Projection of Global Future Lightning Occurrence using only Large-Scale Environmental Variables in CAM5

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Key Points:

- A single-equation based only on environmental variables provides reasonable land and ocean lightning occurrence predictions in CAM5.
- Lightning occurrence is projected to increase at higher latitudes by the end of century, but the long-term trend varies across the tropics.
- Basic state biases and the type of CAPE used can impact current and future predictions of lightning patterns and magnitudes.

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Abstract

This study evaluates a lightning parameterization that utilizes only large-scale environmental variables (i.e., convective available potential energy (CAPE), column moisture, and lifting condensation level (LCL)) for present-day (2017-19) and end-of-century (2098-2100) RCP8.5 climate scenarios in the Community Atmosphere Model version 5 (CAM5). Using a single equation, the present-day prediction can produce a reasonable land/ocean ratio in lightning occurrence. The end-of-century prediction shows relative increases of about 50% over higher-latitude land, but much more variable increases and decreases across mid-latitude ocean and the tropics such that the overall global lightning occurrence is expected to slightly decrease. Lightning occurrence over land predicted from present-day CAM5 is less than that using MERRA-2 reanalysis because of differences in the basic-state variables used as predictors. In addition, the choice of dilute or undilute CAPE will impact future lightning predictions over land, but the environment-only parameterization results are more consistent than a CAPE×precipitation parameterization.

Plain Language Summary

Lightning parameterizations currently being used in climate model studies use output from other physical parameterizations (i.e., cloud ice, precipitation, etc.). These variables have large uncertainties that propagate into the lightning prediction and can vary strongly amongst models, thus requiring scaling factors to produce realistic and consistent lightning predictions. In addition, almost all existing parameterizations require separate land and ocean equations to produce reasonable global lightning patterns, and many still produce unrealistic ratios with too much oceanic lightning. We show here that we can produce a reasonable global lightning occurrence distribution in a climate model using only three large-scale environmental variables derived from temperature and humidity profiles and a single equation applicable to both land and ocean components. While these variables can still have uncertainties and biases amongst models, they are less than the cloud and precipitation outputs, thus providing a more stable framework for assessing lightning changes. Our end-of-century projection under a high-emissions scenario shows relatively large increases in lightning occurrence over land at mid- and high-latitudes in the Northern Hemisphere, but a varying pattern of increases and decreases across the tropics such that the global mean lightning occurrence is expected to slightly decrease by the end of the century.

1 Introduction

Understanding lightning and its relationship with the large-scale environment is important in simulating lightning in global climate models (GCMs) in order to predict how lightning will vary with climate change, and how upper-tropospheric chemistry and wildfires associated with lightning will be impacted (e.g., Krause et al., 2014; Whaley et al., 2024). The large-scale environment plays a key role in storm dynamics, and therefore lightning development. Most previous studies have investigated lightning's relationship with cloud features and precipitation, but few have isolated the role of the large-scale environment for the prediction of lightning.

One of the earliest parameterizations predicted lightning flash rates using only convective cloud-top height (Price & Rind, 1992, hereafter PR92) and has been used as the basis of many other parameterizations (Boccippio, 2002; Luhar et al., 2021; Michalon et al., 1999; Zhang et al., 2021). In a warming climate, parameterizations that use PR92 typically predict a global increase in lightning (Clark et al., 2017; Finney et al., 2018; Krause et al., 2014; Price & Rind, 1994). However, PR92 uses separate land and ocean equations to predict lightning and requires a scaling of these equations to the observed global mean lightning. In addition, convective cloud-top height, especially when output as a grid-scale value from a coarse-resolution GCM, is a highly-derived variable and remains an indirect measure of convective intensity and lightning.

Different cloud and rain variables have since been utilized in lightning parameterizations from GCM output such as convective mass flux (Allen & Pickering, 2002; Grewe et al., 2001; Magi, 2015), upward cloud ice flux (Deierling et al., 2008; Finney et al., 2014; Romps, 2019), convective precipitation (Allen & Pickering, 2002; Magi, 2015; Meijer et al., 2001), cloud droplet concentration (Michalon et al., 1999), graupel mixing ratio and updraft velocities (McCaul et al., 2009; Williams, 2005; Zipser & Lutz, 1994), cold cloud depth (Yoshida et al., 2009), and cloud base height (Lopez, 2016). Most of these parameterizations produce general increases in lightning flash rates for warming climates (Clark et al., 2017; Finney et al., 2016, 2020), except when using ice-based parameterizations (Finney et al., 2018; Romps, 2019). However, these frameworks still require separate land and ocean equations and often need to be scaled to the current global mean lightning to provide a realistic prediction. In addition, Charn and Parishani (2021) found that the ice-based lightning parameterizations may be sensitive to the microphysics scheme used, not necessarily to the variables used to predict lightning, which adds motivation to avoid highly uncertain storm-scale variables as inputs for lightning parameterizations in GCMs.

The inclusion of large-scale environmental variables in predicting lightning in GCMs has become more prevalent in recent years (Romps et al., 2014; Stolz et al., 2015, 2017; Wang et al., 2018; Etten-Bohm et al., 2021) and could help reduce the large uncertainty that is carried when using cloud and convection variables as predictors. Utilizing large-scale variables like convective available potential energy (CAPE) can be beneficial because of how closely it relates to a storm's thermodynamics. Romps et al. (2014) (hereafter R14) used CAPE and precipitation (CAPE$\times$P) over the continental United States (CONUS) to predict lightning flash rate. Evaluating the parameterization in multiple GCMs, R14 found that CAPE increased over CONUS between the current climate and late 21st century in all the models, therefore also increasing the lightning flash rate. It is worthwhile noting that future projection of precipitation sometimes increased and sometimes decreased depending on the GCM and did not constrain the lightning prediction nearly as much as CAPE.

