sources of uncertainty in understanding historical and future climate change. Here we  
30 describe a factor that has not been previously considered that contributes additional un-  
31 certainty in the influence of aerosols on the climate: the temporal variability of aerosol  
32 emissions. We show that when time-variability exists in biomass burning emissions used  
33 in Earth System Model simulations, more solar radiation is absorbed in the Northern  
34 Hemisphere mid- to high-latitudes; a weakening of the influence that biomass burning  
35 aerosols have on the climate. The weakened forcing and climate consequences associated  
36 with subseasonal variations in biomass burning aerosols is attributable to nonlinear aerosol-  
37 cloud interaction effects.

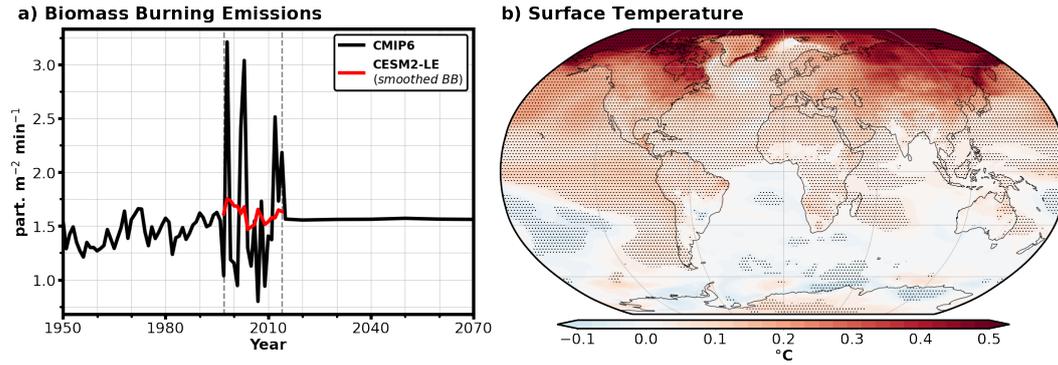
## 38 **1 Introduction**

39 Atmospheric aerosols are a critical component of the climate system, but the complex  
40 processes governing their production, deposition, and interactions with clouds are difficult  
41 to observe and model. Uncertainty in the aerosol forcing is one of the greatest challenges for  
42 understanding historical climate change and projecting near-future climate evolution (Kiehl,  
43 2007; Forster et al., 2021).

44 Previous research on aerosol radiative forcing has focused on the effect of secular change  
45 in aerosol emissions, with little consideration of the impact of shorter timescale variability  
46 in the emissions. For example, the fifth Coupled Model Intercomparison Project (CMIP5;  
47 Taylor et al., 2012) historical and future simulations use biomass burning (BB) emissions es-  
48 timates that are smooth temporally compared to real-world emissions, particularly on inter-  
49 and sub-annual time scales. Real-world BB emissions in the extratropics occur episodically  
50 and stochastically, and may depend on weather conditions (precipitation, drought, lightning)  
51 or human activity (agricultural burning, forest clearing, arson) (Lamarque et al., 2010; van  
52 der Werf et al., 2017).

53 To incorporate more realistic aerosol emissions variability, the latest CMIP (sixth phase;  
54 CMIP6; Eyring et al., 2016) includes BB emissions estimates derived from satellite obser-  
55 vations for historical simulations from 1997 to 2014 (Figure 1a; van Marle et al., 2017).  
56 Historical CMIP6 BB emissions in this time period have much higher temporal variabil-  
57 ity than those used in previous model intercomparison efforts (e.g., the CMIP5 historical  
58 simulations). However, the BB emissions used for CMIP6 prior to 1997 (before satellite mea-  
59 surement capability) are similar to the CMIP5 inventories, with weak temporal variability  
60 (Figure 1a black line; Lamarque et al., 2010; van Marle et al., 2017).

61 Recent analyses in the Community Earth System Model version 2 (CESM2; Danaba-  
62 soglu et al., 2020) have estimated the climate effect of this change in BB emissions variabil-  
63 ity by comparing simulation scenarios with temporally-smoothed BB emissions to scenarios  
64 with time-varying CMIP6 emissions over the 1997 to 2014 period (DeRepentigny et al.,  
65 2022; Fasullo et al., 2022; Heyblom et al., 2022; Rodgers et al., 2021). The largest set  
66 of these comparison simulations is the CESM2 Large Ensemble (CESM2-LE; Figure 1a  
67 Rodgers et al., 2021). Studies using the CESM2-LE show that the sudden change in BB  
68 emissions variability in the CMIP6 late-historical simulations leads to shifts in the climate,  
69 producing increases in simulated downwelling shortwave radiation and enhancing surface  
70 warming (Fasullo et al., 2022, also Figure 1b), increases in atmospheric water vapor and  
71 precipitation (Heyblom et al., 2022), and accelerated Arctic sea ice loss (DeRepentigny et  
72 al., 2022). These studies postulated that nonlinearities in the climate system’s response to  
73 BB aerosols produced these climate effects. However, the coupled climate model simula-  
74 tions used in these studies did not allow for the decoupling of climate forcing and feedback,  
75 making attribution of the cause difficult.



