Performance of a simple reanalysis proxy for U.S. cloud-to-ground lightning

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ABSTRACT

The product of convective available potential energy (CAPE) and precipitation rate has previously been used as a proxy for cloud-to-ground (CG) lightning flash counts in climate change applications. Here the ability of this proxy, denoted CP, to represent the climatology and variability of CG lightning flash counts over the contiguous U.S. (CONUS) during the period 2003–2016 is assessed. CP values computed using the North American Regional Reanalysis are compared with negative and positive polarity CG flash counts from the National Lightning Detection Network. Overall, the proxy performs better on shorter time scales (daily and monthly) than on longer time scales (annual and semi-annual). Proxy performance tends to be worse during the warm season (May–October), when most lightning occurs, and better during the cool season (November–April). The correlation of annually accumulated CONUS CP with CG flash counts is not statistically significant because of poor warm-season performance. Cool season negative CG flash counts are well-correlated with CONUS CP values. Positive CG flash counts (∼7% of all CG flashes) are well correlated with annual values of CONUS CP. The relatively strong relations between CP and CG flash counts in some regions and times of the year at daily resolution provide a benchmark for more complex proxies and suggest that proxy-based extended- and long-range prediction of lightning activity may be feasible to the extent that precipitation rate and CAPE can be predicted.

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1. Introduction

Lightning flash rate is a defining characteristic of thunderstorm evolution. Cloud-to-ground (CG) lightning impacts societies through deaths and injuries, property damage, wildfires, and air quality (Koshak et al. 2015). The importance of CG lightning is a motivation for studying how its characteristics vary under climate change and variability. The relation of lightning with climate, whether in the form of interannual variability or long-term trends, is difficult to infer directly from the observational record because high-quality, spatially complete lightning datasets are often relatively short. Moreover, observational data can at best provide circumstantial information about expected lightning characteristics in climates that differ from the one in which observations are collected, be they future climates or ones in other regions.

Lightning activity in general depends on the dynamics and microphysics of convective clouds, and this dependence has been modeled with varying levels of detail and complexity. Lightning occurrence and flash rates can be simulated with considerable fidelity and realism by combining electrification and lightning parameterizations with models of atmospheric dynamics and microphysics (Mansell et al. 2005; Kuhlman et al. 2006; Fierro et al. 2013). Lightning rates also have been related in a more empirical but effective manner to cloud properties, microphysical parameters, and updrafts generated by convection permitting models (McCaul et al. 2009; Yair et al. 2010; Lynn et al. 2012). Alternatively, lightning flash densities can be diagnosed from the output of convective parameterization schemes in models that do not explicitly resolve clouds (Allen and Pickering 2002; Lopez 2016). Stolz et al. (2017) parameterized storm-scale total lightning density using environmental variables from reanalysis and aerosol data.

However, detailed cloud and microphysical properties are not always readily available from reanalysis, seasonal forecasts, or climate change projections, and are themselves uncertain. There-

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fore, simple proxies for lightning that depend on a few, easily available quantities may provide utility for climate variability and projection applications. Romps et al. (2014) proposed the product of convective available potential energy (CAPE) and precipitation rate as a proxy for the number of CG lightning flashes. The application of this proxy to climate change projections predicts a 50% increase in United States lightning strokes over the 21st century, which is roughly consistent with results for total lightning based on cloud-top height and upward cloud ice flux (Finney et al. 2018). The projected increase in the Romps lightning proxy is driven by robust increases in CAPE, and upward trends in CAPE have been noted in other parts of the world (Murugavel et al. 2012). An attractive feature of the Romps proxy is that there is some theoretical understanding of how its constituents are modulated by short-term climate variability (e.g., ENSO; Ropelewski and Halpert 1987; L'Heureux et al. 2015; Allen et al. 2015b) and long-term change (Held and Soden 2006; Seeley and Romps 2016). Also, its ingredients are standard outputs of many seasonal and subseasonal dynamical forecasting systems and could be used to make extended-range forecasts of lightning activity (Dowdy 2016; Muñoz et al. 2016). Analogous approaches have been used to relate tornado and hail activity with nearby meteorological quantities at monthly and daily resolution (Tippett et al. 2012; Allen et al. 2015a; Tippett et al. 2016; Westermayer et al. 2017). A caveat of empirical proxy-based approaches is that good performance in the current climate does not guarantee good performance in future climates (Stainforth et al. 2007; Camargo et al. 2014).

The goal of this work is to assess the extent to which the ingredients of the Romps proxy, precipitation rate and CAPE, capture recent variability in CG flash counts over the contiguous United States (CONUS). Of course, assessing the performance of the proxy in capturing observed CG flash counts is a necessary, but not sufficient requirement for its use in applications such as climate projections and subseasonal to seasonal (S2S) predictions, which is our long-term goal. Importantly, good performance with reanalysis in no way guarantees comparable performance in climate

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projection or S2S forecast applications. On the other hand, poor performance of the proxy in re-analysis would provide useful indications of its limitations. Also, the choice of the Romps proxy is motivated by the availability of CAPE and precipitation rate in forecast and reforecast datasets such as those of the NOAA Climate Forecast System, version 2 (Saha et al. 2014; Lepore et al. 2018), the S2S Prediction Project Database (Vitart et al. 2016), and the Subseasonal Experiment (SubX) database (Pegion et al. 2018). However, the CAPE values that are available from forecast models can be sensitive to the choice of parcel and use of the virtual temperature correction.

Romps et al. (2014) showed a strong association between daily counts of CONUS CG flashes and the product of CONUS-averages of precipitation rate and CAPE during a single year, 2011. Here we use a longer period (14 years) to see what information is provided by additional years of data regarding seasonal variations in the strength of the association and about the ability of the proxy to capture interannual variability in CG flash counts. Romps et al. (2014) used CAPE cal-culated from radiosonde data and a NOAA River Forecast Centers precipitation product based on rain-gauge and radar data. Here we test the quality of the association between CG flash counts and the CAPE-precipitation product when reanalysis products are used instead of solely observation-based ones. Knowing whether reanalysis products are sufficiently realistic for this application is important because it helps to judge whether such a climate proxy computed from numerical model outputs can be used to forecast or project future CG lightning activity. Furthermore, the use of spa-tially complete reanalysis data allows us to form the product of collocated CAPE and precipitation rate (denoted CP) on a spatially resolved grid and to examine regional features of the association of the CAPE-precipitation product with CG lightning flash counts. A similar study of lightning over Bangladesh, where lightning is an especially dangerous hazard Dewan et al. (2017), found that the CP was more strongly associated with total lightning flash counts during the pre-monsoon season than during the monsoon season (Dewan et al. 2018).

2. Data and methods

a. Data

We use total precipitation rate (mm d^{-1}) and 0-180 hPa most unstable CAPE (J kg^{-1}) data from the North American Regional Reanalysis (NARR; Mesinger and Coauthors 2006). The most un-stable parcel is found by dividing the 0-180 hPa layer into six 30-hPa-deep layers and selecting the one with the largest equivalent potential temperature (no virtual temperature correction). NARR data are provided at 3-hourly resolution. The precipitation rate is based on a 3-hour accumulation. CAPE is the instantaneous value at the start of the 3-hour period. The data are averaged from their 32-km native grid spacing to a $1° \times 1°$ latitude-longitude grid. We choose the 1-degree grid spac-ing to match that of CFSv2 and SubX data because our long-term goal is S2S prediction. NARR precipitation estimates show some advantage over ones from other reanalysis products, especially global reanalysis, likely due to the use of precipitation observations which the NARR assimilates as latent heating profiles (Bukovsky and Karoly 2007; Cui et al. 2017).

Cloud-to-ground (CG) lightning flash counts come from the National Lightning Detection Net-work (NLDN; Cummins and Murphy 2009) and are summed on the same $1° \times 1°$ grid at daily (UTC) resolution. CG detection efficiency is 90%–95% for CG flashes. Only CONUS land points are used in our analysis, although both NARR and NLDN data extend over ocean and into Mexico and Canada. We use NLDN data covering the period 2003–2016 (5114 days) during which the NLDN network is complete and stable (Koshak et al. 2015). There are 9 days with missing NLDN data: 31/12/03, 08/02/04, 08/02/06, 16/01/07, 06/02/07, 18/12/07, 05/12/08, 17/01/09, 16/01/13, and those days are excluded from calculations. A change in the NLDN Total Lightning Processor (TLP) on 18/09/15 may be responsible for a substantial increase noted in the number of positive CG flashes reported during 2016 (Nag et al. 2016).

131 Negative and positive (≥ 15 kiloampere; kA) polarity CG lightning flash counts are analyzed

132 separately to examine whether the proxy performance differs for positive and negative flash counts.

133 Differing proxy performance might be expected since environment, at least at the mesoscale, can

134 affect storm structure and CG flash polarity (Carey and Buffalo 2007). The total of positive and

135 negative CG flashes were analyzed but give results that are very similar to those for negative CG

136 flash counts. The threshold of 15 kA for positive polarity flashes accounts for the tendency of

137 the NLDN to misclassify cloud pulses as low-amplitude, positive CG strokes (Biagi et al. 2007;

138 Cummins and Murphy 2009). The new NLDN TLP removes the 15 kA peak current limit for

139 positive CG flashes. Therefore, to maintain more consistency, we apply our own 15 kA filter

140 to the positive CG flashes in 2015 and 2016. As a consequence, the numbers of positive CG

141 flashes analyzed here for 2015 and 2016 are less than those in the unfiltered NLDN data sets. The

142 majority (93%) of CONUS CG flashes have negative polarity during the period 2003–2016. The

143 ratio of negative polarity CG flashes to total CG flashes shows substantial spatial variations (Fig.

144 1), with ratios above 95% on the Eastern Seaboard, below 85% in the Upper Midwest, and with

145 the lowest values in very narrow band along the West Coast, consistent with the patterns found

146 in individual years (Koshak et al. 2015). Positive polarity CG flashes have been associated with

147 severe thunderstorms in the Midwest (tornadoes, hail, and damaging wind; e.g., MacGorman and

148 Burgess 1994; Carey and Rutledge 2003). However, other regions with frequent severe weather do

149 not show especially elevated percentages of positive CG flashes. Conversely, the high percentages

150 of positive CG flashes along the West Coast occur where severe weather is infrequent (Zajac and

151 Rutledge 2001; Koshak et al. 2015; Medici et al. 2017).

152 Here we use the product of collocated 3-hourly values of CAPE and precipitation rate as a proxy

153 for the number of CG flashes that occur during those three hours in the corresponding grid cells,

154 and we denote this quantity as CP. Using a proxy based on collocated values allows us to compare

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155 it with CG flash counts on a regional as well as CONUS-wide basis. Three-hourly CP values are

156 summed over time to form daily, monthly, seasonal, and annual values; they are summed over

157 space to form regional CONUS values. CP values are scaled to facilitate their comparison with

158 CG flash counts. The scaling factor is computed so that the area-weighted sum of CP values over

159 the period 2003–2016 matches the number of CONUS flashes, depending on polarity. In other

160 words,

$$\text{scaling factor} = \frac{\text{area-weighted sum (CP)}}{\text{sum (CG flashes)}}.$$

161 The scaling factor for negative polarity CG flashes is 64.17 flashes / J kg^{-1} mm day^{-1} and 4.79

162 flashes / J kg^{-1} mm day^{-1} for positive polarity CG flashes. On the $1° \times 1°$ grid,

$$\text{CP (scaled to negative CG flash counts)} = 64.17 \times \text{CAPE} \times \text{precipitation} \times \cos \phi,$$

163 and

$$\text{CP (scaled to positive CG flash counts)} = 4.79 \times \text{CAPE} \times \text{precipitation} \times \cos \phi,$$

164 where ϕ is latitude in radians, and $\cos \phi$ accounts for the varying grid cell area. The same scaling

165 factor is used in all months and locations. All comparisons between CP and CG flashes use scaled

166 CP, and we drop the word scaled hereafter.

167 *b. Methods*

168 We assess regional behavior by spatially aggregating CP and CG flashes at the level of NOAA

169 climate regions (Karl and Koss 1984). The states in each region are listed in Supplemental Table

170 S1. The spatial structure of CP and CG flashes are compared using pattern correlations computed

171 for the points east of 105°W with the map mean removed (Wilks 2011). The pattern correla-

172 tions are computed using points east of 105°W to focus on the region where the vast majority of

173 CG flashes are recorded and to avoid giving credit for simply matching the east-west gradient.

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174 The temporal association between CP and CG flashes is measured using correlation and mean-

175 squared error (MSE), where the error is the difference of CP and the number of CG flashes. MSE

176 is normalized by the CG flash variance (at the same temporal resolution) to allow comparison

177 of error levels for regions and seasons with disparate levels of CG flash activity. In addition to

178 daily, monthly, and annual aggregation, we also look at totals for six-month warm (May–October)

179 and cool (November–April) seasons, with the cool season consisting of the 13 complete seasons

180 2003/2004–2015/2016 for which data are available. For interannual correlations (14 years), the

181 critical correlation value at the 5% significance level for rejecting the null hypothesis of no corre-

182 lation is about 0.46 for a one-tailed test and 0.53 for a two-tailed test.