Although the R14 parameterization performed well over CONUS, it did not translate well on a global scale because it could not distinguish between land and ocean (Romps et al., 2018). Cheng et al. (2021) had better success using a different equation over ocean, but a similar issue as discussed previously occurs with an arbitrary separation of land and ocean equations to predict lightning. Stolz et al. (2015, 2017) were better able to differentiate land and ocean lightning environments by using a combination of cloud and environmental parameters in a multiple linear regression model, but still did not completely capture the spatial pattern of global lightning, overpredicting over the ocean and underpredicting over land (Stolz et al., 2021).

Etten-Bohm et al. (2021) (hereafter EB21) presented a lightning parameterization based solely on large-scale environmental variables, with the goal of limiting the issues and uncertainty in other parameterizations mentioned previously. EB21 evaluated a number of covariate sets from reanalysis output and each prediction represented the spatial pattern of lightning occurrence well, including a distinction between land and ocean using just one equation. They found that the use of three environmental variables (CAPE, lifting condensation level [LCL], and column saturation fraction [r]) and their interactions provided the best basis for a GCM parameterization in terms of performance and simplicity.

The main goals of this study are to implement and evaluate this EB21 environment-only lightning parameterization in the high-resolution (25 km) Community Atmosphere Model version 5 (CAM5), project end-of-century global lightning occurrence changes, and determine the environmental factors most important to the changes. Additionally, we will assess how the EB21 parameterization performs compared to the CAPE×P parameterization over land, including sensitivity tests using different CAPE calculations (i.e., dilute and undilute) since there aren't standard definitions of CAPE in GCMs.

2 Data and Methods

EB21 utilized a logistic regression trained on Tropical Rainfall Measuring Mission (TRMM) Lightning Imaging Sensor (LIS) observations (Kummerow et al., 1998) and Modern-Era Retrospective Analysis for Research and Application Version 2 (MERRA-2) reanalysis data (Gelaro et al., 2017) to predict lightning occurrence based on 3-hourly, 0.5° input. EB21 tested three predictor sets increasing in complexity from model **a** to **c**. Only model **b** (with predictors CAPE, LCL, r, and their interactions) will be evaluated in this study since it provided the best balance between simplicity and performance amongst the three models. The parameterization outputs the predicted probability of lightning occurrence at each grid point from zero (0% chance) to one (100% chance).

The GCM environmental predictors for this study were obtained from a 0.25° resolution, free-running version of CAM5 (Meehl et al., 2019; Neale et al., 2012). Three-hourly temperature, LCL, and specific humidity fields were interpolated to a 0.5° grid to match the LIS and MERRA-2 datasets. CAPE and r were then computed from the temperature and specific humidity profiles, and all variables were standardized to have a mean of zero and a standard deviation of 1. The CAM5 predictors for present day (2017-19) were input into the EB21 parameterization, which was further applied to the end-of-century (2098-2100) simulation under the Representative Concentration Pathway (RCP) 8.5 scenario to assess the relative impact of a warming climate on lightning production. Note that since CAM5 is free running, the years chosen may not specifically correspond to those years, but using three years should still provide a reasonable mean representation of the present-day and future climates.

CAPE can be obtained directly from CAM5 output, but CAM5 uses a dilute-plume model where entrainment of environmental air is incorporated (Neale et al., 2008). Using the CAPE×P parameterization, Charn and Parishani (2021) found that lightning predictions varied depending on how CAPE was calculated, with undilute CAPE projecting a $\sim 7\%/\mathrm{K}$ increase in lightning and dilute CAPE only projecting a $\sim 1\%/\mathrm{K}$ increase. The authors noted that neither case is completely correct, and flash rates predicted using CAPE×P are likely somewhere between the two cases. Only undilute CAPE will be used in Sections 3.1 and 3.2, with a caveat that greater decreases could be projected as a result. Sensitivity tests using dilute CAPE will be presented in Section 3.3.

3 Results

3.1 CAM5 Lightning Projection

CAM5 fields were input into the logistic regression from EB21 to compute a predicted mean lightning occurrence and compared to the International Space Station (ISS) LIS (Blakeslee et al., 2020, Figure 1a) for present day (2017-19). Although the lightning parameterization was trained with TRMM LIS observations, the ISS expands on the latitudinal extent of TRMM (from 35° to 54°) and allows for greater comparison with CAM5's global output. Following EB21, elevation over 1500 meters is removed because of the inaccurate predictions from the logistic regression, likely due to the LCL term. Whaley et al. (2024) found improvements by disregarding the LCL term over high elevation in version 5.1 of the Canadian Earth System Model (CanESM). Figure 1b is similar to Figure 9c in EB21 except for using years 2017-19 and all latitudes. The overall magnitudes increase in Figure 1b as a result of the standardization of the predictors to have a mean of zero and a standard deviation of 1. The fields change when extending to higher latitudes, resulting in different standardized variables, and therefore predictions.

The MERRA-2 lightning predictions in Figure 1b match the LIS observations well (as expected since the parameterization was trained using MERRA-2 data), albeit with some overprediction over the ocean. For example, the land/ocean lightning occurrence ratio observed by ISS LIS is 5.1, while the MERRA-2 ratio for the same latitude range is 2.2. However, these ratios are much closer to one another than the land/ocean flash rate ratios reported by Charn and Parishani (2021) between observations and five other lightning parameterizations, some of which had land/ocean lightning ratios less than 1.