**Figure 1. Biomass burning (BB) emissions used for CMIP6 and the effect of high BB emissions variability on surface temperature in CESM2.** Panel (a) shows the annual mean biomass burning (BB) emissions averaged over 50–70°N prescribed for CMIP6 (black line) and a second smoothed emissions inventory used for 50 members of the Community Earth System Model Large Ensemble version 2 (CESM2-LE) over the recent historical period (red line), in particles  $\text{m}^{-2} \text{min}^{-1}$ . The vertical grey dashed lines delineate the period of high BB emissions variability in the CMIP6 prescribed BB emissions (1997–2014). Panel (b) shows the difference in surface temperature between the CMIP6 emissions ensemble members and smoothed BB emissions ensemble members in the CESM2-LE during 1997–2014 (average of 50 CMIP6 emissions ensemble members minus average of 50 smoothed BB emissions ensemble members; in  $^{\circ}\text{C}$ ). Stippling signifies 90% confidence (Text S7). See Text S1 for a further description of CESM2-LE and BB emissions therein.

76 Here, we use idealized Earth System Model (ESM) simulations to show that the tem-  
 77 poral variability of BB aerosol emissions substantially impacts the magnitude of the forcing  
 78 attributable to these emissions. We show that BB emissions variability impacts BB aerosol  
 79 forcing because of a nonlinear response of aerosol-cloud interactions to atmospheric aerosol  
 80 concentrations. Our study provides direct evidence that temporal variability of BB aerosol  
 81 weakens the time-averaged aerosol cloud radiative effect in a state-of-the-art ESM, and that  
 82 temporal smoothing will lead to a much stronger BB aerosol radiative effect.

## 83 2 Methods

84 To quantify the impact that greater interannual variability in biomass burning (BB)  
 85 emissions has on the total radiative forcing attributable to these emissions, we conduct  
 86 simulations using the Community Earth System Model version 2 (CESM2; Danabasoglu  
 87 et al., 2020) with idealized BB emissions perturbations. In each simulation we configure

88 CESM2 in the same way as the CESM2-LE (Text S1), but fix sea surface temperatures  
 89 (SSTs), sea ice concentrations, and all forcings (except BB emissions) to the 2000 climatology  
 90 (mean monthly values from 1995 to 2005). We use three different simulations, each of which  
 91 treat BB emissions variability differently (Figure 2). Each simulation is run for 54 years.

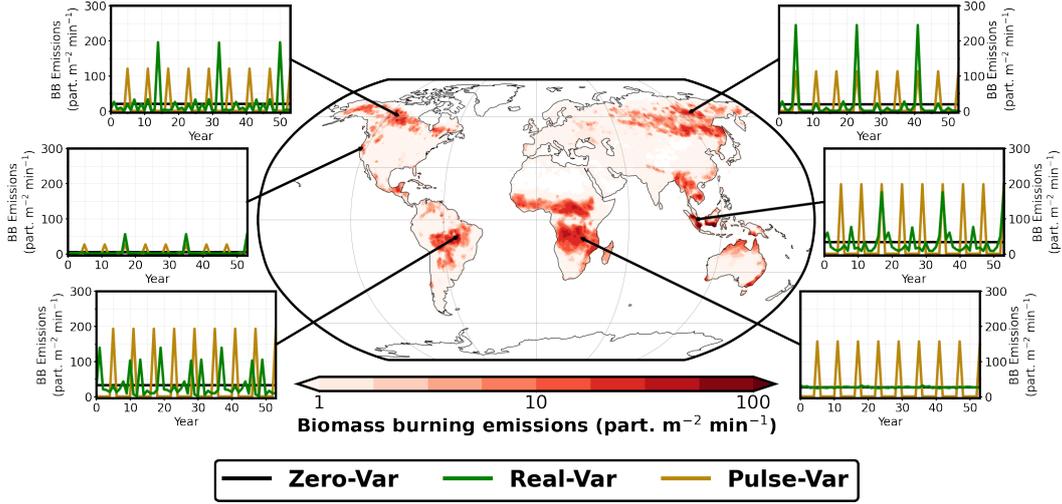
92 The first simulation (hereafter “Real-Var”; Figure 2 green line) uses BB emissions as  
 93 prescribed for CMIP6 historical simulations from 1997 to 2014 (van der Werf et al., 2017;  
 94 van Marle et al., 2017). The emissions estimates for this period are thus taken to represent  
 95 a best estimate of real-world BB emissions. The second simulation (hereafter “Pulse-Var”;  
 96 Figure 2 yellow line) prescribes an idealized high-temporal variability emissions scenario  
 97 where all emissions for each grid cell occur every six years in phase with all other grid cells.  
 98 Total emissions in years that simulate a pulse of BB emissions are equal to six times the  
 99 annual mean emissions from the Real-Var experiment at each grid cell; during other years  
 100 BB emissions are zero. A third experiment (hereafter “Zero-Var”; Figure 2 black line) uses  
 101 emissions based upon a climatology that repeats each year, and thus has no interannual  
 102 variability in BB emissions. It is important to note that due to the aggregation of emissions  
 103 in time, the Pulse- and Zero-Var inventories are also spatially smoother than the Real-Var  
 104 inventory.