3. Results

183

a. Regional scaling of CP and CG flashes

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185 Although CP is scaled to match the CONUS total of CG flashes, the ratio of CG flashes to CP

186 shows distinct regional variations (Fig. 2), which presumably reflect the differing frequency of

187 rainfall processes and cloud properties that are not accounted for in CP. Also, the spatial variations

188 in the ratio of CG flashes to CP may indicate a role for additional thermodynamic factors such as

189 wet-bulb temperature (Koshak et al. 2015), mid-level humidity (Westermayer et al. 2017), warm

190 cloud depth (Stolz et al. 2017), or equilibrium level temperature (Bright et al. 2004; Taszarek et al.

191 2017). Deficiencies in reanalysis CAPE might also be a factor (Gensini et al. 2014; King and

192 Kennedy 2019). Values of the ratio of negative CG flashes to CP are slightly above one in the

193 Northeast, where aerosol concentrations are relatively large (van Donkelaar et al. 2015). The ratio

194 of negative flashes to CP is near one east of the Rockies, and substantially greater than one west

195 of 105°W, until along the West Coast where the ratio is much less than one. The picture for pos-

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itive CG flashes is similar, but without elevated ratio values in the Northeast and with a stronger

gradient from values greater than one in the Northern Rockies and Upper Midwest to values less

than one in the Southeast. The single scaling factor applied to CP for each polarity matches the

behavior in the East because 91.0% of the negative polarity CG flashes and 93.4% of the positive

polarity CG flashes occur east of 105°W. Previous studies have noted that ice-based precipita-

tion processes are dominant in the arid Southwestern US, and the ratio of convective rainfall to

lightning (rainfall yield) is relatively low there (Petersen and Rutledge 1998). Mülmenstädt et al.

(2015) found that ice-phase clouds were more frequent in the western half of the CONUS and

that liquid-phase clouds were more frequent east of the Rockies. Lower lifted condensation level

heights in the East (not shown) are suggestive of lower cloud bases and conditions favoring warm

rain processes with greater precipitation efficiency. Fuchs et al. (2015) compared total lightning

flash rates in Colorado, Oklahoma, Alabama, and the District of Columbia, and hypothesized that

storms with high cloud base heights or shallow warm cloud depths have less warm-phase precipi-

tation and more mixed-phase precipitation and lightning. The low ratio of CG flash count to CP in

a narrow band along the West Coast may be related to onshore flow of maritime air masses with

fewer cloud condensation nuclei or dynamically weaker convection that develops offshore and at

coastal boundaries (Zipser 1994; Xu et al. 2012; Holle et al. 2016). Despite some regional scaling

deficiencies, CP matches CG flash counts relatively well in the areas where the vast majority of

CONUS CG lightning occurs.

b. Daily associations of CONUS totals

We first consider the association of daily CONUS CG flash counts with CAPE alone. The

correlation of daily CONUS CG flash counts with CONUS-averaged CAPE from NARR over

the period 2003–2016 is larger (values of 0.86 and 0.8, respectively, for counts of negative and

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219 positive CG flashes; Fig. 3) than that found by Romps et al. (2014) for CAPE computed from

220 radiosonde data for the single year 2011 ($r = 0.72$). In fact, there is some expectation that reanal-

221 ysis CAPE might be more representative of large-scale features than would be CAPE computed

222 from radiosonde data, since radiosonde data contain small-scale variability that may not be rep-

223 resentative of the large-scale nearby environment. Lepore et al. (2016) found a stronger relation

224 between gauge-measured rainfall extremes and CAPE from reanalysis than with CAPE based on

225 nearby radiosonde measurements. Also, the use of time-averaged reanalysis CAPE and precipi-

226 tation possibly mitigates the difficulty of using observed collocated CAPE and precipitation that

227 is caused by CAPE being released by convection (Romps et al. 2014). On the other hand, daily

228 CONUS-averaged precipitation from NARR shows a slightly weaker relation with CG flash counts

229 (correlation values of 0.36 and 0.43 for negative and positive CG flash counts, respectively; Fig. 3)

230 than the $r = 0.54$ reported by Romps et al. (2014) using a NOAA River Forecast Centers precipita-

231 tion product based on rain-gauge and radar data. Daily CONUS CP has a slightly stronger relation

232 with flash counts (correlation values of 0.89 and 0.87 for negative and positive polarity, respec-

233 tively; Fig. 3) than does CAPE alone. We note that including precipitation rate has the potential

234 to introduce some dependence on aerosols since rain rate increases with aerosol level (Koren et al.

235 2012).

236 *c. Annual cycle and climatology*

237 CONUS CP and CG flash counts have strikingly similar annual cycles, both at daily and monthly

238 resolution, with peak values in summer and much smaller values in the cool season (Fig. 4).

239 The increase in CG occurrence from spring to summer is gradual and followed by a somewhat

240 sharper decay after August (Holle et al. 2016). Annual cycles at daily-resolution are computed by

241 averaging the 14 values (2003–2016) available for each calendar day with February 29 excluded.

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242 The daily resolution annual cycle shows that CONUS CP appears to resolve some sub-monthly

243 features that are likely specific to this set of years. The largest discrepancies between the annual

244 cycles of CONUS CP and negative CG flash counts (clearest at monthly resolution) occur in July–

245 August, when CP values are too low, and in September–October when CP values are too high (Fig.

246 4). There is also good agreement between the annual cycles of CONUS CP and positive CG flash

247 counts, with a tendency of CP values to be too low in spring (March–May) and too high in summer

248 and early fall (June–September).

249 The similarity of the annual cycles of CONUS CP and CG flash counts means that some of

250 the variance of CG flash counts at daily resolution explained by CP (Fig. 3) is a consequence of

251 CP accurately capturing the seasonality of CG flash counts. In fact, the annual cycle of CP at

252 daily resolution, a quantity with no year-to-year variation, explains 63% and 52% of the variance

253 of negative and positive daily CONUS CG flash counts, respectively. The annual cycle of CP at

254 daily resolution explains nearly as much variance of daily negative and positive CONUS CG flash

255 counts as do their own annual cycles, which explain 66% and 54%, respectively.

256 CP captures the annual cycle of lightning occurrence at the regional level and monthly resolution

257 to varying degrees (Fig. 5). Because a single (polarity-dependent) factor is used to scale CP,

258 the differing performance of CP in matching the relative magnitude and phasing of the regional

259 seasonal cycles provides another indication of the extent to which CAPE and precipitation alone

260 are adequate to provide a statistical description of CG flash counts. For the most part, both the

261 magnitude of the CG annual cycle and its phasing are well-matched by that of CP in regions east

262 of the Rockies. Because the majority of lightning flashes occur in the eastern half of the country,

263 the scaling factor is disposed to match the magnitude there. In the Upper Midwest, where the

264 ratio of positive to negative CG flashes is relatively large, the CP annual cycle is stronger than

265 that of the negative CG flashes and better matches the annual cycle magnitude of the positive CG

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flashes. CP overestimates negative CG flashes in the Upper Midwest during July–August and underestimates them in the Plains. The largest differences in annual cycle magnitude are present in the Southwest, Northwest, and West regions, where CP is substantially too low compared to both negative and positive CG flash counts. These annual cycle biases indicate that a lightning proxy potentially could benefit from taking into account physical factors that are different in these regions (e.g., warm cloud depth) and that are not captured by reanalysis precipitation and CAPE. Alternatively, regionally-varying, empirical corrections could be applied to CP as is done to the output of numerical weather and climate prediction models.

CP shows the largest phase errors in the Northwest and West. CP in the Northwest peaks in May–June, while CG flash counts peak in June–August and have stronger seasonality (greater peak to trough differences). In the West, CP shows a bimodal structure, with a peak in August and a secondary peak in early spring, while CG flash counts have a unimodal distribution, with a peak in July and stronger seasonality. CP tends to match the annual cycle of positive CG flashes more poorly than it does negative ones, especially in the Southeast, Northeast and Central regions where CP overestimates the peak magnitude.

The annual spatial distribution of CP is more similar to that of negative CG flashes than that of positive CG flashes (Fig. 6). The annual spatial distribution of negative CG flashes is nearly indistinguishable from all CG flashes (not shown). Compared to counts of positive CG flashes, corresponding CP values are too low in the middle of the CONUS (Oklahoma, Kansas, and Nebraska) and too large along the Southeast coast, and over Florida. Centered pattern correlations between the climatological monthly maps of NLDN flash counts and the CP proxy computed for the CONUS region east of 105°W show good agreement for negative polarity flashes throughout the year but are relatively poor for positive CG flashes during June–October (Table 1), which are

months when CP values tend to be too high in the Southeast, Northeast, and Central regions and too low in the Plains region (Fig. 5).

d. Seasonality in the strength of daily associations

We compute the correlation between daily CONUS CG flash counts and CP values for each of the twelve calendar months separately to examine how the strength of the association between daily CP values and flash counts varies through the calendar. By removing the mean of each calendar month from the daily data, we remove much of the contribution of the annual cycle to the correlation of daily values computed in Section 3b, though some months have considerable climatological mean changes within the month (e.g., August). The correlation between daily CONUS CP and CG flash counts by calendar month is very similar for negative, positive, and all polarity flashes (Table 2), and shows a clear seasonality with lower values in summer and fall. The median correlation between daily CONUS CP and all CG flash counts by calendar month is 0.88 during the months of November through May, while it is 0.70 during the months of June through October.

The normalized daily MSE shows a consistent picture, with larger relative errors in the months of June through November (Table 2). The daily normalized MSE is relatively low during the months of November through April, with a median of 24% and 36% for negative and positive CG flash counts, respectively. However, during the months of May through October, the median daily normalized MSE is 66% and 65%, respectively, for negative and positive CG flash counts. Normalized MSE values greater than one for negative CG flashes in September and October indicate that the errors are greater than would result from replacing the daily CP values with the monthly average over the period. Higher daily errors during the months of peak lightning occurrence might be expected to accumulate and limit the ability of CP to capture year-to-year variations of seasonal and annual totals.

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₃₁₂ *e. Interannual variability*

₃₁₃   We now examine the ability of CP to match year-to-year variations in monthly, six-month, and

₃₁₄ annual values of CG flash counts. At annual resolution, there is no substantial correlation of

₃₁₅ CONUS CP with counts of negative CG flashes ($r = 0.09$; Fig. 7) or with counts of all CG flashes

₃₁₆ ($r = 0.03$, not shown). To some extent, this lack of association between annual values of CONUS

₃₁₇ CP and negative CG flashes is unexpected since daily values are well-correlated, both in an overall

₃₁₈ sense that includes seasonality, and when focusing on individual months. Time averaging often

₃₁₉ reduces noise and enhances statistical relations, but, in this case, time averaging serves to high-

₃₂₀ light deficiencies of CP during the warm season. Dewan et al. (2018) also found low correlation

₃₂₁ of annual numbers of total flashes over Bangladesh with CP, but found a statistically significant

₃₂₂ relation with CAPE, which is not present here (not shown). The correlation of annual CONUS CP

₃₂₃ with counts of positive CG flashes is considerably larger ($r = 0.8$; Fig. 7), although that correla-

₃₂₄ tion drops to 0.52 when the largest annual value (2016) is removed. The large number of positive

₃₂₅ CG flashes recorded in 2016 could be due to the new flash type classification technique that is

₃₂₆ based on the examination of multiple waveform parameters, which was employed within the TLP

₃₂₇ as indicated in Nag et al. (2016).