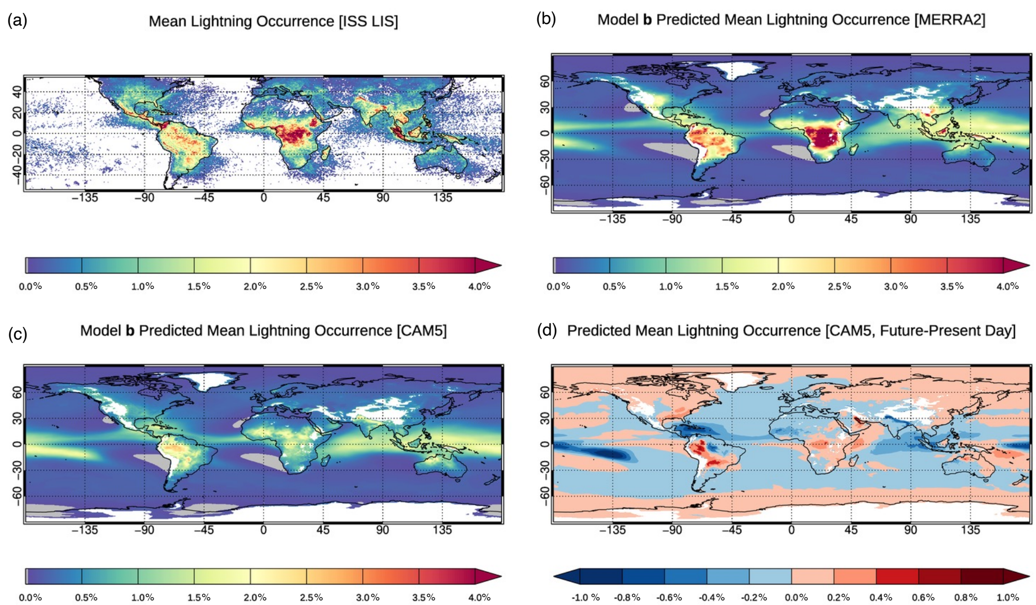

Figure 1. Present-day (2017-2019) lightning occurrence (in %) from (a) ISS LIS observations and (b) MERRA-2 and (c) CAM5 predictions using the EB21 parameterization. (d) CAM5 lightning occurrence difference between end-of-century (2098-2100) and present-day.

When applied to CAM5 environmental variables, the EB21 lightning parameterization produces a large underprediction over land (Figure 1c). However, expected regional variations still exist, including more lightning over the Amazon and central Africa compared to other land regions and greater overall lightning occurrence over land compared to ocean with a land/ocean ratio of 1.5. This result is promising considering that the parameterization does not have separate equations for land and ocean and does not scale the prediction to match the global mean lightning observations, which most previous lightning parameterizations have done (e.g., Clark et al., 2017). An environment-only lightning parameterization would also be expected to be more consistent between different GCMs, since cloud and precipitation variables, highly parameterized in GCM themselves, can vary much more widely compared to environmental variables (e.g., Charn & Parishani, 2021; Romps et al., 2014). However, discrepancies between the basic-state input parameters must exist between MERRA-2 and CAM5 to account for the difference in the lightning predictions in Figures 1b and c, which will be addressed in Section 3.2.

The EB21 parameterization was further applied to output from a CAM5 end-of-century high-emissions climate run. Figure 1d indicates varied future changes in lightning occurrence over both land and ocean with increases (decreases) shown in red (blue). While many land regions indicate increasing lightning occurrence, including most higher latitude land in the Northern Hemisphere, the southeastern US, western Amazon, central Africa, and eastern Australia, other land regions show decreases, such as the central US, northeastern Amazon, Sahel, Indian subcontinent, and western Australia. The ocean shows large absolute decreases over regions that tend to have more lightning in present-day CAM5, like the South Pacific convergence zone, Caribbean Sea, Atlantic ITCZ, and Indian Ocean. Lightning is projected to increase over the ocean near the edges of these higher lightning occurrence regions. Despite many regions of increases, including higher-latitude land regions that show a relative increase of $\sim$50%, the global mean lightning occurrence is predicted to decrease by about 5%. These results are generally consistent with end-of-century predictions using the EB21 parameterization on output from CanESM5.1 (Whaley et al., 2024).

Figure 1d contrasts with many previous studies that have shown more widespread increases (Clark et al., 2017; Finney et al., 2016; Romps et al., 2014; Schumann & Huntrieser, 2007; Williams, 2005) or decreases (Jacobson & Streets, 2009) in global tropical lightning flash rates in a warming climate. However, lightning parameterizations are not only sensitive to the parameters used (Finney et al., 2018; Romps, 2019), but also the methodologies used to train the parameterization and the models in which they are implemented. For example, Finney et al. (2020) used a high-resolution, convection-permitting model and the McCaul et al. (2009) ice-based lightning parameterization to investigate lightning day changes (similar to lightning occurrence) regionally and found a similar, albeit opposite, varied pattern to the one presented in Figure 1d over Africa.

3.2 Basic-state Variable Analysis

To evaluate environmental factors driving differences between the MERRA-2 and CAM5 present-day lightning predictions and changes in the projected mean lightning occurrence between present-day and end-of-century climate scenarios in CAM5, the three predictors (LCL, r, and undilute CAPE) are investigated separately. Figure 2 (left column) shows histograms of each variable over land (green) and ocean (blue) from MERRA-2 (solid) and CAM5 (dashed). While the MERRA-2 and CAM5 environmental variable distributions show general similarities, there are some notable differences that help explain the discrepancies between their lightning predictions in Figure 1. For example, while LCLs maximize around 900 hPa in both datasets (Figure 2a), offsets occur as LCLs get higher. For MERRA-2, land has relatively more LCLs between 850 and 650 hPa compared to ocean, while the opposite is true for CAM5 where the ocean has higher LCLs than land. Higher LCLs (more convective environment) would increase lightning occurrence (as shown in EB21), providing one reason why lightning occurrence is underpredicted over land and overpredicted over ocean in CAM5.