105 All simulations use fixed SSTs to allow the direct quantification of the effective radiative  
 106 forcing (ERF) in the absence of most feedbacks (Text S2; Hansen et al., 2005; Forster et  
 107 al., 2021). Because the time-integrated emissions are equal across these three simulations,  
 108 differences in ERF are attributable entirely to differences in the variability of BB emissions.

### 109 **3 Results**

#### 110 **3.1 The Effects of Emissions Variability on the Aerosol Forcing**

111 Figure 3a–c shows that the BB aerosol effective radiative forcing (ERF) weakens (i.e.,  
 112 becomes less negative) when emissions vary in time (as in Real-Var and Pulse-Var) com-  
 113 pared to when there is no interannual variability (as in Zero-Var). We denote the change in  
 114 ERF due to BB emissions variability as  $\Delta\text{ERF}_{\text{BBVar}}$ , computed as the difference in the ERF  
 115 between scenarios with time-varying emissions (Pulse-Var and Real-Var) and Zero-Var. The  
 116  $\Delta\text{ERF}_{\text{BBVar}}$  is strongest over regions of high column-integrated aerosol concentration vari-  
 117 ability (Figure S1), particularly over the NH mid- to high-latitudes from June–September  
 118 (JJAS; the period of most active fires in this region; see Figure S2 for annual mean differ-