₃₂₈   The correlation between warm season (May–October) CONUS CP and CG flashes is roughly the

₃₂₉ same as for annual values ($r = 0.05$ and $r = 0.76$ for negative and positive polarity, respectively;

₃₃₀ Fig. 7). Annual counts of CG flashes are dominated by warm season values in the sense that warm

₃₃₁ season flashes account for 89% of negative CG flashes and 83% of positive CG flashes during

₃₃₂ the period 2003–2016 (Supplemental Tables S2 and S3) and in the sense that warm season counts

₃₃₃ of CG flashes are highly correlated with annual values ($r = 0.97$ and $r = 0.99$, for negative and

₃₃₄ positive flashes, respectively). During the cool season (November–April), CONUS CP shows a

335 fairly good association with negative ($r = 0.74$; Fig. 7), positive ($r = 0.89$; Fig. 7) and all ($r = 0.79$,

336 not shown) CG flash counts. The good association of CONUS CP with the number of CG flashes

337 of both polarities during the cool season is possible because the correlation between the number of

338 negative and positive cool season CONUS CG flashes is 0.69. In contrast, the correlation between

339 the number of negative and positive warm season CONUS CG flashes is -0.32.

340   The correlations of monthly values of CONUS CP with negative CG flashes (first line of Table

341 3) are considerably higher than the annual or warm season correlations, though the correlations for

342 months during the warm season (median correlation 0.47) tend to be lower than for months during

343 the cool season (median correlation 0.87). Correlations of positive CG flash counts with monthly

344 CONUS CP are above 0.85 during six months of the year and fall below 0.5 only in August and

345 October (first line of Table 4), with a tendency toward lower correlations during warm season

346 months (median correlation 0.65) compared to cool season months (median correlation 0.87). The

347 lower correlations during some warm season months is consistent with relatively low correlations

348 and poor normalized MSE at daily resolution during warm season months noted earlier (Table 2).

349   At the regional level, correlations between monthly CP and negative CG flash counts are over-

350 all higher than those at the CONUS level, particularly during warm season months (May through

351 October) when 87% of the regional correlations are greater than CONUS ones (Table 3). Lower

352 correlation with increasing spatial aggregation is consistent with regionally varying magnitude er-

353 rors. Correlations of monthly CP and negative CG flash counts show some indication of relatively

354 lower values in warm season months in the Southeast, Northeast, and South regions, which pro-

355 duce more than 68% of the annual CONUS number of negative CG flashes (Supplemental Table

356 S2). Correlations of monthly CP and positive CG flash counts show some reduced values during

357 warm season months in the South and Southeast regions (Table 4) but are otherwise fairly strong,

358 except in the Central, Upper Midwest, and Plains regions during some cool season months. De-

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spite clear deficiencies in the South and Southeast regions during the warm season, which likely contribute to poor CONUS performance, the relation between monthly CP and CG flash counts is strong in many regions and during many times of the year, demonstrating the strong potential for CP as an indicator of monthly tendencies in regional CG flash counts.

Maps of the correlation between warm and cool season CP and CG flashes show large-scale features that are consistent with the analysis at the NOAA region level, as well as fairly high correlations at the gridpoint level in many areas (Fig. 8). Correlations of warm season CP with negative CG flash counts are mostly positive but very modest in the Southeast, Northeast, and parts of the South, consistent with the regional analysis. Correlations between warm season CP and negative CG flash counts are weakly negative in an area that includes the borders of Colorado, Wyoming, Nebraska, and Kansas where the ratio of intra-cloud lightning to CG flashes is known to be large and which is often associated with inverted or complex charge structures (Carey and Rutledge 1998; Medici et al. 2017). Misclassification of cloud pulses as CG flashes as well as in-correct assignment of first peak polarity have been noted in the Kansas-Nebraska area (Cummins and Murphy 2009). Warm season correlations between CP and negative CG flash counts are also weakly negative in smaller areas along the West Coast, and around Butte, Montana, and Colum-bus, Georgia. Cool season correlations between CP and CG flash counts of both polarities are similar and generally higher than warm season ones across the southeastern half of the CONUS. Correlations between warm season CP and positive CG flashes are overall higher than for negative CG flashes over most of the CONUS, with low correlations mostly limited to Florida and states to its immediate north (Fig. 8). Maps of annual correlations (not shown) are similar to those for the warm season.

Warm season normalized MSE exceeds one in many areas for both polarities, indicating errors that are larger than the climatological variance, especially west of 105°W where mean biases are

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383 large (Fig. 9). For negative CG flashes, the warm season normalized MSE east of the Rockies is

384 mostly less than one except in areas that include Wisconsin and eastern Minnesota, the Gulf Coast,

385 and eastern North Carolina. On the other hand, the warm season normalized MSE for positive CG

386 flashes is large across the Southeast and Northeast regions, indicating magnitude miscalibration

387 since correlations are good there (Fig. 8). The normalized cool season MSE is lower overall

388 than the warm season MSE for both polarities, except in the Northwest and on the West Coast.

389 Cool season normalized MSE is lower overall for negative CG flashes than for positive ones. Both

390 polarities have large normalized MSE over southern Florida in the cool season. Annual normalized

391 MSE maps (not shown) are similar to warm season ones.

392 **4. Summary**

393 We have compared the product of collocated CAPE and precipitation (denoted CP) taken from

394 the North American Regional Reanalysis with counts of negative and positive cloud-to-ground

395 (CG) lightning flashes from the National Lightning Detection Network (NLDN) over the con-

396 tiguous U.S. (CONUS). Our analysis includes CONUS-wide and regional characteristics on daily,

397 monthly, and annual resolution for the period 2003–2016. This analysis extends the findings of

398 Romps et al. (2014) who considered one year of CONUS-aggregated daily values from 2011.

399 Overall, the association of CP with lightning flashes on the daily, monthly, and seasonal scale

400 tends to be stronger during the cool season (November–April) than during the warm season (May–

401 October). Interannual correlations between CP and flash counts tend to be stronger for positive

402 CG flashes than for negative ones.

403 Daily values of CONUS CP are highly correlated with both positive and negative CG flash

404 counts, explaining more than 75% of their daily variance (Fig. 3). Some of this association (more

405 than 60% of the variance) is a reflection of the strong seasonal cycles of CONUS CP and CG flash

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counts and their good phase agreement (Fig. 4). However, daily variations of CONUS CP and CG flash counts with respect to their monthly climatologies are still strongly related, but with stronger associations in the cool season (November–April) than in the warm season (May–October) when most lightning occurs (Table 2). The normalized (relative to climatological variance) daily mean-squared error (MSE) of CONUS values is also larger in the warm season, and this lower accuracy translates into lower interannual correlations (Fig. 7) and higher normalized MSE for monthly totals in the warm season (Table 3), especially for negative polarity flashes, which are the vast majority of CG flashes. The low correlation in summer months might indicate that CP is better related to storm occurrence than to the total number of CG flashes within a storm. This lack of association during the warm season when the majority of lightning occurs results in there being essentially no correlation between the annual values of CP and corresponding numbers of either negative or total CG lightning flashes. There is, however, a good correlation between warm season and annual counts of positive CG flashes with CP (Fig. 7). Cool season CP correlates well with both counts of positive and negative CG flashes.

We find that the ratio of CP to CG flash counts varies considerably on a regional basis, with the greatest difference found in the arid Southwest, where the ratio of CG flashes to CP is substantially higher than in between regions east of the Rockies (Fig. 2). The ratio of CG flashes to CP is lowest along the West Coast, where there are fewer cloud condensation nuclei and where maritime air masses can penetrate. At the level of NOAA climate regions, despite some errors in magnitude, CP matches the annual cycle in all regions fairly well except the Northwest and West (Fig. 5). Correlations of annual CP with CG flash counts at the regional level are generally higher for positive than for negative CG flash counts ((Tables 3 and 4). Regional correlations of annual CP and negative CG flash counts are especially low in the South and Northeast, where more than 35% of all negative CONUS CG flashes occur. The relatively weak association between CP and counts

of negative CG flashes in these areas during the warm season explains the lack of correlation
between annual CONUS CP and negative CG flash counts. In these regions, correlations between
cool season CP and CG flash counts are generally stronger than for warm season values. This
finding is roughly consistent with those of Dewan et al. (2018) who found higher correlations
between CP and total lightning flash count for the pre-monsoon season than for the monsoon
season.

Maps of the correlation between annual values of CP and CG flash counts show positive values
over most of the CONUS, with some spatially limited exceptions (Fig. 8). In general, correlations
with CP are stronger for positive CG flash counts and stronger during the cool season for both
polarities. Despite the positive correlations at the gridpoint level, interannual variability of CP
values are not well-calibrated with CG flash counts. Maps of normalized MSE show relatively
low error levels for both polarities during the cool season for most of the CONUS except for large
errors on the West Coast, the Northwest, and southern Florida (Fig. 9). Normalized MSE is small
during the warm season for positive CG flash counts in a swath that extends from Texas northeast
to the Great Lakes.

5. Discussion

The suitability of CP for S2S forecasting applications cannot be concluded from this study.
However, assessment with subseasonal reforecast data has been encouraging (Tippett and Koshak
2018). In principle, the utility of CP for S2S forecasting is at least limited by its performance with
reanalysis data and the extent that its constituents can be forecast. The high correlations between
CP and CG flash counts across large portions of the U.S. show that this simple proxy captures
considerable variability. Conversely, we have also identified regions and times of the year when
CP values are not strongly correlated with CG flash counts, and this weakness suggests the need

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for improvements in the proxy. The degree to which CP can be predicted in advance is unknown beyond submonthly lead times. There are indications that the CP ingredients, precipitation and CAPE, can be predicted with some skill. U.S. precipitation is already forecast with current forecast systems with some skill at subseasonal (DelSole et al. 2017) and seasonal (Becker et al. 2014) time-scales. However, skill tends to be lowest in the warm season. Seasonal values of CAPE have been demonstrated to be predictable as well (Jung and Kirtman 2016). On the other hand, even in many locations where correlations between CP and CG flash counts are high, the MSE is also relatively high, indicating that the CP proxy is not calibrated to match CG flash counts. In these cases, there is the potential to correct CP values on a regional basis to match CG flash counts. Alternatively, this lack of calibration can also be interpreted as indicating that the proxy can be improved with the addition of other factors that are important for characterizing lightning activity, though perhaps at the risk of losing its attractive simplicity.

The 14 years of data used in this study are not adequate to answer fully the question of whether CP is useful proxy for long-term climate applications. Over the period of study, the annual number of CONUS CG flashes varied from a high of 2.7×10^7 flashes in 2004 to a low of 1.8×10^7 flashes in 2012, a range of about 35% of the annual average of 2.3×10^7 flashes. However, this variation in the annual number CONUS CG flashes was not well captured by the CP proxy. This poor performance in describing interannual variability of CONUS CG flash counts does not necessarily mean that this approach is poorly suited to climate change applications but does raise concerns about the applicability of the proxy to climate change applications.

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Supporting information

Table S1. States in NOAA climate regions.

Table S2. Percent of negative NLDN CG flashes occurring in each NOAA region and month 2003–2016. Values of 0.00 indicate less than 0.01%.

Table S3. Percent of positive NLDN CG flashes occurring in each NOAA month 20032016. Values of 0.00 indicate less than 0.01.

References

Allen, D. J., and K. E. Pickering, 2002: Evaluation of lightning flash rate parameterizations for use in a global chemical transport model. *J. Geophys. Res.*, **107**, 4711, doi:10.1029/2002JD002066.