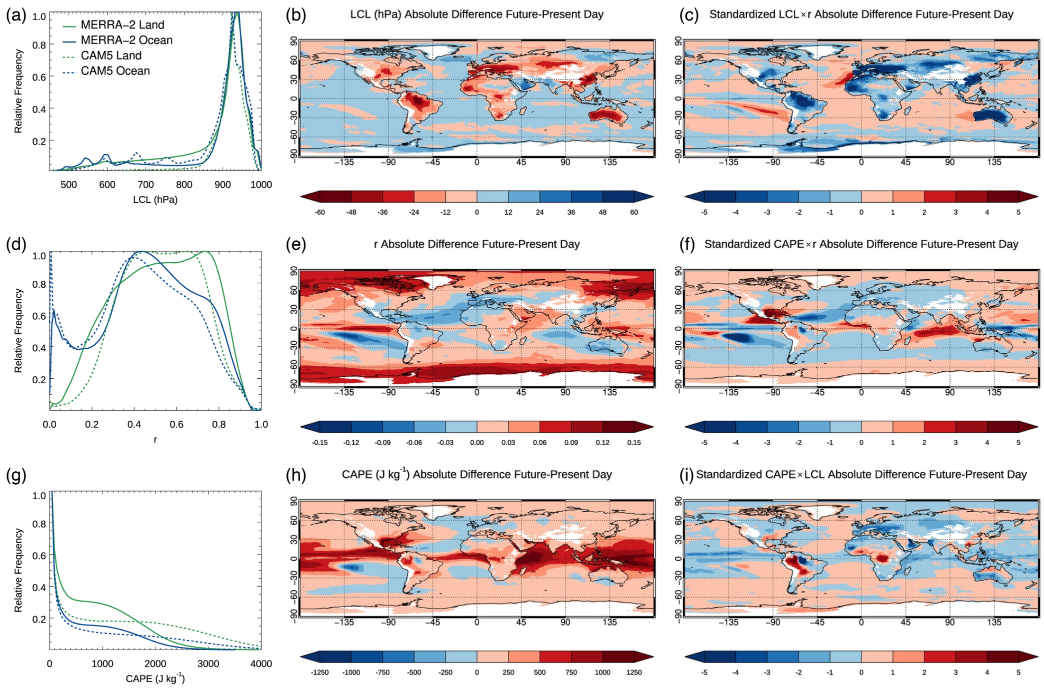

Figure 2. Histograms of land and ocean environmental variables for MERRA-2 and CAM5 for (a) LCL, (d) r, and (g) undilute CAPE for present day. Absolute differences between CAM5 end-of-century and present-day climates for (b) LCL, (e) r, and (h) CAPE and standardized interactions (c) LCL and r, (f) CAPE and r, and (i) CAPE and LCL.

In addition, Figure 2d shows that CAM5 r is shifted left (indicating a drier environment) compared to MERRA-2 over both land and ocean at r values where lightning is most likely to occur (i.e., r $>$ 0.7, EB21). This shift also helps explain why large lightning underpredictions happen over land in CAM5, while the drier ocean environments likely offset the higher LCLs making the CAM5 ocean lightning prediction more similar to MERRA-2.

The CAPE distribution comparisons are more nuanced. Figure 2g indicates that MERRA-2 has a higher occurrence of moderate CAPE (up to 1800 J kg^{-1}) compared to CAM5, but that CAM5 produces more CAPE values $>$ 1800 J kg^{-1}. EB21 showed that essentially any positive CAPE would enhance lightning occurrence so it is unclear how these distribution differences would contribute to MERRA-2 and CAM5 lightning prediction differences.

To evaluate the spatial variability of the environmental variables and their potential contribution to end-of-century lightning changes, the middle column of Figure 2 shows the absolute change between the future and present-day for each of the individual predictors from CAM5. Red represents changes that would be expected to enhance lightning occurrence, and blue is the opposite. Note that we standardize individual predictors around their mean values before they are input into the logistic regression such that the standardized inputs (not shown) will shift to be more negative (blue) for r and CAPE because their mean individual change at the end of the century is greater than zero, while the mean LCL change is around zero.

Figure 2b shows that LCL decreases up to 60 hPa almost everywhere over land (i.e., attains higher heights) by 2100, except for a handful of regions like Saudi Arabia and the Indian subcontinent where LCLs increase by 15-30 hPa (i.e., become lower in height). The opposite is true almost everywhere over the ocean, where LCL values are projected to increase and thus lower in height by the end of the century, although the magnitude of change is much smaller than over land. The LCL changes in Figure 2b only partially align with the lightning changes in Figure 1d (i.e., the LCL pattern suggests large lightning increases over land and smaller decreases over ocean globally) so other variables and their interactions remain at play.

Future r shows large increases in CAM5 pole-ward of 45°N and 45°S and more varied changes over land and ocean in the tropics and subtropics (Figure 2e). Changes in r often offset the influence of LCL on end-of-century lightning occurrence. For example, decreases in lightning over the eastern Amazon, West Africa, Siberia, and western Australia are more consistent with the r pattern. However, changes in lightning over the western Amazon, Congo, Indian subcontinent, and China remain more consistent with the LCL pattern. Alaska is one of the few land regions where the sign change is consistent between LCL, r, and lightning occurrence. Over ocean, r appears to play an important role in the lightning decreases over the Southeast Pacific, Caribbean, tropical North Atlantic, and near-equatorial Indian Ocean.