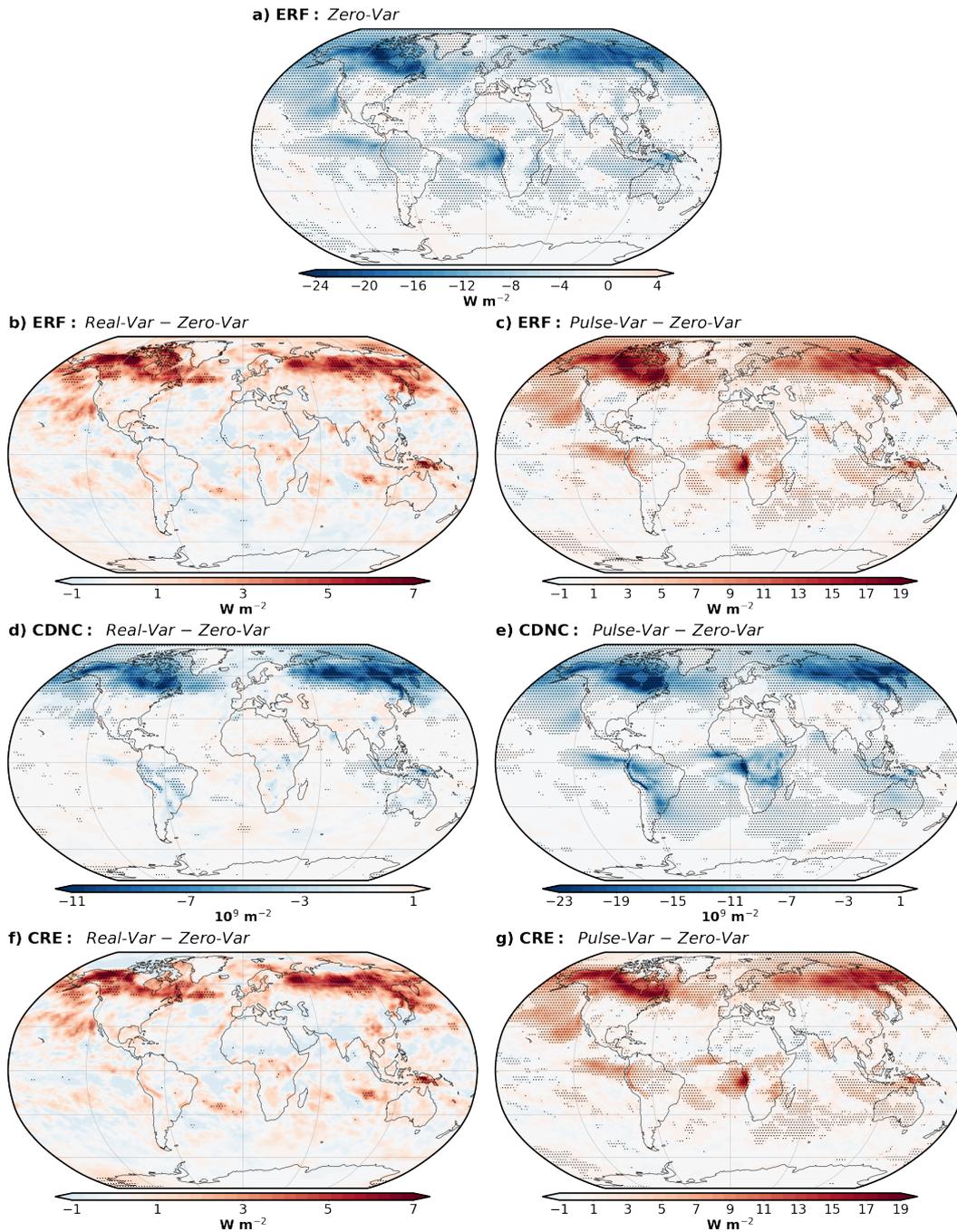


**Figure 2.** Idealized simulations to quantify changes in effective radiative forcing (ERF) due to biomass burning (BB) emissions variability. The center image shows the time-integrated emissions rate of BB emissions for all scenarios (in particles  $\text{cm}^{-2} \text{s}^{-1}$ ) in red, while the surrounding insets show the time evolution of BB emissions from Zero-Var, Real-Var, and Pulse-Var (black, green, and brown lines, respectively) at selected locations.

119 ence). For example, averaged from  $50\text{--}70^\circ\text{N}$ , we find a  $+1.1 \text{ W}\cdot\text{m}^{-2}$  ( $+0.1 \text{ W}\cdot\text{m}^{-2}$  global)  
 120 annual mean and  $+2.7 \text{ W}\cdot\text{m}^{-2}$  ( $+0.42 \text{ W}\cdot\text{m}^{-2}$  global) JJAS mean ERF weakening in the  
 121 Real-Var experiment relative to Zero-Var. In effect, episodic BB emissions leads to a weaker  
 122 (i.e. less negative) aerosol forcing associated with biomass burning.

123 **3.2 Differences in Forcing are Driven by Differences in the Cloud Radiative**  
 124 **Effect**

125 ERF sensitivity to emissions variability (i.e.,  $\Delta\text{ERF}_{\text{BBVar}}$ ) is due to a weaker time-  
 126 averaged cloud response to aerosol emissions when BB emissions are variable. Figure 3d–g  
 127 shows how time-averaged cloud properties are affected by BB emissions variability. Each  
 128 panel displays selected JJAS cloud property changes for the higher variability simulation  
 129 compared to the Zero-Var simulation (Real-Var and Pulse-Var simulations in the left and  
 130 right column respectively; also see Figure S3 for annual mean change). Averaged cloud  
 131 droplet number concentration (CDNC; Figure 3d,e) is smaller in the simulations with higher  
 132 interannual BB variability. Similar to ERF changes, the largest sensitivity in CDNC is found  
 133 in regions where BB emissions interannual variability is large (i.e. predominately over the



**Figure 3.** Change in effective radiative forcing (ERF) and cloud properties due to biomass burning emissions variability. Panel (a) shows the June–September (JJAS) mean absolute ERF due to BB emissions in the Zero-Var experiment (relative to no BB emissions). Panels (b)–(g) show the JJAS mean change in ERF (denoted  $\Delta\text{ERF}_{\text{BBVar}}$ ; in  $\text{W}\cdot\text{m}^{-2}$ ; b and c), vertically integrated cloud droplet number concentration (CDNC; in  $10^9 \text{ m}^{-2}$ ; d and e), and total (long and shortwave) cloud radiative effect (CRE; in  $\text{W}\cdot\text{m}^{-2}$ ; f and g) due to BB emissions variability in the Real-Var (left column) and Pulse-Var (right column) experiments. Changes due to BB emissions variability are defined as the variability experiments minus the Zero-Var experiment. Stippling signifies 90% confidence (Text S7).

134 NH mid- to high-latitudes land regions). There are similar reductions in cloud amount and  
 135 liquid water path (Figure S4).

136 The time-averaged increase in absorbed radiation due to changes in clouds is shown in  
 137 Figure 3f,g as the cloud radiative effect (CRE). The CRE change due to BB emissions vari-  
 138 ability is highly correlated with  $\Delta\text{ERF}_{\text{BBVar}}$ : global Pearson pattern correlation coefficient  
 139 of the annual means of 0.87 in the Real-Var experiment and 0.93 in the Pulse-Var experi-  
 140 ment. These correlations, and the similar magnitudes of CRE and  $\Delta\text{ERF}_{\text{BBVar}}$ , indicates  
 141 that  $\Delta\text{ERF}_{\text{BBVar}}$  is driven by changes in time-averaged cloud properties when BB emissions  
 142 are variable.