Allen, J. T., M. K. Tippett, and A. H. Sobel, 2015a: An empirical model relating U.S. monthly hail occurrence to large-scale meteorological environment. *J. Adv. Model. Earth Syst.*, **7**, 226–243,

doi:10.1002/2014MS000397.

Allen, J. T., M. K. Tippett, and A. H. Sobel, 2015b: Influence of the El Niño/Southern Oscillation on tornado and hail frequency in the United States. *Nat. Geosci.*, **8**, 278–283, doi:10.1038/ngeo2385.

Becker, E., H. v. den Dool, and Q. Zhang, 2014: Predictability and forecast skill in NMME. *J. Climate*, **27**, 5891–5906, doi:10.1175/JCLI-D-13-00597.1.

Biagi, C. J., K. L. Cummins, K. E. Kehoe, and E. P. Krider, 2007: National Lightning Detection Network (NLDN) performance in southern Arizona, Texas, and Oklahoma in 2003–2004. *J. Geophys. Res.*, **112**, D05 208, doi:10.1029/2006JD007341.

Bright, D. R., M. S. Wandishin, R. E. Jewell, and S. J. Weiss, 2004: A physically based parameter for lightning prediction and its calibration in ensemble forecasts. *Preprints, 22nd Conf. on Severe Local Storms*, Amer. Meteor. Soc.

Bukovsky, M. S., and D. J. Karoly, 2007: A brief evaluation of precipitation from the North American Regional Reanalysis. *J. Hydrometeor*, **8**, 837–846, doi:10.1175/JHM595.1.

Camargo, S. J., M. K. Tippett, A. H. Sobel, G. A. Vecchi, and M. Zhao, 2014: Testing the performance of tropical cyclone genesis indices in future climates using the HIRAM model. *J. Climate*, **27**, 9171–9196, doi:10.1175/JCLI-D-13-00505.1.

Carey, L. D., and K. M. Buffalo, 2007: Environmental control of cloud-to-ground lightning polarity in severe storms. *Monthly Weather Review*, **135 (4)**, 1327–1353, doi:10.1175/MWR3361.1, URL https://doi.org/10.1175/MWR3361.1.

Carey, L. D., and S. A. Rutledge, 1998: Electrical and multiparameter radar observations of a severe hailstorm. *J. Geophys. Res.*, **103**, 13 979–14 000, doi:10.1029/97JD02626.

23

Carey, L. D., and S. A. Rutledge, 2003: Characteristics of cloud-to-ground lightning in severe and nonsevere storms over the central United States from 1989–1998. *J. Geophys. Res.*, **108**, 4483, doi:10.1029/2002JD002951.

Cui, W., X. Dong, B. Xi, and A. Kennedy, 2017: Evaluation of reanalyzed precipitation variability and trends using the gridded gauge-based analysis over the CONUS. *J. Hydrometeor.*, **18**, 2227–2248, doi:10.1175/JHM-D-17-0029.1.

Cummins, K. L., and M. J. Murphy, 2009: An overview of lightning locating systems: History, techniques, and data uses, with an in-depth look at the U.S. NLDN. *IEEE Trans. Electromagn. Compat.*, **51**, 499–518, doi:10.1109/TEMC.2009.2023450.

DelSole, T., L. Trenary, M. K. Tippett, and K. Pegion, 2017: Predictability of week 3-4 average temperature and precipitation over the contiguous United States. *J. Climate*, **30**, 3499–3512, doi:10.1175/JCLI-D-16-0567.1.

Dewan, A., M. F. Hossain, M. M. Rahman, Y. Yamane, and R. L. Holle, 2017: Recent lightning-related fatalities and injuries in Bangladesh. *Wea. Climate Soc.*, **9**, 575–589, doi: 10.1175/WCAS-D-16-0128.1.

Dewan, A., E. T. Ongee, R. M., M. M. Rahman, and R. Mahmood, 2018: Lightning activity associated with precipitation and CAPE over Bangladesh. *Int. J. Climatol*, **38**, 1649–1660, doi: 10.1002/joc.5286.

Dowdy, A. J., 2016: Seasonal forecasting of lightning and thunderstorm activity in tropical and temperate regions of the world. *Sci. Rep.*, **6**, 20 874, doi:10.1038/srep20874.

Fierro, A. O., E. R. Mansell, D. R. MacGorman, and C. L. Ziegler, 2013: The implementation of an explicit charging and discharge lightning scheme within the WRF-ARW model: Benchmark

simulations of a continental squall line, a tropical cyclone, and a winter storm. *Mon. Wea. Rev.*, **141**, 2390–2415, doi:10.1175/MWR-D-12-00278.1.

Finney, D. L., R. M. Doherty, O. Wild, D. S. Stevenson, I. A. MacKenzie, and A. M. Blyth, 2018: A projected decrease in lightning under climate change. *Nature Climate Change*, **8**, 210–213, doi:10.1038/s41558-018-0072-6.

Fuchs, B. R., and Coauthors, 2015: Environmental controls on storm intensity and charge structure in multiple regions of the continental United States. *J. Geophys. Res. Atmos.*, **120**, 6575–6596, doi:10.1002/2015JD023271.

Gensini, V. A., T. L. Mote, and H. E. Brooks, 2014: Severe-thunderstorm reanalysis environments and collocated radiosonde observations. *J. Appl. Meteor. Climatol.*, **53**, 742–751, doi:10.1175/JAMC-D-13-0263.1.

Held, I. M., and B. J. Soden, 2006: Robust responses of the hydrological cycle to global warming. *J. Climate*, **19**, 5686–5699, doi:10.1175/JCLI3990.1.

Holle, R. L., K. L. Cummins, and W. A. Brooks, 2016: Seasonal, monthly, and weekly distributions of NLDN and GLD360 cloud-to-ground lightning. *Mon. Wea. Rev.*, **144**, 2855–2870, doi:10.1175/MWR-D-16-0051.1.

Jung, E., and B. P. Kirtman, 2016: Can we predict seasonal changes in high impact weather in the United States? *Environ. Res. Lett.*, **11**, 074 018, doi:10.1088/1748-9326/11/7/074018.

Karl, T. R., and W. J. Koss, 1984: Regional and National Monthly, Seasonal, and Annual Temperature Weighted by Area, 1895-1983. Historical climatology series 4-3, National Climatic Data Center, Asheville, NC. 38 pp.

King, A. T., and A. D. Kennedy, 2019: North American supercell environments in atmospheric reanalyses and RUC-2. *J. Appl. Meteor. Climatol.*, **58**, 71–92, doi:10.1175/JAMC-D-18-0015.1.

Koren, I., O. Altaratz, L. A. Remer, G. Feingold, J. V. Martins, and R. H. Heiblum, 2012: Aerosol-induced intensification of rain from the tropics to the mid-latitudes. *Nat. Geosci.*, **5**, 118–122, doi:10.1038/ngeo1364.

Koshak, W. J., K. L. Cummins, D. E. Buechler, B. Vant-Hull, R. J. Blakeslee, E. R. Williams, and H. S. Peterson, 2015: Variability of CONUS lightning in 2003–12 and associated impacts. *J. Appl. Meteor. Climatol.*, **54**, 15–41, doi:10.1175/JAMC-D-14-0072.1.

Kuhlman, K. M., C. L. Ziegler, E. R. Mansell, D. R. MacGorman, and J. M. Straka, 2006: Numerically simulated electrification and lightning of the 29 June 2000 STEPS supercell storm. *Mon. Wea. Rev.*, **134**, 2734–2757, doi:10.1175/MWR3217.1.

Lepore, C., M. K. Tippett, and J. T. Allen, 2018: CFSv2 monthly forecasts of tornado and hail activity. *Wea. Forecasting*, **33**, 1283–1297, doi:10.1175/WAF-D-18-0054.1.

Lepore, C., D. Veneziano, and A. Molini, 2016: Temperature and CAPE dependence of rainfall extremes in the eastern United States. *Geophys. Res. Lett.*, **42**, 74–83, doi:10.1002/2014GL062247, 2014GL062247.

L'Heureux, M., M. K. Tippett, and A. G. Barnston, 2015: Characterizing ENSO coupled variability and its impact on North American seasonal precipitation and temperature. *J. Climate*, **28**, 4231–4245, doi:10.1175/JCLI-D-14-00508.1.

Lopez, P., 2016: A lightning parameterization for the ECMWF Integrated Forecasting System. *Mon. Wea. Rev.*, **144**, 3057–3075, doi:10.1175/MWR-D-16-0026.1.

Lynn, B. H., Y. Yair, C. Price, G. Kelman, and A. J. Clark, 2012: Predicting cloud-to-ground and intracloud lightning in weather forecast models. *Wea. Forecasting*, **27**, 1470–1488, doi: 10.1175/WAF-D-11-00144.1.

MacGorman, D. R., and D. W. Burgess, 1994: Positive cloud-to-ground lightning in tornadic storms and hailstorms. *Mon. Wea. Rev.*, **122**, 1671–1697, doi:10.1175/1520-0493(1994) 122⟨1671:PCTGLI⟩2.0.CO;2.

Mansell, E. R., D. R. MacGorman, C. L. Ziegler, and J. M. Straka, 2005: Charge structure and lightning sensitivity in a simulated multicell thunderstorm. *J. Geophys. Res.*, **110**, D12 101, doi:10.1029/2004JD005287.

McCaul, E. W., S. J. Goodman, K. M. LaCasse, and D. J. Cecil, 2009: Forecasting lightning threat using cloud-resolving model simulations. *Wea. Forecasting*, **24**, 709–729, doi:10.1175/ 2008WAF2222152.1.

Medici, G., K. L. Cummins, D. J. Cecil, W. J. Koshak, and S. D. Rudlosky, 2017: The intra-cloud lightning fraction in the contiguous United States. *Mon. Wea. Rev.*, doi:10.1175/ MWR-D-16-0426.1.

Mesinger, F., and Coauthors, 2006: North American Regional Reanalysis. *Bull. Amer. Meteor. Soc.*, **87**, 343–360, doi:10.1175/BAMS-87-3-343.

Mülmenstädt, J., O. Sourdeval, J. Delanoë, and J. Quaas, 2015: Frequency of occurrence of rain from liquid-, mixed-, and ice-phase clouds derived from A-Train satellite retrievals. *Geophys. Res. Lett.*, **42**, 6502–6509, doi:10.1002/2015GL064604.

27

Muñoz, Á. G., J. Díaz-Lobatón, X. Chourio, and M. J. Stock, 2016: Seasonal prediction of lightning activity in North Western Venezuela: Large-scale versus local drivers. *Atmos. Res.*, **172–173**, 147–162, doi:10.1016/j.atmosres.2015.12.018.

Murugavel, P., S. D. Pawar, and V. Gopalakrishnan, 2012: Trends of convective available potential energy over the Indian region and its effect on rainfall. *Int. J. Climatol.*, **32**, 1362–1372, doi:10.1002/joc.2359.

Nag, A., M. J. Murphy, and J. A. Cramer, 2016: Update to the U.S. National Lightning Detection Network. *24th International Lightning Detection Conference & 6th International Lightning Meterology Conference*, San Diego, CA.

Pegion, K., and Coauthors, 2018: The Subseasonal Experiment (SubX): A multi-model subseasonal prediction experiment. *Bull. Amer. Meteor. Soc.*, Submitted.

Petersen, W. A., and S. A. Rutledge, 1998: On the relationship between cloud-to-ground lightning and convective rainfall. *J. Geophys. Res.*, **103**, 14 025–14 040, doi:10.1029/97JD02064.

Romps, D. M., J. T. Seeley, D. Vollaro, and J. Molinari, 2014: Projected increase in lightning strikes in the United States due to global warming. *Science*, **346**, 851–854, doi:10.1126/science.1259100.

Ropelewski, C., and M. Halpert, 1987: Global and regional scale precipitation patterns associated with the El Niño/Southern Oscillation. *Mon. Wea. Rev.*, **115**, 1606–1626.

Saha, S., and Coauthors, 2014: The NCEP Climate Forecast System Version 2. *J. Climate*, **27**, 2185–2208, doi:10.1175/JCLI-D-12-00823.1.