Lastly, CAPE shows end-of-century absolute increases almost everywhere, especially across the rainy regions of the tropical oceans with most areas increasing 500 to 1250 J kg^{-1} (Figure 2h). These increases are consistent with Romps (2016) who found that CAPE should increase in a warming climate following the Clausius-Clapeyron relation, and J. Chen et al. (2020) who showed similar CAPE differences globally between 1980-99 and 2081-2100. There are only a few areas in which notable decreases in CAPE occur: the Southeast Pacific, central Amazon, and Atlantic Ocean along 20°N. While the largest absolute CAPE changes are projected to occur over the ocean, the oceanic pattern is generally not consistent with the end-of-century lightning changes in Figure 1d, whereas the relatively smaller CAPE changes over land appear to be more relevant, especially over the Southeast US, South America, central Africa, and eastern Australia.

The difference in standardized interactions between future and present day are plotted in the right column of Figure 2. Note that the interaction terms account for 19% of the relative importance in the logistic regression, while the individual predictors account for the other 81% (EB21). Also, all columns are multiplied by -1 since all interactions have negative coefficients and we still want to represent conditions likely to lead to increases in lightning in red, and decreases in blue. The LCL×r interaction results in lightning decreasing almost everywhere over land, offsetting the large LCL height increases. However, most places over oceanic locations would result in a net increase in lightning from this interaction. CAPE×r shows a more variable global signature, while the CAPE×LCL interaction appears to best align with the future lightning changes in CAM5, which is consistent with EB21 as the CAPE×LCL term is the most important of the three interactions.

Figure 2 shows that CAPE, LCL, and r all play an important role in predicting lightning in present and future climate scenarios, but large regional variability exists. For example, r and CAPE are the most relevant variables over South America (i.e., their end-of-century predictions are most similar to the overall prediction in Figure 1), while LCL is the only variable that predicts an increase in lightning over Australia (albeit overly intense such that the negative predictions from the other variables appear to mute this overprediction). The interactions improve the predictive potential of the logistic regression, including helping mitigate some of the overprediction over the ocean that plagues other lightning parameterizations.

3.3 Dilute vs Undilute CAPE

While LCL and r are either direct outputs or found by a straightforward calculation from GCM environmental variables, CAPE has numerous formulations. Undilute CAPE is about an order of magnitude larger than dilute CAPE, so we consider them spanning the range of possible CAPE values. Recall that dilute CAPE is output by CAM5, while undilute CAPE must be calculated but is closer to the CAPE used in previous parameterization studies, including EB21 and R14. We use total precipitation in the following CAPE×P calculations, but note that two of the four precipitation data sets in Romps et al. (2018) were convective-only. However, the use of convective precipitation doesn't qualitatively change our results.

Figure 3 shows the change in end-of-century lightning occurrence for the EB21 parameterization and flash rate for CAPE×P using undilute and dilute CAPE. Similar to Charn and Parishani (2021), we scaled each present-day prediction to match the mean land ISS LIS lightning observations to more fairly compare future changes. The EB21 and R14 parameterizations produce very similar patterns of lightning increases and decreases using undilute CAPE (Figures 3a and c). EB21 produces larger increases in lightning occurrence when using dilute CAPE (Figure 3b), but the pattern of negative and positive changes still strongly resembles the undilute CAPE result in Figure 3a.

The largest difference occurs when dilute CAPE is used in R14 (Figure 3d). Almost all land regions show end-of-century decreases in flash rate, especially in the tropics. Charn and Parishani (2021) also showed larger decreases in flash rate using dilute CAPE in various formulations of CAPE×P in a +4 K sea-surface temperature (SST) simulation of a superparameterized version of CAM, although the decreases were not as dramatic as seen here. The sign of change between the EB21 undilute and dilute CAPE results (Figures 3a and b) is more consistent because the predictors are normalized about their mean before being used in the parameterization. The inclusion and interactions with the other environmental inputs also limits large changes due to only one variable.

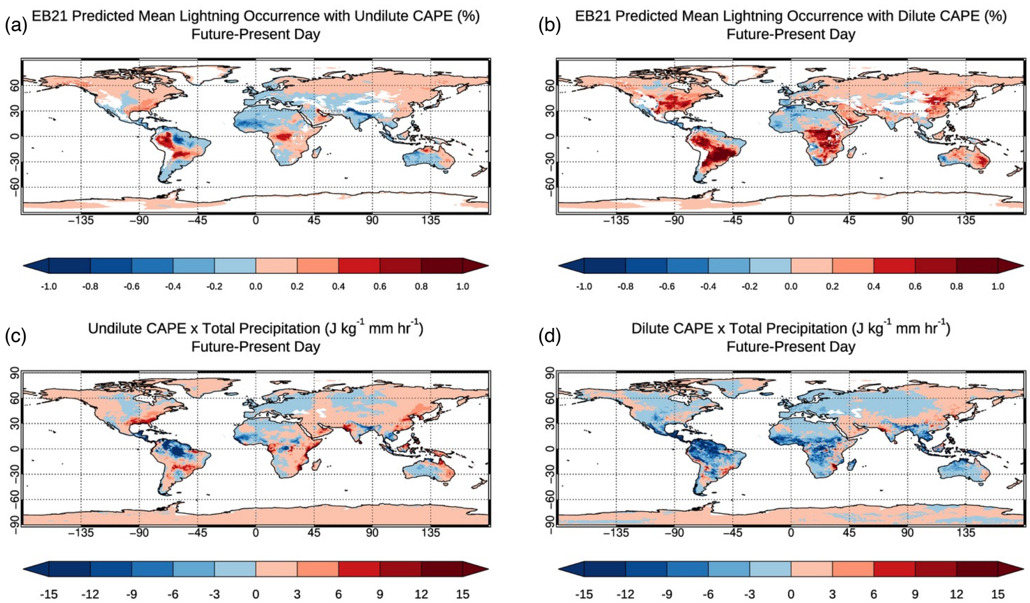

Figure 3. Predictions after present-day scaling to ISS LIS land values of CAM5 end-of-century land-only lightning occurrence (in %) using the EB21 parameterization with (a) undilute and (b) dilute CAPE and flash rate (in J kg^{-1} mm hr^{-1}) using the R14 CAPE×P parameterization with (c) undilute and (d) dilute CAPE.