143 We note that there is a small region over Arctic land where there is increased absorbed  
 144 radiation that is not due to changes in clouds (Figure S5a,b; shown as clear-sky top of  
 145 atmosphere net radiative flux). The increase in absorbed radiation in the absence of clouds  
 146 is due to a decrease in land-surface albedo over the same region (Figure S5c,d), which is  
 147 a feedback resulting from the difference in forcing. Though the configuration and method  
 148 used here to quantify the ERF is a widely accepted approach (Text S2; also see Hansen  
 149 et al., 2005; Smith et al., 2020; Forster et al., 2021), it does allow for the possibility that  
 150 computed changes in ERF are due differences in land-surface feedbacks not corrected for  
 151 in our computation (Text S2). We replicated the Real-Var experiment in an aquaplanet  
 152 configuration with CESM2 (in which land surfaces are replaced with an idealized ocean;  
 153 Text S3; Marshall et al., 2007) and find qualitatively similar results (Figure S6). From  
 154 this, we conclude the climate response to BB emissions variability is not driven by land  
 155 surface interactions. Though nonlinear land feedbacks, such as the land surface albedo,  
 156 may be amplifying the change in ERF (as computed in this study) due to differences in BB  
 157 emissions variability, they are not the driver of the model response.

### 158 **3.3 Differences in Cloud Radiative Effect are due to Nonlinear Aerosol- 159 Cloud Interactions**

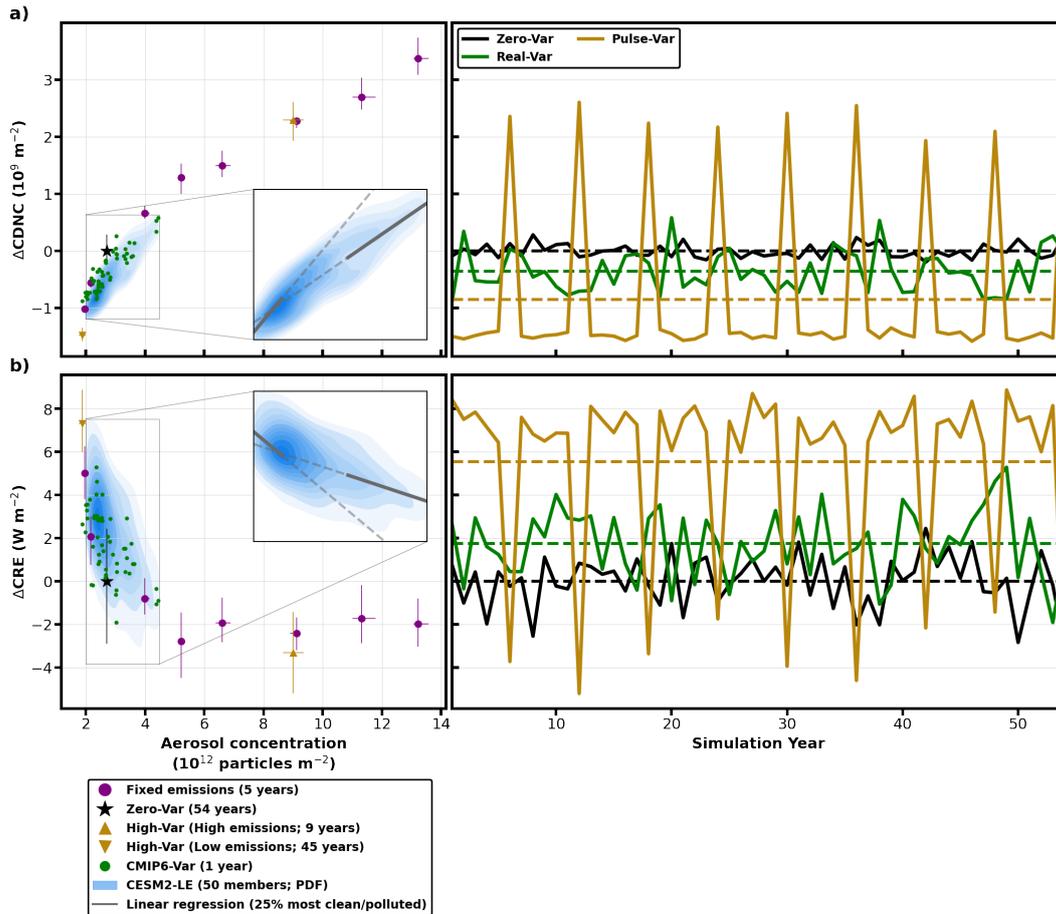
160 We now show that the time-averaged CRE weakens when BB emissions are more vari-  
 161 able because of a nonlinear relationship between atmospheric aerosol concentrations and  
 162 their effects on cloud properties. Figure 4 shows the time- and area-averaged relationship  
 163 between aerosol concentration, CDNC, and CRE across multiple simulations over 50–70°N  
 164 during JJAS. Shown in this figure are the cloud responses to varying fixed BB emissions