Seeley, J. T., and D. M. Romps, 2016: Why does tropical convective available potential energy (CAPE) increase with warming? *Geophys. Res. Lett.*, **42**, 10 429–10 437, doi:10.1002/2015GL066199.

Stainforth, D. A., M. R. Allen, E. R. Tredger, and L. A. Smith, 2007: Confidence, uncertainty and decision-support relevance in climate predictions. *Philos Transact A Math Phys Eng Sci*, **365**, 2145–2161, doi:10.1098/rsta.2007.2074.

Stolz, D. C., S. A. Rutledge, J. R. Pierce, and S. C. van den Heever, 2017: A global lightning parameterization based on statistical relationships among environmental factors, aerosols, and convective clouds in the TRMM climatology. *J. Geophys. Res. Atmos.*, **122**, 7461–7492, doi:10.1002/2016JD026220.

Taszarek, M., H. E. Brooks, and B. Czernecki, 2017: Sounding-derived parameters associated with convective hazards in europe. *Monthly Weather Review*, **145 (4)**, 1511–1528, doi:10.1175/MWR-D-16-0384.1, URL https://doi.org/10.1175/MWR-D-16-0384.1.

Tippett, M. K., and W. J. Koshak, 2018: A baseline for the predictability of U.S. cloud-to-ground lightning. *Geophys. Res. Lett.*, **45**, 10,719–10,728, doi:10.1029/2018GL079750.

Tippett, M. K., C. Lepore, and J. E. Cohen, 2016: More tornadoes in the most extreme U.S. tornado outbreaks. *Science*, **354**, 1419–1423, doi:10.1126/science.aah7393.

Tippett, M. K., A. H. Sobel, and S. J. Camargo, 2012: Association of U.S. tornado occurrence with monthly environmental parameters. *Geophys. Res. Lett.*, **39**, L02 801, doi:10.1029/2011GL050368.

van Donkelaar, A., R. V. Martin, M. Brauer, and B. L. Boys, 2015: Global Annual PM2.5 Grids from MODIS, MISR and SeaWiFS Aerosol Optical Depth (AOD), 1998-2012. NASA Socioeconomic Data and Applications Center (SEDAC), Palisades, NY, doi:10.7927/H4028PFS.

Vitart, F., and Coauthors, 2016: The subseasonal to seasonal (S2S) prediction project database. *Bull. Amer. Meteor. Soc.*, **98**, 163–173, doi:10.1175/BAMS-D-16-0017.1.

Westermayer, A. T., P. Groenemeijer, G. Pistotnik, R. Sausen, and E. Faust, 2017: Identification of favorable environments for thunderstorms in reanalysis data. *Meteorol. Z.*, **26**, 59–70, doi: 10.1127/metz/2016/0754.

Wilks, D. S., 2011: *Statistical Methods in the Atmospheric Sciences:An Introduction*. Academic Press.

Xu, W., R. F. Adler, and N.-Y. Wang, 2012: Improving geostationary satellite rainfall estimates using lightning observations: Underlying lightning–rainfall–cloud relationships. *J. Appl. Meteor. Climatol.*, **52**, 213–229, doi:10.1175/JAMC-D-12-040.1.

Yair, Y., B. Lynn, C. Price, V. Kotroni, K. Lagouvardos, E. Morin, A. Mugnai, and M. d. C. Llasat, 2010: Predicting the potential for lightning activity in Mediterranean storms based on the Weather Research and Forecasting (WRF) model dynamic and microphysical fields. *J. Geophys. Res.*, **115**, D04 205, doi:10.1029/2008JD010868.

Zajac, B. A., and S. A. Rutledge, 2001: Cloud-to-ground lightning activity in the contiguous United States from 1995 to 1999. *Mon. Wea. Rev.*, **129**, 999–1019, doi:10.1175/ 1520-0493(2001)129⟨0999:CTGLAI⟩2.0.CO;2.

Zipser, E. J., 1994: Deep cumulonimbus cloud systems in the Tropics with and without lightning. *Mon. Wea. Rev.*, **122**, 1837–1851, doi:10.1175/1520-0493(1994)122⟨1837:DCCSIT⟩2.0.CO;2.

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TABLE 1. Centered pattern correlation between climatological CP and NLDN CG flash counts east of 105°W.

Polarity	J	F	M	A	M	J	J	A	S	O	N	D
Total	0.89	0.90	0.95	0.96	0.94	0.88	0.85	0.86	0.80	0.78	0.91	0.92
Negative	0.88	0.90	0.95	0.96	0.94	0.87	0.84	0.85	0.80	0.78	0.90	0.91
Positive	0.89	0.87	0.92	0.95	0.88	0.68	0.51	0.67	0.69	0.75	0.90	0.91

TABLE 2. Correlation and normalized MSE of daily CONUS CP and NLDN values pooled by month.

						Correlation						
Polarity	J	F	M	A	M	J	J	A	S	O	N	D
All	0.87	0.90	0.89	0.90	0.86	0.74	0.69	0.68	0.70	0.71	0.80	0.88
Negative	0.87	0.90	0.89	0.89	0.85	0.73	0.67	0.66	0.69	0.70	0.79	0.87
Positive	0.88	0.90	0.87	0.89	0.86	0.70	0.66	0.68	0.73	0.72	0.83	0.90
						Normalized MSE						
Polarity	J	F	M	A	M	J	J	A	S	O	N	D
All	0.24	0.21	0.22	0.21	0.37	0.60	0.62	0.63	1.08	0.99	0.66	0.23
Negative	0.25	0.21	0.23	0.23	0.40	0.61	0.65	0.66	1.11	1.03	0.74	0.29
Positive	0.40	0.39	0.33	0.27	0.29	0.67	0.64	0.64	0.77	0.66	0.32	0.42

TABLE 3. Correlation of monthly averages of negative NLDN flash counts and CP. Low-skill values (less than

0.5) are indicated in bold. Correlation of annual average are provided in the final column.

Region	J	F	M	A	M	J	J	A	S	O	N	D	Annual
CONUS	0.85	0.90	0.88	0.84	0.51	0.66	**0.36**	**0.34**	**0.46**	0.81	0.84	0.96	**-0.09**
South	0.74	0.87	0.76	0.76	0.66	**0.32**	**0.41**	**0.34**	0.63	0.65	0.63	0.87	**0.02**
Southeast	0.90	0.91	0.91	0.82	0.87	0.85	0.76	**0.45**	0.74	0.88	0.95	0.95	0.67
Northeast	0.67	0.94	0.91	0.88	0.72	0.83	0.65	0.52	0.62	0.75	0.87	0.91	**0.16**
Central	**0.48**	**0.42**	0.91	**0.20**	0.83	0.85	0.88	0.56	0.76	0.93	0.80	**0.38**	0.62
Upper Midwest	0.50	0.71	0.95	0.79	0.63	0.77	0.75	0.72	0.65	0.92	0.74	0.61	0.56
Plains	**0.11**	0.88	0.94	0.91	0.63	0.61	**0.43**	0.74	0.85	0.59	0.60	**0.06**	**0.11**
Southwest	0.65	0.75	0.90	0.90	0.90	0.83	0.60	0.60	0.59	0.93	0.79	**0.35**	0.74
Northwest	**0.40**	**0.32**	**0.29**	0.61	0.72	0.90	0.70	0.94	0.97	**0.43**	**0.36**	0.71	0.60
West	0.84	0.78	**0.27**	0.61	0.80	0.81	0.75	0.92	0.85	0.86	**0.27**	**0.43**	0.64

TABLE 4. Correlation of monthly averages of positive NLDN flash counts and CP. Low-skill values (less than

0.5) are indicated in bold. Correlation of annual average are provided in the final column.

Region	J	F	M	A	M	J	J	A	S	O	N	D	annual
CONUS	0.86	0.96	0.86	0.85	0.66	0.64	0.72	**0.48**	0.80	**0.41**	0.87	0.97	0.80
South	0.59	0.90	0.77	0.75	0.83	**0.49**	**0.41**	**0.22**	0.70	**0.41**	0.63	0.96	**0.43**
Southeast	0.93	0.92	0.84	0.82	0.83	0.50	0.56	**0.41**	0.59	0.56	0.90	0.93	0.67
Northeast	0.80	0.96	0.92	0.96	0.64	0.93	0.80	0.66	0.82	0.71	0.97	0.98	0.87
Central	0.61	**0.31**	0.88	**0.25**	0.89	0.92	0.88	0.81	0.98	0.88	0.77	**0.40**	0.89
Upper Midwest	**0.32**	0.79	0.82	0.95	0.91	0.92	0.81	0.72	0.90	0.90	0.74	**0.49**	0.81
Plains	**0.25**	0.95	0.92	0.96	0.84	0.79	0.88	0.80	0.90	**0.40**	0.67	**0.17**	0.80
Southwest	0.76	0.79	0.96	0.92	0.84	0.64	0.50	0.82	0.50	0.91	0.79	**0.15**	0.59
Northwest	0.88	0.57	0.71	0.60	0.59	0.90	0.83	0.93	0.97	0.73	0.65	0.88	0.67
West	0.86	0.81	**0.47**	0.62	0.66	0.94	0.88	0.86	0.84	0.89	0.58	0.51	0.64

LIST OF FIGURES

Ratio (%) of negative CG flashes to total 2003-2016

FIG. 1. Ratio in percent of the number of negative polarity CG flashes to the total number of CG flashes 2003–2016.

FIG. 2. Ratio of the number of negative polarity (left) and positive polarity (right) NLDN flash counts to CP.
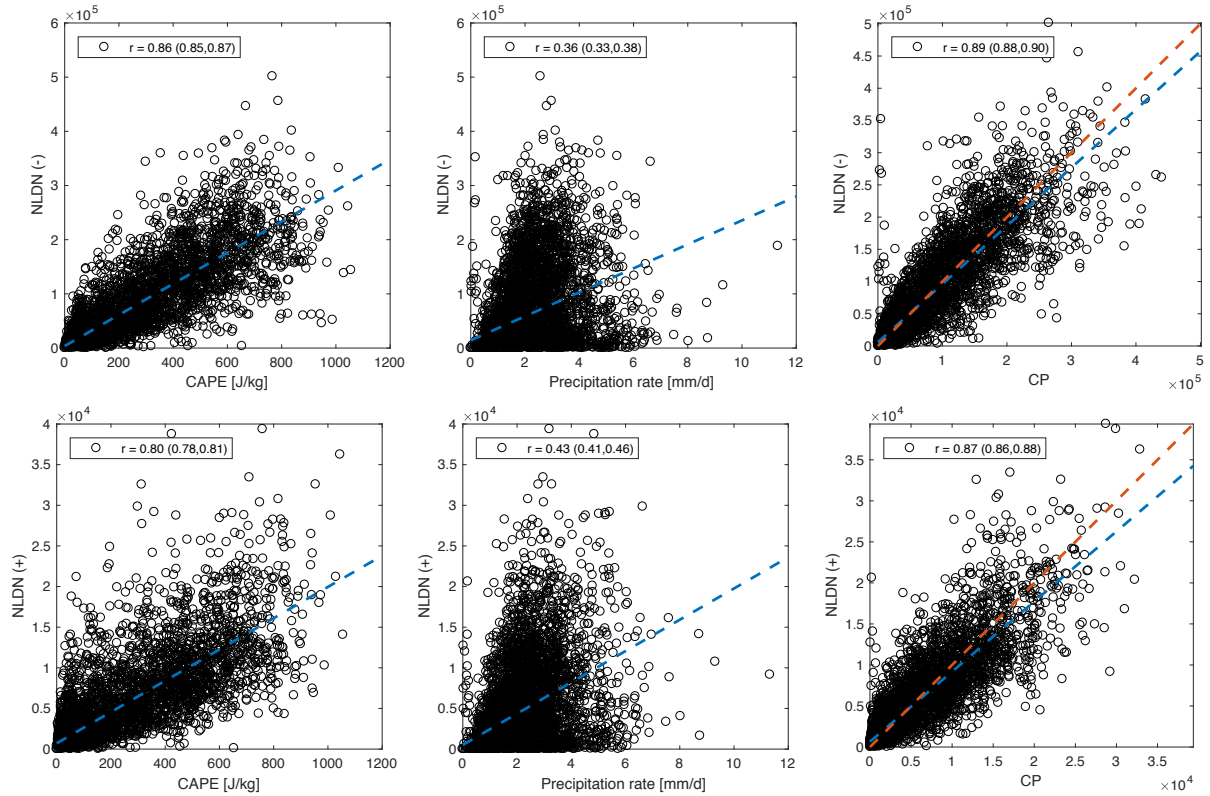
FIG. 3. Scatter plots of daily values of the CONUS-average of CAPE (first column), precipitation rate (second column), and scaled CP (third column) with daily counts of negative (first row) and positive (second row) CG flashes. Correlation values and 95% bootstrap confidence intervals (10,000 bootstrap samples) are shown in the legend. Blue dashed lines are regression lines, and red dashed lines in the right two panels are the one-to-one lines.
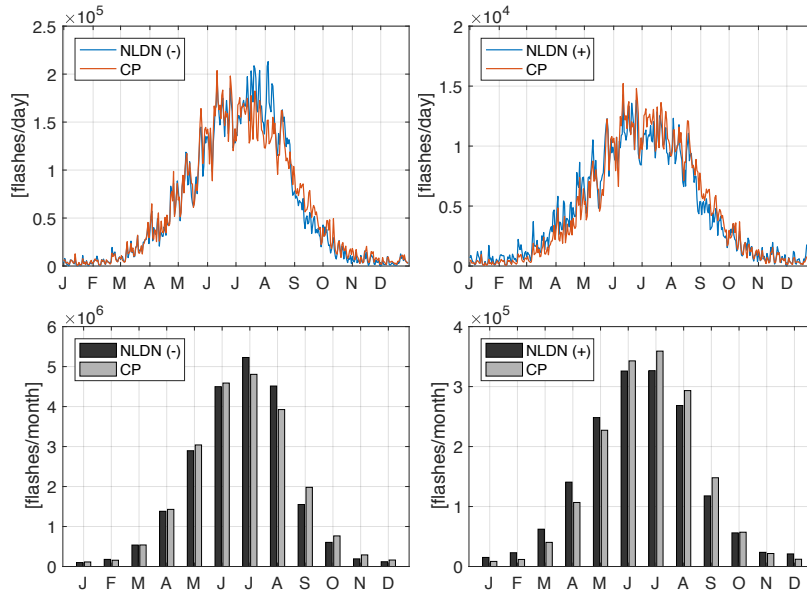
FIG. 4. Annual cycles of CP and NLDN CG flash counts at daily (top row) and monthly (bottom row)
resolution for negative (left column) and positive (right column) polarity.

