https://doi.org/10.5194/egusphere-2026-3212
Preprint. Discussion started: 13 July 2026

Lightning in global chemistry-climate models: A review of parameterizations, evaluations, and future projections

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Abstract. Chemistry-climate models are our main tool to project how global lightning activity may change in a warmer world. However, the spatial and temporal scales involved in cloud electrification are too small to be explicitly resolved, so lightning is typically simulated using empirical relationships with proxy variables such as cloud top height (CTH), convective precipitation, convective available potential energy times precipitation, or upward ice flux. This review summarizes existing global lightning parameterizations, their skill in reproducing observed lightning patterns, and their projected future changes.

We identify 16 parameterizations (including some variants) that have been applied in global modelling studies, with CTH — the earliest developed — remaining the most widely used. Most parameterizations predict total lightning, while cloud-to-ground lightning is rarely computed directly. Several parameterizations, including CTH, reproduce observed spatial lightning patterns reasonably well ($r > 0.7$), whereas precipitation-based methods perform worse (r often < 0.6). Most approaches underestimate lightning over central Africa and in mid-to-high latitudes, while overestimating activity over the Amazon and Maritime Continent. They also struggle to capture the observed land-ocean contrast in lightning activity and tend to underestimate temporal variability from diurnal to inter-annual scales.

Future projections show large uncertainty, ranging from an 11% decrease to a 44% increase in lightning frequency per degree global warming. The mean across all parameterizations is +4.4±7.6% K^{-1}, while the mean across all projections (which are strongly biased towards CTH) is +7.5±7.9% K^{-1}. Although there is a broad agreement that lightning activity will increase in high latitudes, the tropical response remains highly uncertain.

https://doi.org/10.5194/egusphere-2026-3212
Preprint. Discussion started: 13 July 2026

1 Introduction

1.1 Lightning impacts

Lightning is an important natural source of nitrogen oxides (NO_X) in the middle and upper troposphere, an important precursor of ozone (O_3) and the hydroxyl radical (OH), reducing the lifetime of methane (CH_4), thereby exerting strong influences on atmospheric chemistry and climate (Schumann and Huntrieser, 2007). Recent studies, including aircraft observations (Brune *et al.*, 2021) and laboratory experiments (Jenkins *et al.*, 2021), have revealed substantial production of lightning-generated OH. This production of OH may have a major impact on tropospheric chemistry, significantly influencing the levels of tropospheric carbon monoxide (CO), O_3, and reactive nitrogen (Mao *et al.*, 2021). On ground, lightning poses hazards to infrastructure, people, and animals (Yair, 2018). Lightning also affects vegetation, either directly when lightning strikes a tree (Krause *et al.*, 2025; Yanoviak *et al.*, 2020) or indirectly by igniting wildfires (Krause *et al.*, 2014; Felsberg *et al.*, 2018). It is thus crucial to adequately represent lightning in global atmospheric models to reliably project changes in lightning activity in a warmer climate and associated impacts on nature and society.

1.2 Lightning generation

Although there is an ongoing debate about the precise trigger of lightning, it is well established that it requires strong electric fields generated by charge separation within clouds (Lopez, 2016), while recent research has proposed the photoelectric effect in air as a potential factor in lightning initiation (Pasko *et al.*, 2025). The dominant explanation for electrification is the non-inductive mechanism, in which charge separation results from collisions between small ice particles or snowflakes (grown by vapour diffusion) and larger graupel particles (formed by accretion of supercooled water droplets) in the mixed-phase region (between the 0°C and –40 °C isotherms) of the cloud (Takahashi, 1978; Price, 2013). These conditions are typically found in the presence of strong updrafts in storms, i.e. areas with strong convective activity, which carry the hydrometeors into the mixed-phase region and enhance the collisions between particles. Once charges are exchanged, lighter, positively charged ice particles are carried upward by convection, while heavier, negatively charged graupel pellets maintain lower in the cloud. This results in a dipole structure in thunderstorm clouds, with positive charges in the upper part of the cloud and negative charge below. At temperatures above –10 °C, the polarity of charge transfer is often reversed, leading to a thin positive layer near the cloud base. Lightning occurs once the electric field surpasses a critical threshold.

1.3 Lightning distribution

Recent estimates suggest that almost 60 lightning flashes occur worldwide every second (Cecil *et al.*, 2026b)—significantly higher than previously believed (Cecil *et al.*, 2014), largely due to updated estimates of the sensors' detection efficiency. Around one quarter of all flashes reaches the ground, while the remainder occurs within clouds. Earlier studies assumed that the cloud-to-ground (CG) fraction increases with latitude (Price and Rind, 1993; Prentice and Mackerras, 1977), but combining up-to-date datasets of total and CG lightning indicates this may actually not be the case (Fig. 1). The spatial-temporal variability of lightning is driven by climatic conditions. Most lightning occurs over tropical land areas, where intense solar heating drives deep convection (Fig. 1). Among these regions, Central Africa experiences the highest lightning activity, followed by South America and Southeast Asia, whereas the ranking is reversed for precipitation (Price, 2013; Williams, 2005). At finer spatial

https://doi.org/10.5194/egusphere-2026-3212
Preprint. Discussion started: 13 July 2026

scale, the highest mean flash densities are over Lake Maracaibo in Venezuela, while regions such as Cuba and northern Pakistan also reach comparable peak values (Cecil *et al.*, 2026b). Interestingly, lightning is rare over the very rainy maritime regions along the Intertropical Convergence Zone. Different mechanisms have been proposed to be responsible for the land-ocean contrast in lightning activity, including the aerosol hypothesis (more aerosols over land result in more numerous, smaller cloud droplets and potentially more intense convection) and the thermal hypothesis (the land warms faster, enhancing convection) (Williams and Stanfill, 2002; Qie *et al.*, 2024; Abbott *et al.*, 2025), but the issue is still debated and might be explained by a combination of several factors.