165 rates (purple), as well as Real-Var (green) and Pulse-Var (yellow) simulations. Figure 4 also  
 166 shows responses to varying aerosol concentrations in the CESM2-LE during the simulated  
 167 high BB emissions variability period from 1997 to 2014 (blue; shown as probability density  
 168 function). From Figure 4, it is clear that CDNC and CRE depend nonlinearly on aerosol  
 169 concentration ( $Aer$ ): the magnitude of the slopes  $\frac{\partial CDNC}{\partial Aer}$  and  $\frac{\partial CRE}{\partial Aer}$  are much larger at  
 170 lower aerosol concentrations than higher concentrations. This nonlinear response is appar-  
 171 ent across the fixed aerosol emissions simulations, as well as in the Real-Var experiment and  
 172 CESM2-LE.

173 Nonlinearity in aerosol-cloud interactions are expected from both modelling and obser-  
 174 vational studies. As aerosol concentrations increase, they less effectively nucleate to become  
 175 cloud droplets (Twomey, 1977; Rissman et al., 2004; Reutter et al., 2009; Carslaw et al.,  
 176 2013; Bougiatioti et al., 2016; Kacarab et al., 2020). Because cloud droplet nucleation  
 177 becomes less effective at higher aerosol concentrations, the relationship between aerosol  
 178 concentration and CRE is nonlinear. The nonlinear response to BB emissions influences  
 179 the temporal evolution of the simulations, seen in the right column of Figure 4. When  
 180 emissions are higher than the Zero-Var case, the incremental change in CDNC and CRE is  
 181 smaller in magnitude than when emissions are lower than the Zero-Var case. As a result,  
 182 over low emissions years, there is a larger increase in absorbed solar energy (relative to the  
 183 Zero-Var baseline) compared to the decrease in absorbed solar energy over high emissions  
 184 years, explaining the time-averaged effects seen in Figure 3.

185 We use a heuristic model to demonstrate that nonlinearities in aerosol-cloud interactions  
 186 lead to a weakening of the time-averaged CRE if aerosol emissions are variable in time.  
 187 Figure 5a shows distributions representative of the 50–70°N area mean aerosol concentration  
 188 resulting from emissions in the Zero-Var (normal distribution; black) and Real-Var (log-  
 189 normal distribution; green) experiments, both of which have the same mean (overlapping  
 190 vertical green and black lines). Note that the Zero-Var distribution has some variability (i.e.,  
 191 width) because of meteorological variability within these simulations, not BB emissions  
 192 variability itself, which is nil. Figure 5b shows nonlinear (logarithmic; solid) and linear  
 193 (dashed) functions describing two separate inferred relationships between aerosol emissions  
 194 and CRE, derived from Figure 4b (see Text S4 for further description).

195 Figure 5c shows the projected distributions of CRE using the functions shown in Figure  
 196 5b. Comparing CRE distributions resulting from nonlinear (solid lines) and linear (dashed



**Figure 4. Responses of CDNC and CRE to varying aerosol emissions for June–September (JJAS) averaged over 50–70°N, relative to a reference zero variability run.** The left column shows the relationship between column-integrated aerosol concentrations and (a) column-integrated CDNC or (b) CRE for a collection of years (number of years displayed in the legend) drawn from each experiment. The average and range of that collection is shown by marker and whiskers. The “High” and “Low” statistics are produced by averaging the years which do and do not have BB emissions in the Pulse-Var experiment, respectively. “Fixed emissions” experiments scale the Zero-Var BB emissions. CISM2-LE probability density functions (PDF) represent changes of each year in the high BB emissions variability simulations relative to the ensemble annual mean from the low BB emissions variability simulations of the CISM2-LE historical simulations from 1997 to 2014 (see Text S1 for a description of different CISM2-LE ensemble members). The right column shows the time evolution of the of CDNC and CRE from the Zero-Var, Real-Var, and Pulse-Var simulations. The horizontal dashed line represents the JJAS mean for the entire simulation period.