4 Conclusions

The EB21 lightning parameterization, which utilizes LCL, CAPE, r, and their interactions, was implemented in CAM5 for present-day (2017-19) and end-of-century (2098-2100) RCP8.5 climate scenarios. Compared to observations from ISS LIS, the CAM5 present-day prediction generally captures the global lightning occurrence pattern but underpredicts lightning over land and overpredicts over the ocean. This is a perennial problem with almost all GCM lightning parameterizations (e.g., Charn & Parishani, 2021; Clark et al., 2017), but the EB21 parameterization produces a better land/ocean lightning ratio than most other schemes when applied to CAM5 fields and does so with a single equation not separated by land and ocean. The land/ocean ratio improves even further when the EB21 parameterization is applied to MERRA2 fields, which can be explained by differences in the individual basic-state predictors. For example, LCLs are higher over land in MERRA-2 compared to CAM5, while the opposite is true over ocean, causing relatively higher lightning occurrence over land for MERRA-2 and over ocean for CAM5. In addition, land and ocean environments are drier in CAM5 for moist environments compared to MERRA-2, causing even further underpredictions of lightning occurrence over land for CAM5, although the drier ocean environments offset the overly high oceanic LCLs to some extent in the EB21 logistic regression formulation.

The end-of-century lightning projection from CAM5 shows variable increases and decreases over both land and ocean, although higher latitude land regions show across-the-board increases in frequency, which has implications for increased wildfires in locations that typically don't experience much lightning (Y. Chen et al., 2021; Whaley et al., 2024). The large regional variability in positive and negative lightning changes, especially in the tropics, is of significance as many previous studies (e.g., Finney et al., 2018) have found either widespread increases or decreases for tropical lightning activity in a warming climate. The resulting global mean lightning occurrence is projected to slightly decrease by the end of the century, which is consistent with the lower end of the range of flash rate changes found in Clark et al. (2017) based on results from eight lightning parameterizations using CAM5 output. When the EB21 parameterization is run with dilute CAPE instead of undilute CAPE, it provides a more consistent future lightning prediction than a CAPE×P parameterization. The EB21 parameterization is simple and stable to moderate variations in input parameters, providing an attractive alternative to lightning parameterizations that rely on variables output from convective, cloud, and microphysics schemes.

Acknowledgments

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5 Open Research

5.1 Data Availability Statement

ISS LIS data were obtained from NASA GHRC (`https://ghrc.nsstc.nasa.gov/lightning/data/data_lis_iss.html`) and MERRA-2 data were obtained from NASA GMAO (`https://gmao.gsfc.nasa.gov/reanalysis/MERRA-2/`). The processed CAM5 data is available on the Texas Data Repository (`https://dataverse.tdl.org/dataset.xhtml?persistentId=doi:10.18738/T8/58NOQU`).

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Figure 1.