Negative
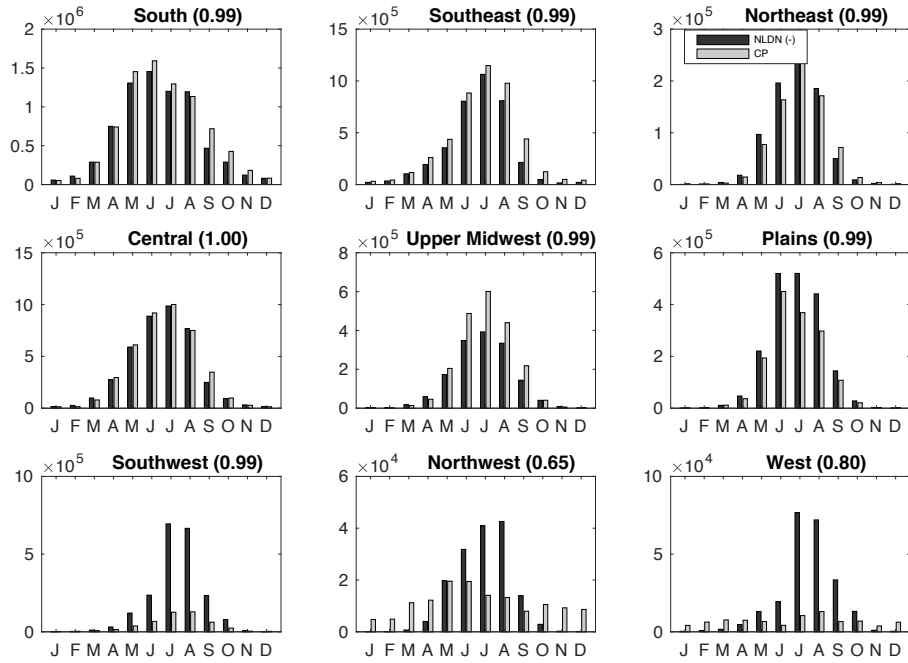
Positive
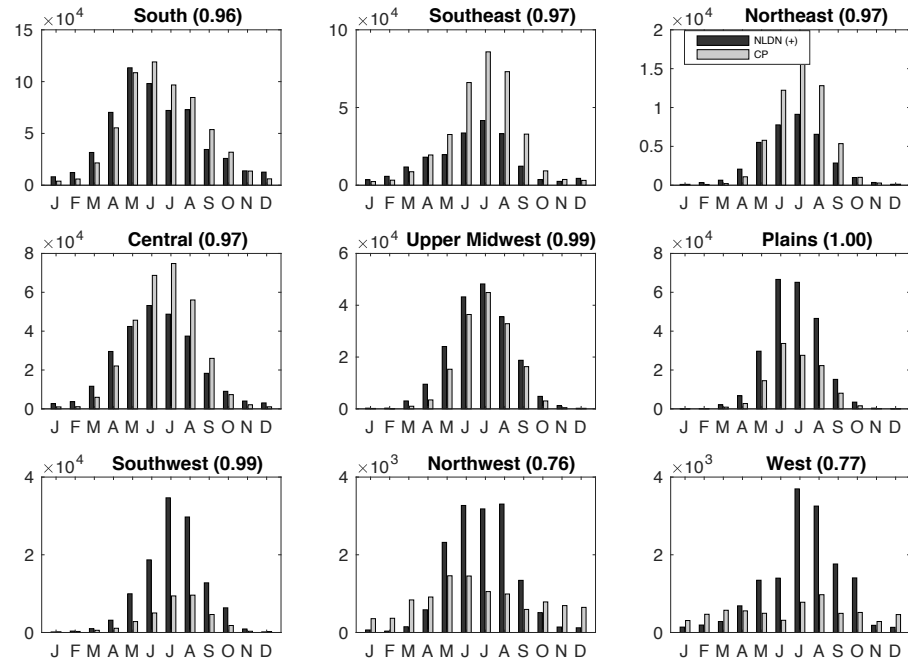
₇₁₇ FIG. 5. Regional climatology for NOAA climate regions. Upper panels are for negative CG flash counts and

₇₁₈ lower panels are for positive CG flash counts. The correlation is given in parentheses.
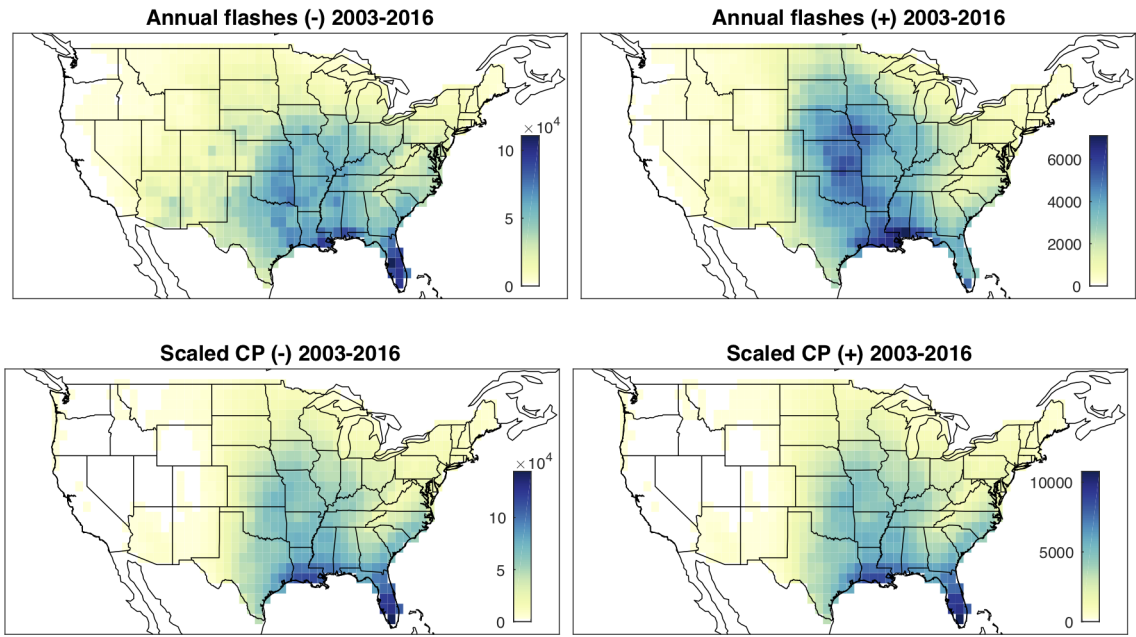
FIG. 6. Annual averages of negative and positive polarity lightning flashes and the corresponding maps of CP.
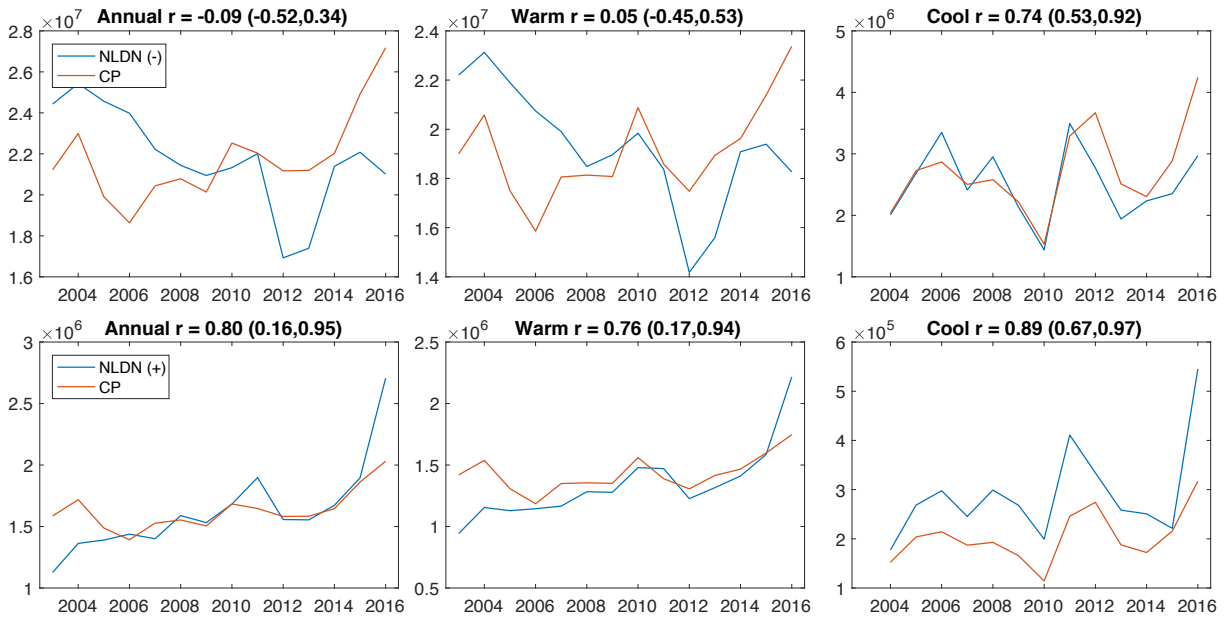
₇₁₉ FIG. 7. Time series 2003–2016 of annual (first column), warm season (May-October; second column) and
₇₂₀ cool season (November–April; third column) values of CP and NLDN CG flash counts for negative polarity
₇₂₁ (first row) and positive polarity (second row). Correlation values and 95% bootstrap confidence intervals (10000
₇₂₂ bootstrap samples) are shown in the titles.