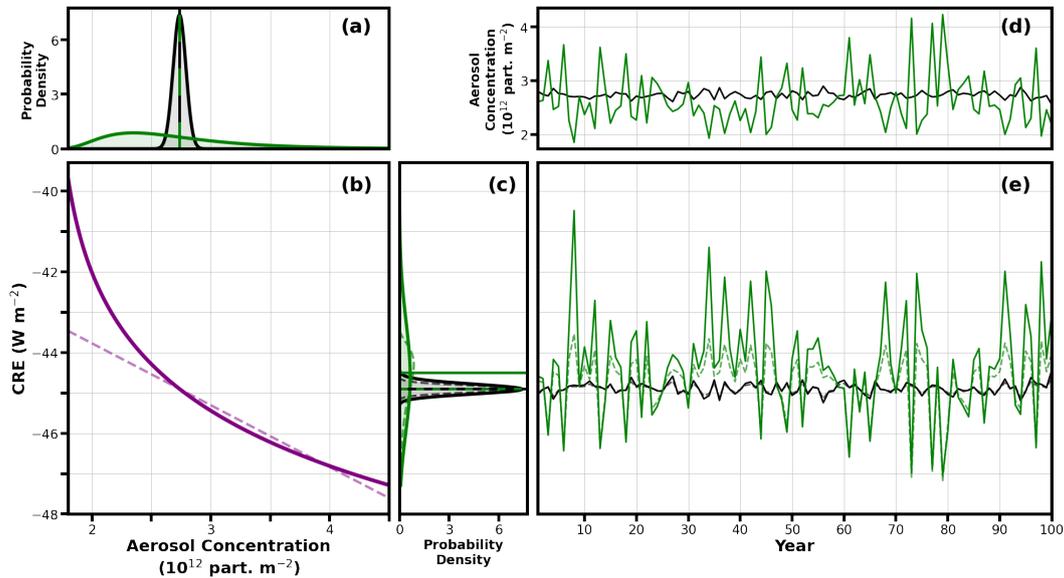
197 lines) aerosol-CRE functions shows the effect of nonlinearity in the aerosol-CRE relationship  
198 (Figure 5c). First, any aerosol distribution will be skewed towards weakened CRE values as  
199 the nonlinear aerosol-CRE function deviates further from the linear function at lower aerosol  
200 concentrations than at higher concentrations. Second, realistic emissions variability (such  
201 as in Real-Var) has a much higher frequency of low emissions years (where the nonlinear  
202 relationship deviates the most from the linear function) compared to high emission years,  
203 resulting in further CRE weakening. The combination of these two effects results in a weaker  
204 mean CRE for the log-normal emissions distribution when using the nonlinear aerosol-  
205 CRE function (horizontal solid green line) compared to the linear aerosol-CRE function  
206 (horizontal dashed green and black lines). We note that the mean CRE is also weaker for  
207 the normal emissions distribution when using the nonlinear aerosol-CRE function (horizontal  
208 solid black line) compared to if the linear aerosol-CRE function is used, though the change  
209 is small (and not visible on Figure 5c) as the variability is low.

210 Two synthetic time series of aerosol concentrations (Figure 5d) and the resulting CRE  
211 values (Figure 5e) confirm the time-averaged effect leading to differences in mean CRE  
212 shown in the time series in Figure 4. When emissions are low (and CRE is less negative), a  
213 nonlinear aerosol-CRE relationship results in much weaker (less negative) CRE values than  
214 if the relationship is linear (compare large positive deviations in CRE due to nonlinear and  
215 linear aerosol-CRE relationships).

## 216 4 Discussion

### 217 4.1 A Need for More Idealized Experiments

218 To-date, there have been few sets of experiments that can be used to infer the impacts  
219 of BB emissions variability on the climate system. To the best of our knowledge, there has  
220 only been experiments conducted by Fasullo et al. (2022) and DeRepentigny et al. (2022),  
221 the CESM2-LE (Rodgers et al., 2021), and those performed for this study (Section 2). As  
222 the only difference in forcing is the treatment of BB emissions variability, these experiments  
223 can be used to directly quantify the impact of BB emissions variability on the climate.  
224 Furthermore, here we have conducted a set of idealized ESM simulations in the absence of  
225 climate feedbacks that allow us to quantify the difference in radiative forcing attributed to  
226 BB emissions variability.



**Figure 5. Idealized cloud radiative effect (CRE) response to varying aerosol concentrations.** Panel (a) shows probability density functions (PDF) of aerosol concentrations representative of Real-Var and Zero-Var BB emissions scenarios (green and black, respectively). Panel (b) shows the cloud radiative effect (CRE) response to aerosol concentration derived from CESM2 (nonlinear; solid purple) and a linear response (dashed purple). Panel (c) shows the resulting CRE PDFs from the nonlinear and linear aerosol-CRE responses (solid and dashed lines, respectively). Panel (d) shows a 100-year emissions time series randomly drawn from the high and zero aerosol emissions variability concentration PDFs (green and black lines, respectively). Panel (e) shows the resulting CRE from emissions shown in panel (d) from the nonlinear and linear aerosol-CRE responses (solid and dashed lines, respectively).

227 It is important to assess how the radiative forcing is affected in more ESMs to under-  
228 stand how model-specific aerosol and cloud microphysics parameterizations may affect the  
229 forcing uncertainty attributable to aerosol emissions variability. For example,  $\Delta\text{ERF}_{\text{BBVar}}$   
230 may be particularly noticeable in CESM2 as it has relatively strong aerosol-cloud inter-  
231 actions (Smith et al., 2020). Therefore, understanding the strength of the  $\Delta\text{ERF}_{\text{BBVar}}$  in  
232 ESMs is important for the design of future intercomparisons. Further idealized experiments,  
233 such as those described here, are necessary to detect and quantify the effect of aerosol vari-  
234 ability on the effective radiative forcing due to aerosol-cloud interactions in a variety of  
235 ESMs.