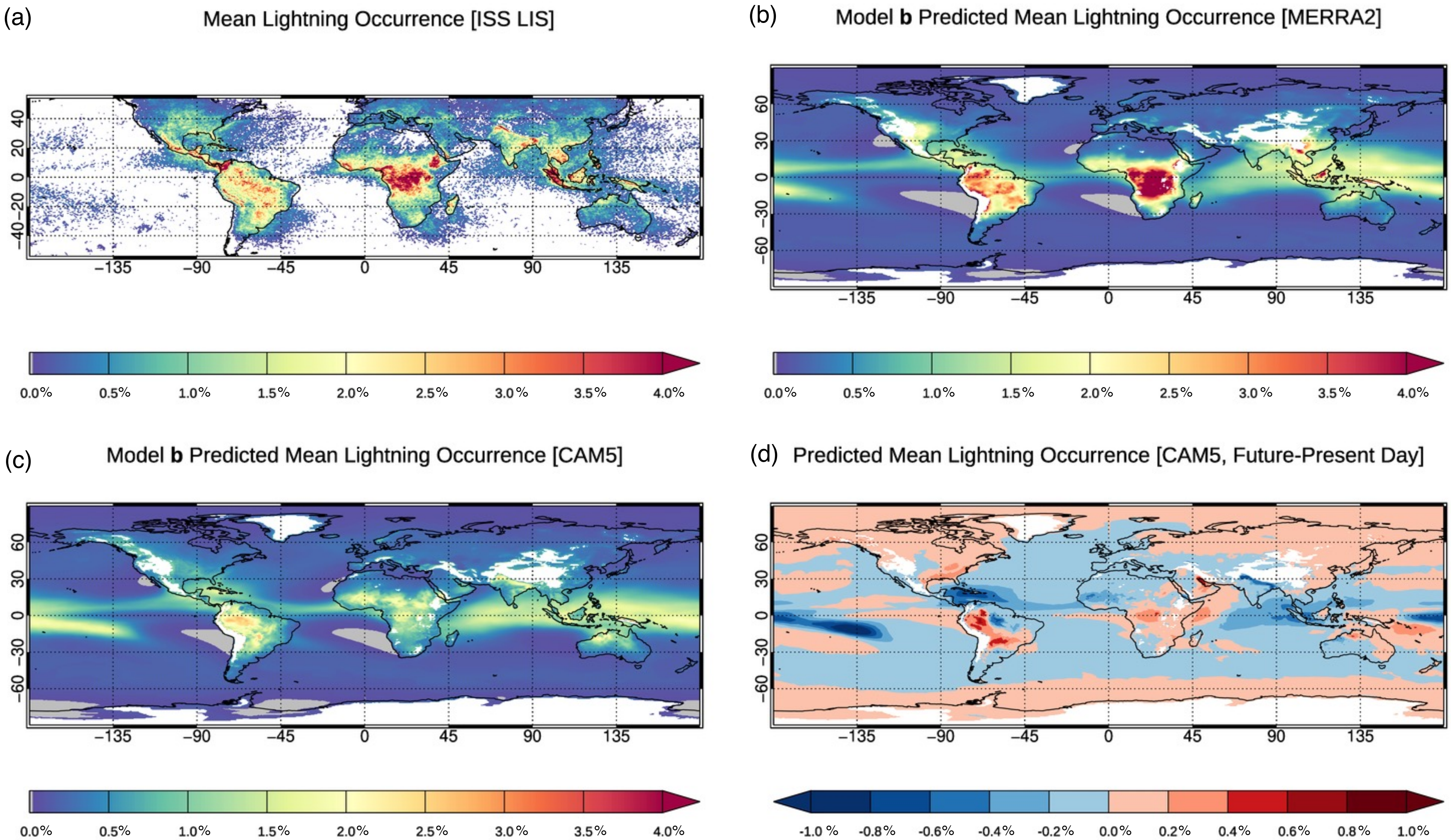
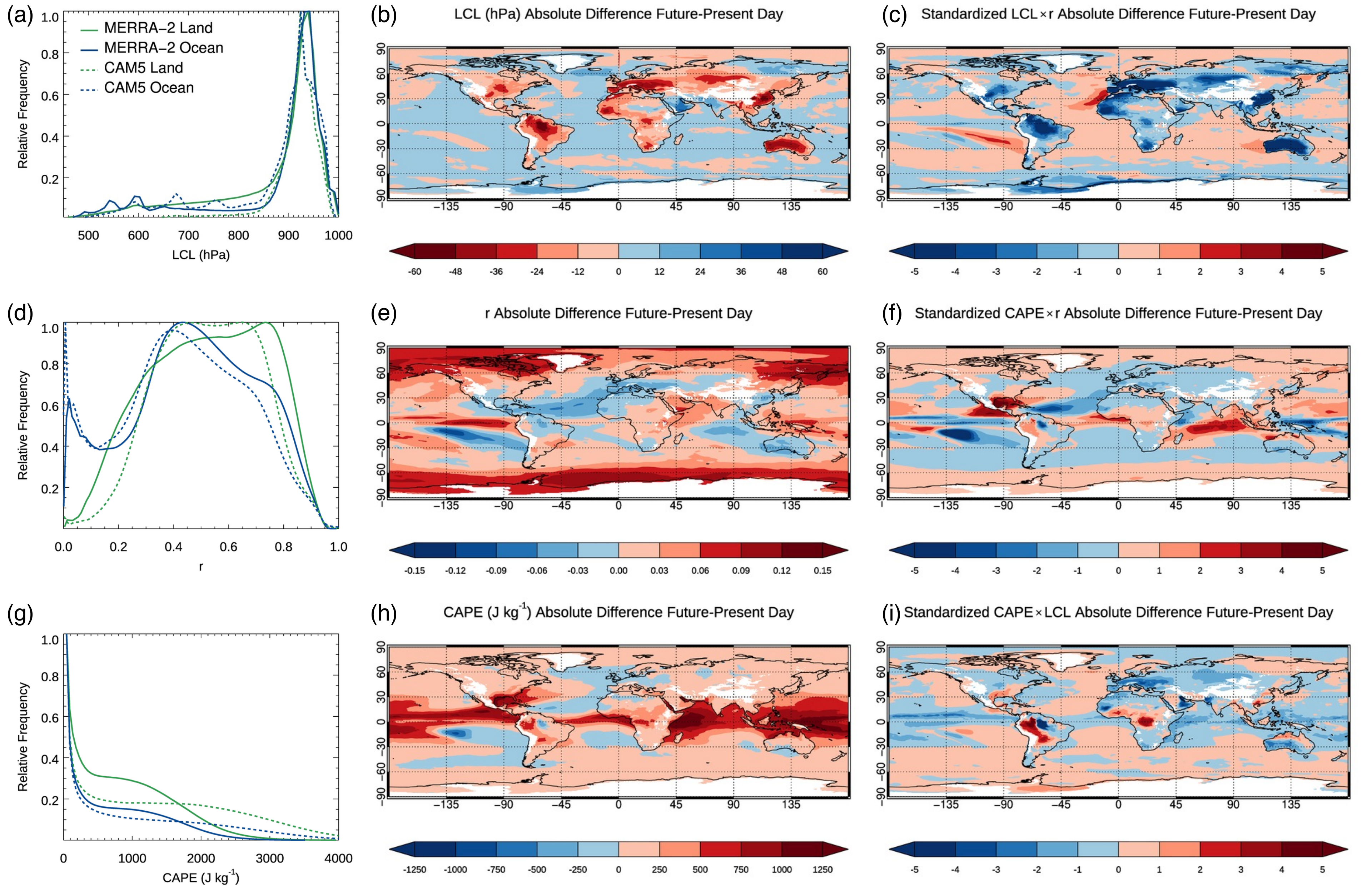
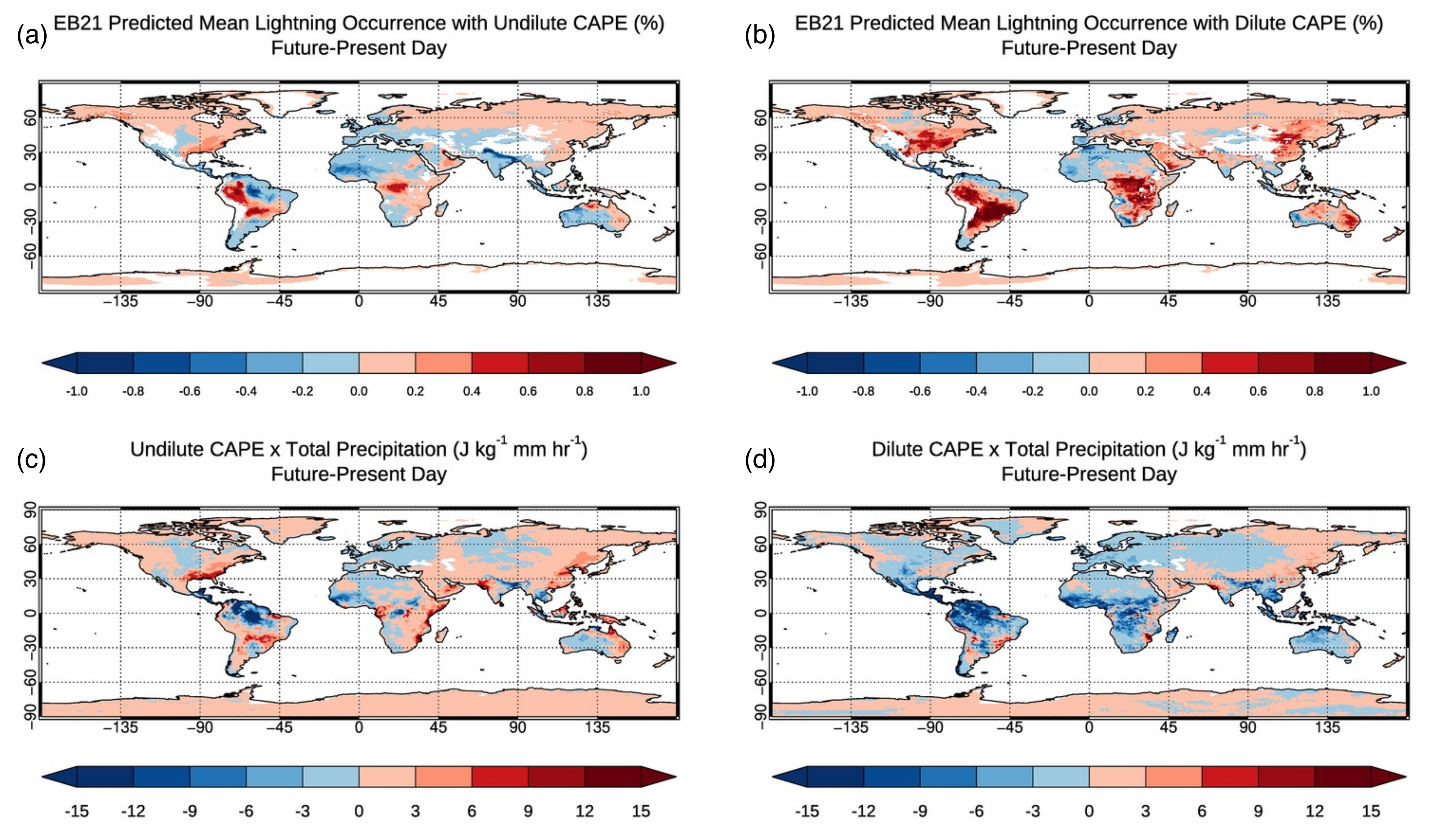