Warm season correlation (-)   **Cool season correlation (-)**

Warm season correlation (+)   **Cool season correlation (+)**
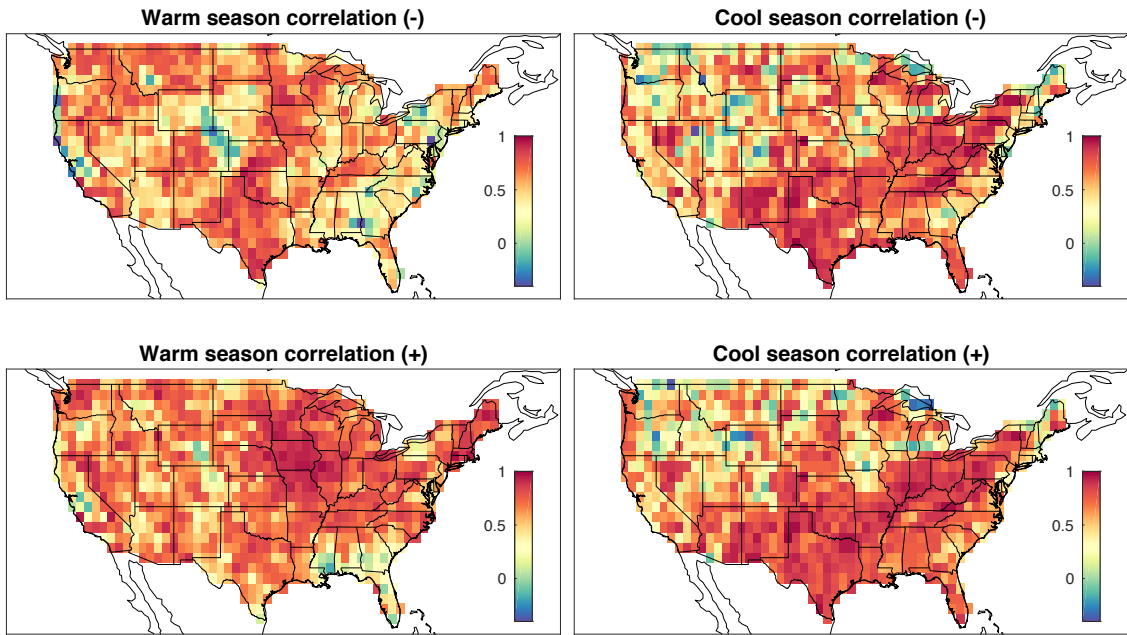
FIG. 8. Correlation of CP with negative (top row) and positive (bottom row) CG flashes during the warm (May–October; left column) and cool (November–April; right column) seasons 2003–2016.

Warm season normalized MSE (-) · **Cool season normalized MSE (-)** · **Warm season normalized MSE (+)** · **Cool season normalized MSE (+)**
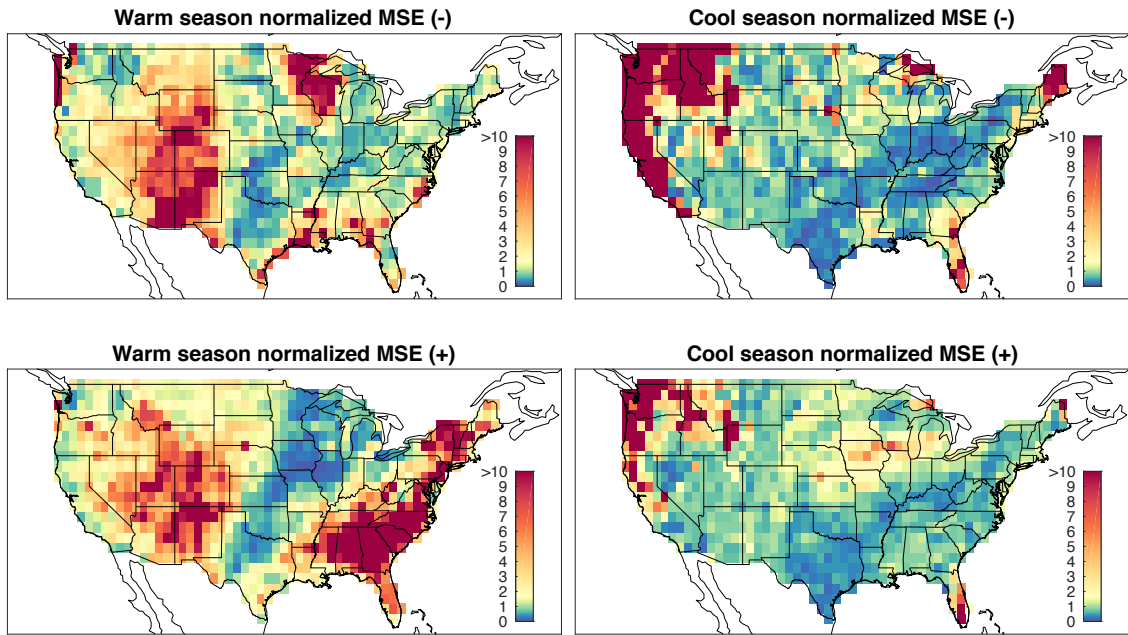
FIG. 9. Normalized (relative to climatological variance) MSE of the difference of CP with negative (top row) and positive (bottom row) CG flashes during the warm (May–October; top row) and cool (November–April; bottom row) seasons 2003–2016.

List of Supporting information tables

Table S1. States in NOAA climate regions.

South	TX, OK, LA, AR, KS, MS.
Southeast	FL, AL, GA, SC, NC, VA
Northeast	MD, DE, PA, NJ, NY, CT, RI, VT, MA, NH, ME.
Central	TN, MO, IL, IN, OH, KY, WV.
Upper Midwest	IA, MN, WI, MI.
Plains	WY, NE, MT, ND, SD.
Southwest	AZ, NM, UT, CO.
Northwest	OR, ID, WA.
West	CA, NV.

734 Table S2. Percent of negative NLDN CG flashes occurring in each NOAA region and month 2003–2016.

735 Values of 0.00 indicate less than 0.01%.

Region	J	F	M	A	M	J	J	A	S	O	N	D	annual
South	0.10	0.16	0.48	0.89	1.63	3.69	4.88	3.71	0.98	0.22	0.07	0.10	16.92
Southeast	0.26	0.50	1.32	3.44	5.99	6.67	5.50	5.48	2.15	1.33	0.56	0.37	33.58
Northeast	0.08	0.12	0.45	1.26	2.71	4.07	4.53	3.52	1.14	0.42	0.15	0.07	18.52
Central	0.01	0.01	0.08	0.27	0.79	1.60	1.80	1.53	0.66	0.19	0.04	0.00	6.98
Upper Midwest	0.00	0.00	0.05	0.22	1.01	2.39	2.39	2.03	0.66	0.13	0.01	0.00	8.89
Plains	0.00	0.01	0.02	0.08	0.44	0.90	1.16	0.85	0.23	0.04	0.01	0.00	3.75
Southwest	0.00	0.01	0.05	0.14	0.55	1.08	3.19	3.05	1.07	0.36	0.03	0.01	9.56
Northwest	0.00	0.00	0.00	0.02	0.09	0.15	0.19	0.20	0.06	0.01	0.00	0.00	0.72
West	0.00	0.00	0.01	0.02	0.06	0.09	0.35	0.33	0.15	0.06	0.00	0.00	1.09
CONUS	0.45	0.82	2.46	6.34	13.29	20.64	23.98	20.71	7.11	2.77	0.88	0.55	100.00

Ratio (%) of negative CG flashes to total 2003-2016

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Ratio of NLDN flashes (-) to CP   **Ratio of NLDN flashes (+) to CP**
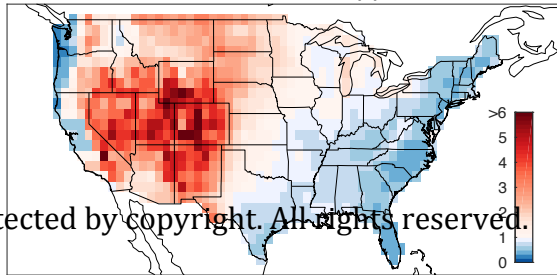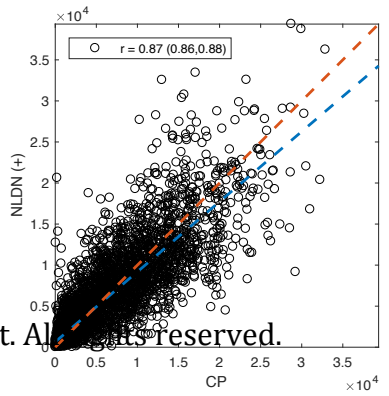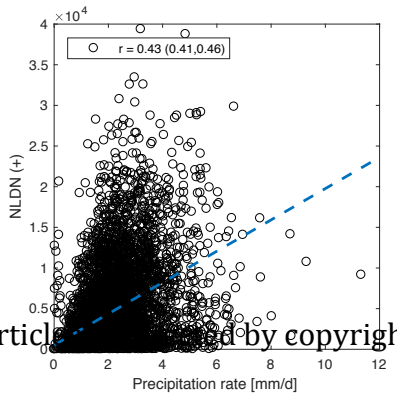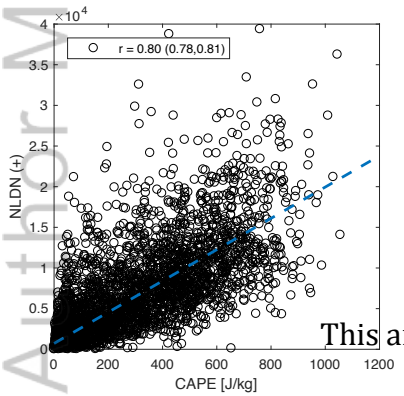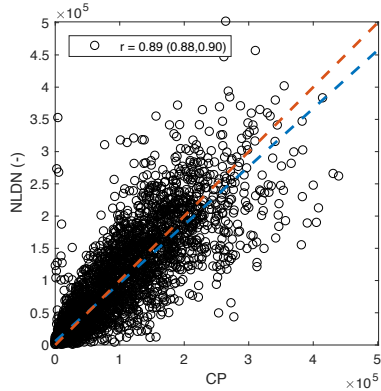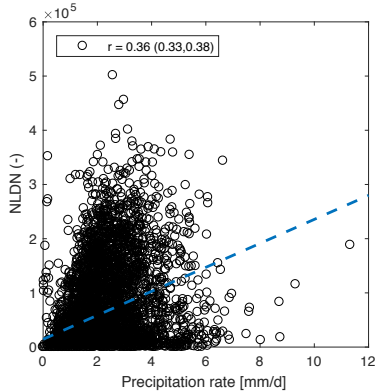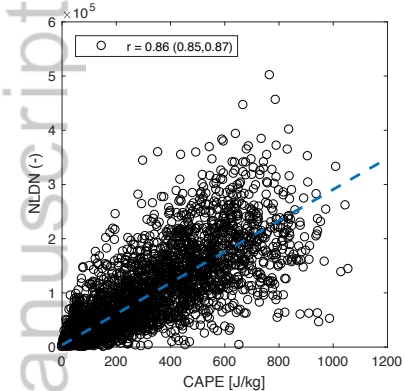
Negative