236 Current model intercomparison projects (i.e., those for CMIP6) are not adequate to  
237 attribute changes in the climate to differences in BB emissions variability because it is  
238 unlikely that quantifying statistically robust differences in climate is feasible without a direct  
239 comparison between high and low BB emissions variability scenarios. Indeed, we find that  
240 robust evidence of non-linearity between yearly BB emissions and CRE is not evident when  
241 we analyze only the 50 CESM2-LE ensemble members subject to CMIP6 BB emissions (Text  
242 S6). Similarly, we do not find evidence of nonlinearity in individual ESM output submitted  
243 to the CMIP6 historical Atmospheric Model Intercomparison Project (AMIP; Figure S7;  
244 Gates et al., 1999; Eyring et al., 2016).

## 245 4.2 Implications

246 The temporal variability in BB aerosol emissions changes the climate forcing attributable  
247 to these aerosols. In particular, we show that realistic BB emissions variability leads to a  
248 weaker (lower amplitude) negative forcing, compared to low emissions variability. This ef-  
249 fect is particularly strong and widespread over the NH mid- to high-latitudes. This ERF  
250 change (reduction in the magnitude of the total aerosol forcing) induced by BB emissions  
251 variability is due to nonlinear aerosol-cloud interaction effects.

252 These findings are of particular importance when considering the total aerosol forcing  
253 over historical periods and into the future. Most emissions inventories neglect realistic  
254 interannual variability (e.g., van Marle et al., 2017; Hoesly et al., 2018; O'Neill et al.,  
255 2016), which would lead to a more negative ERF due to aerosol-cloud interaction effects  
256 ( $\text{ERF}_{\text{ACI}}$ ). Furthermore, many modelling approaches used to evaluate  $\text{ERF}_{\text{ACI}}$  do not  
257 prescribe realistic variability in aerosol emissions, if at all. For example, the Radiative

258 Forcing Model Intercomparison Project (RFMIP) uses either fixed present-day or CMIP6  
259 historical aerosol emissions that include only secular trends to quantify the radiative forcing  
260 of aerosols in CMIP6 ESMs; they do not include realistic BB emissions variability prior to  
261 1997 (Pincus et al., 2016). Likewise, emissions prescribed for future projection scenarios  
262 (after 2014) also neglect temporal variability in aerosol emissions (recall Figure 1a); Riahi  
263 et al., 2017). We also note that, while the issues have been discussed here in the context  
264 of the interannual variability of BB emissions, these issues may also be relevant to other  
265 emissions that are sensitive to natural and anthropogenic variability (e.g., DMS emissions  
266 that are sensitive to ocean variability).

267 As treatments of aerosol variability differ in the historical, present-day, and future  
268 scenario simulations, significant biases in the total aerosol forcing may be present. The  
269 inclusion of interannual variability for some years, and neglect of it in others, will introduce  
270 discrepancies and discontinuities in the aerosol forcing that may be significant (such as  
271 spurious sea ice trends, as shown in DeRepentigny et al., 2022). To properly evaluate  
272 aerosol forcings and model past, present, and future climates, the temporal variability of  
273 aerosol emissions should be treated consistently and more realistically.

274 Past (prior to the satellite era) and future biomass burning aerosol emissions (and  
275 thus their variability) are uncertain. They will depend on many different factors, includ-  
276 ing changes in fire weather and fuel loads. As ESMs simulate aerosol-cloud interactions  
277 using more and more complex physics, they must also consider how BB aerosol emissions  
278 variability has changed through the past and into the future. Ideally, emissions variabil-  
279 ity should be prescribed with a carefully stated, well understood set of assumptions with  
280 impacts that can be evaluated and quantified. Alternatively, to avoid any assumptions of  
281 emissions variability, prognostic fire models should be integrated into the next generation  
282 of ESMs.

## 283 **5 Open Research**

284 This material is based upon work supported by the National Center for Atmospheric Re-  
285 search (NCAR). CESM2-LE data are available here [https://www.cesm.ucar.edu/projects/  
286 community-projects/LENS2/](https://www.cesm.ucar.edu/projects/community-projects/LENS2/). Information on the release of the CESM2-LE is available  
287 here <https://doi.org/10.5194/esd-12-1393-2021>. The CMIP6 data used for calculat-  
288 ing cloud radiative effects from multiple Earth System Models (see Figure S7) are pub-

289 licly available through the World Climate Research Programme CMIP6 website ([https://](https://esgf-node.llnl.gov/search/cmip6/)  
290 [esgf-node.llnl.gov/search/cmip6/](https://esgf-node.llnl.gov/search/cmip6/)).

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