(a)
Mean Lightning Occurrence [ISS LIS]
(b)
Model **b** Predicted Mean Lightning Occurrence [MERRA2]
(c)
Model **b** Predicted Mean Lightning Occurrence [CAM5]
(d)
Predicted Mean Lightning Occurrence [CAM5, Future-Present Day]
−135 −90 −45 0 45 90 135
−40 −20 0 20 40
−60 −30 0 30 60
0.0% 0.5% 1.0% 1.5% 2.0% 2.5% 3.0% 3.5% 4.0%
-1.0 % -0.8% -0.6% -0.4% -0.2% 0.0% 0.2% 0.4% 0.6% 0.8% 1.0%

Figure 2.



(a)
MERRA–2 Land
MERRA–2 Ocean
CAM5 Land
CAM5 Ocean
Relative Frequency
LCL (hPa)
(b)
LCL (hPa) Absolute Difference Future-Present Day
(c)
Standardized LCL × r Absolute Difference Future-Present Day
(d)
Relative Frequency
r
(e)
r Absolute Difference Future-Present Day
(f)
Standardized CAPE × r Absolute Difference Future-Present Day
(g)
Relative Frequency
CAPE (J kg^{-1})
(h)
CAPE (J kg^{-1}) Absolute Difference Future-Present Day
(i)
Standardized CAPE × LCL Absolute Difference Future-Present Day

Figure 3.


(a)
EB21 Predicted Mean Lightning Occurrence with Undilute CAPE (%)
Future-Present Day
(b)
EB21 Predicted Mean Lightning Occurrence with Dilute CAPE (%)
Future-Present Day
(c)
Undilute CAPE x Total Precipitation (J kg^{-1} mm hr^{-1})
Future-Present Day
(d)
Dilute CAPE x Total Precipitation (J kg^{-1} mm hr^{-1})
Future-Present Day
90
60
30
0
−30
−60
−90
−135
−90
−45
0
45
90
135
-1.0 -0.8 -0.6 -0.4 -0.2 0.0 0.2 0.4 0.6 0.8 1.0
-15 -12 -9 -6 -3 0 3 6 9 12 15