Positive
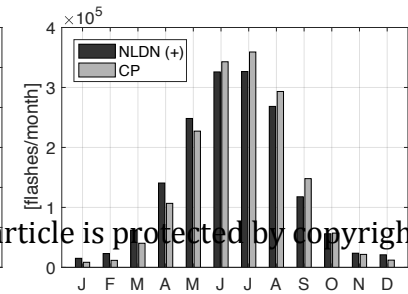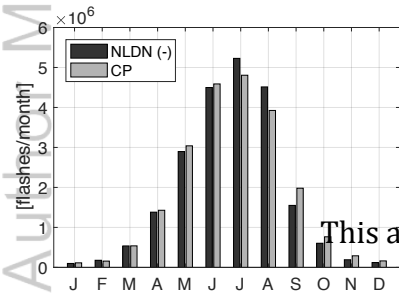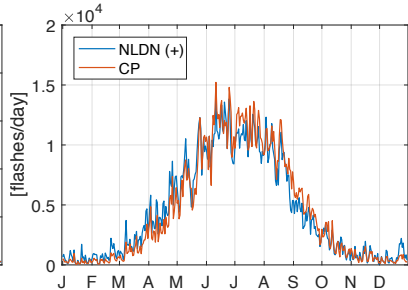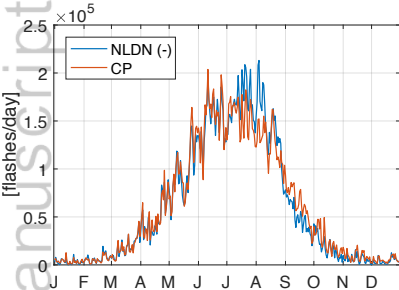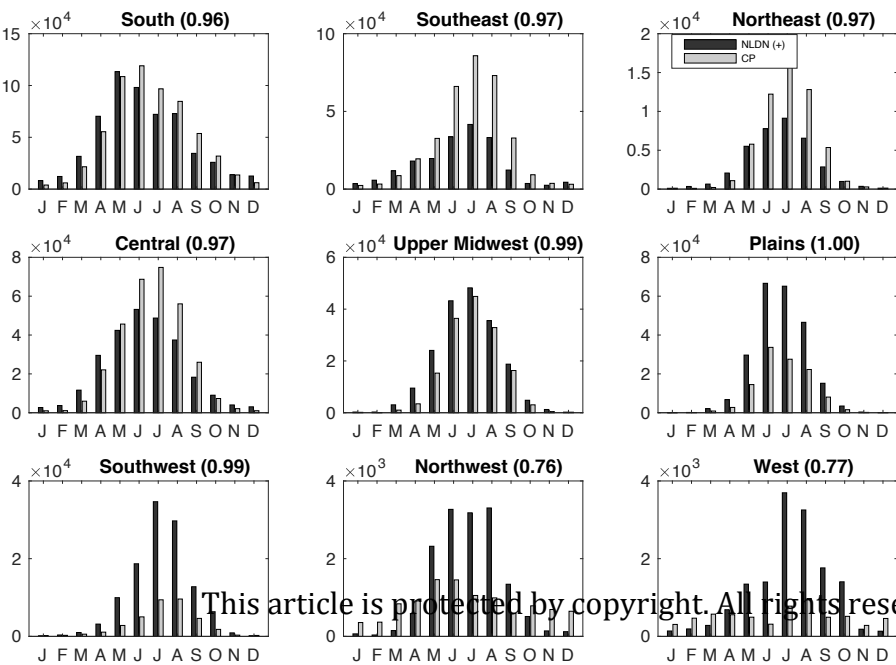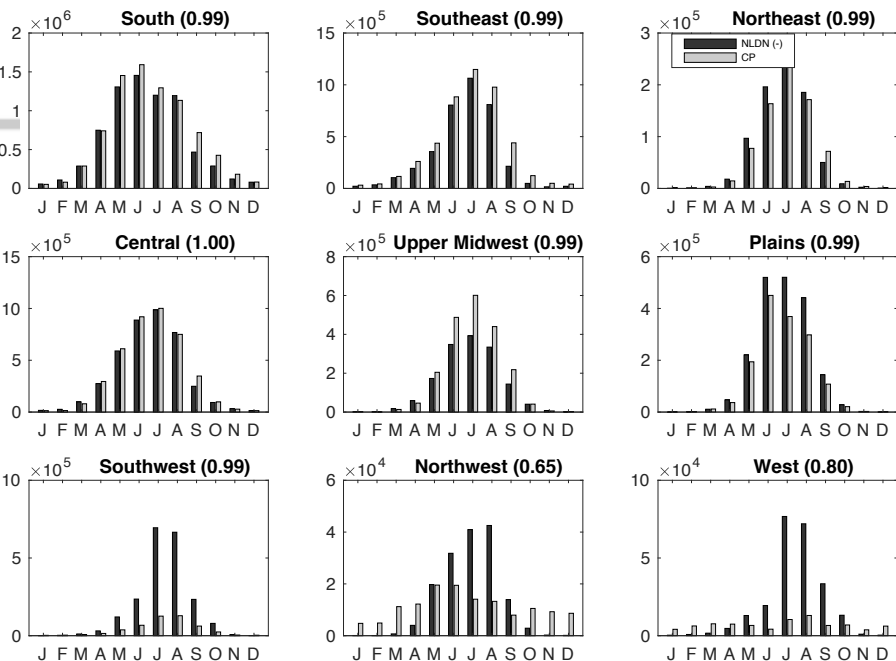
Annual flashes (-) 2003-2016
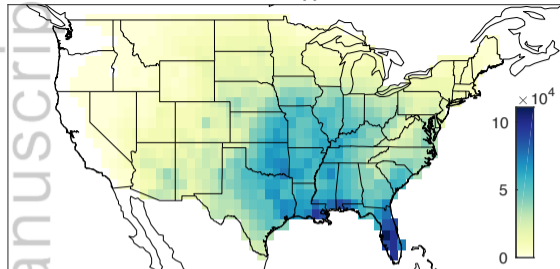
Annual flashes (+) 2003-2016
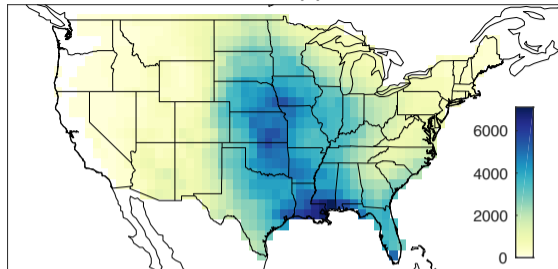
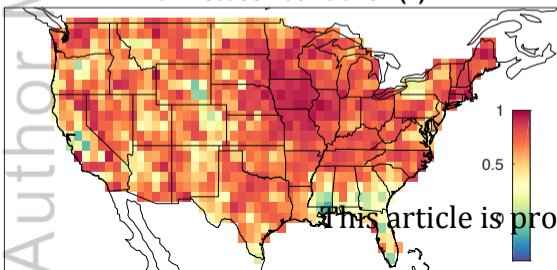**Scaled CP (-) 2003-2016**

Scaled CP (+) 2003-2016

Warm season correlation (-) | **Cool season correlation (-)**
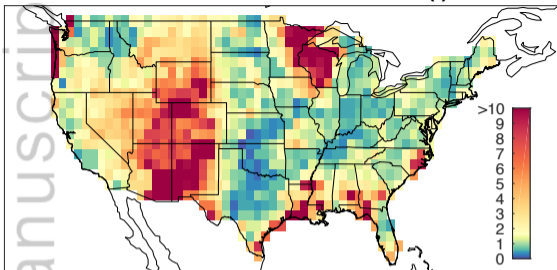
Warm season correlation (+) | **Cool season correlation (+)**
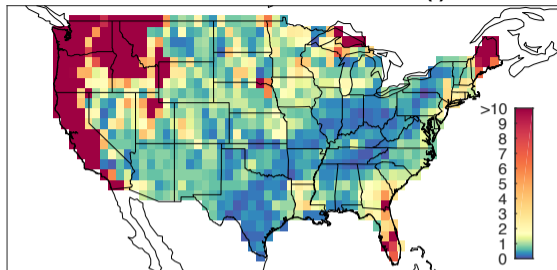
Warm season normalized MSE (-)   **Cool season normalized MSE (-)**
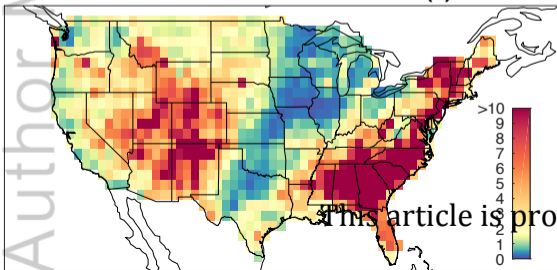
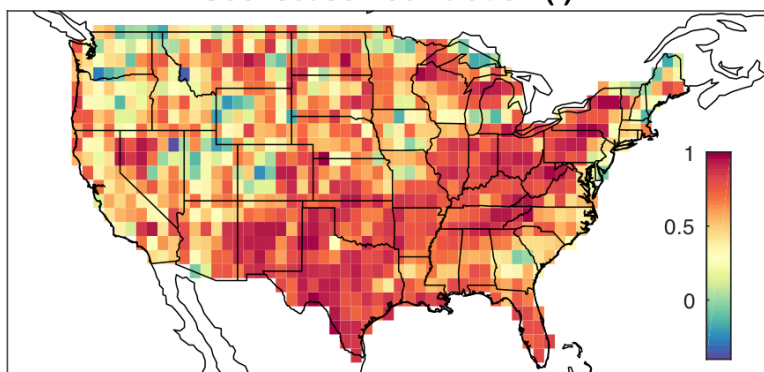**Warm season normalized MSE (+)**   **Cool season normalized MSE (+)**
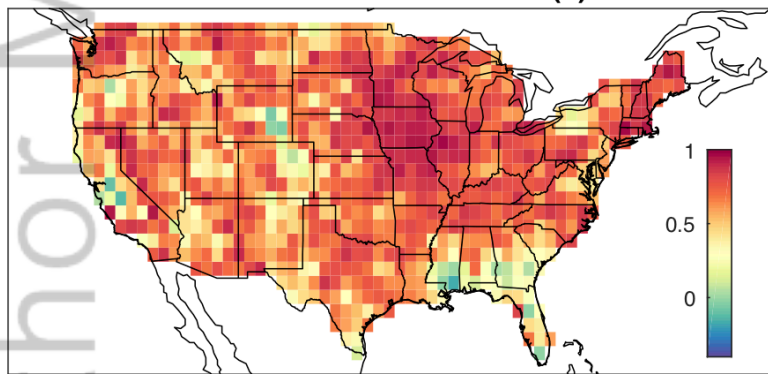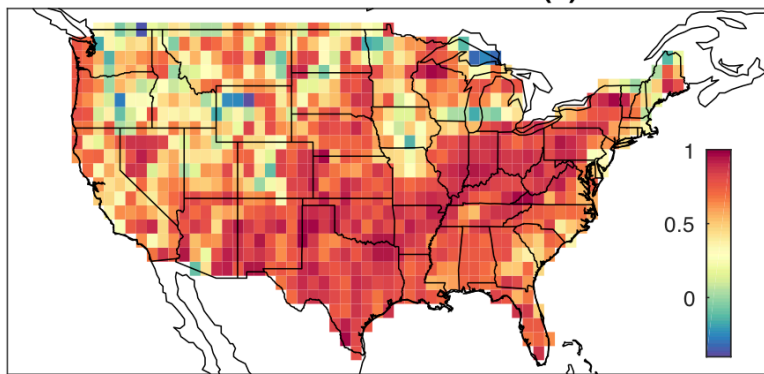
Warm season correlation (-)   Cool season correlation (-)
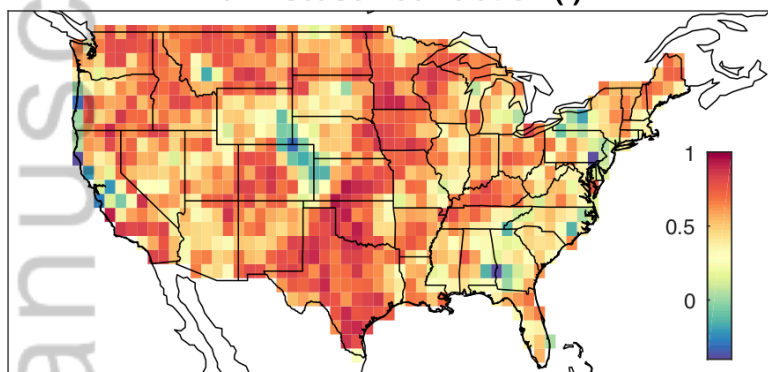
Warm season correlation (+)   Cool season correlation (+)

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