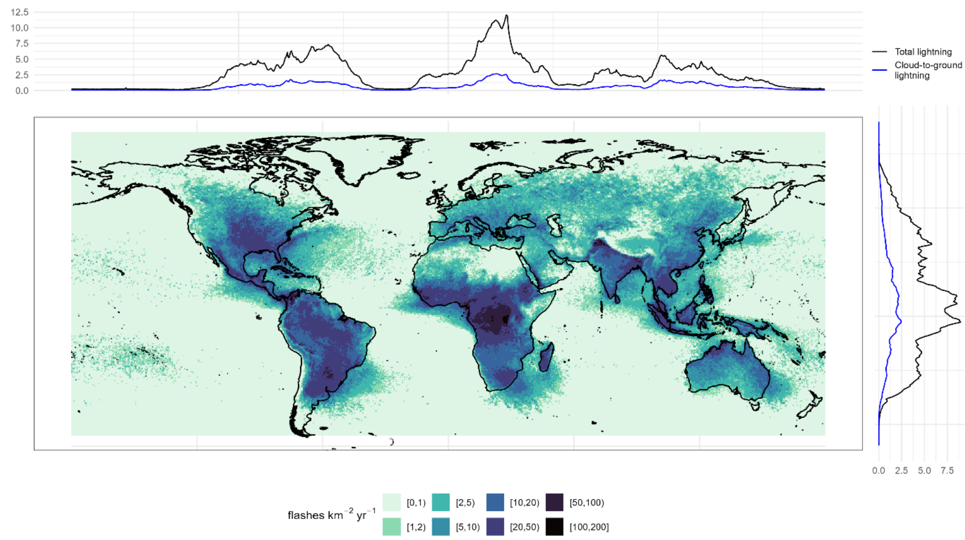

Fig. 1: Total lightning distribution (1995-2023) according to the satellite-based combined climatology from Optical Transient Detector (OTD) and Lightning Imaging Sensor (LIS) (Cecil, 2025). The longitudinal and latitudinal mean lightning densities [flashes km^{-2} yr^{-1}] are shown on the top and right of the map. Black lines display total lightning according to OTD/LIS, while blue lines display cloud-to-ground lightning according to the ground-based FLASHMAP dataset (Qu *et al.*, 2026).

1.4 Relationship between temperature and lightning

On short time scales, there is a clear relationship between temperature fluctuations and lightning activity (Williams, 2005). For example, lightning activity over land is higher during hot afternoons than during the cooler night and higher during summer than during winter (Schumann and Huntrieser, 2007). The inter-annual variability of lightning also shows a strong correlation with El Niño-related temperature fluctuations (Murray *et al.*, 2012; Williams, 1992). Using space-borne lightning observations and reanalysis data, Reeve and Toumi (1999) estimated a 40±14% increase in lightning activity per degree increase in average land wet-bulb temperature, a measure that incorporates both air temperature and humidity. A follow-up study found a lightning sensitivities of 17±7% per degree increase in seasonal surface air temperature (Ma *et al.*, 2005). However, whether the observed relationship between temperature and lightning also holds on even longer time scales, such as decades to centuries, remains uncertain. This is largely due to the limited availability of reliable long-term lightning observations, which hinders our ability to fully assess how lightning responds to climate change. High-quality satellite observations only cover a period of around 25

https://doi.org/10.5194/egusphere-2026-3212
Preprint. Discussion started: 13 July 2026

years and do not reveal a clear trend in (sub)tropical lightning activity (Blakeslee *et al.*, 2020; Cecil *et al.*, 2026b). In contrast, thunderstorm day counts, which extend further back, suggest increasing activity in many lightning hotspots over the past four decades. However, they are only an indirect proxy, and regional trends in thunderstorm days and lightning frequency during the overlapping period do not always align (Lavigne *et al.*, 2019). Holzworth *et al.* (2021) reported an enhancement in the fraction of lightning strokes detected by the ground-based World Wide Lightning Location Network (WWLLN) occurring above 65°N between 2010 and 2020, coinciding with a concurrent increase in temperature. Nevertheless, additional years of data are required to robustly assess potential temperature correlations and to disentangle the possible influence of the solar cycle. Given these observational constraints, estimates of how lightning responds to historical—and especially future—climate change rely primarily on climate model simulations.

In this review, we examine existing approaches for representing lightning in global chemistry-climate models, evaluate their ability to reproduce present-day lightning patterns, and discuss their projections under a warmer climate. Relevant studies were identified through a Web of Science search using the term "lightning AND (parameterization OR parameterisation) AND model" and by examining references cited in the retrieved papers as well as by our own knowledge of the scientific literature.

2 Lightning parameterizations in global chemistry-climate models

Global climate models and chemical transport models are our main tools to estimate how lightning activity may change in the future. However, the microphysical processes that drive cloud electrification involve temporal and spatial scales that are too fine to be explicitly resolved even by state-of-the-art global climate models due to computational constraints (Murray, 2018). Consequently, lightning cannot be simulated directly and must instead be represented through so-called parameterizations—empirical or theoretical relationships that link lightning activity to larger-scale proxy variables available from the model. These parameterizations generally aim to predict either the lightning flash rate (F, flashes per unit time per model or satellite grid cell), the flash density (f, flashes per unit time and area), or lightning occurrence (a probability that can be binarized using a threshold). In many model configurations, global scaling factors have to be applied to reproduce the global lightning frequency observed from space (Tost *et al.*, 2007; Finney *et al.*, 2014; Gordillo-Vázquez *et al.*, 2019). In chemical transport models it is also common to apply additional scaling factors to improve simulations of lightning-produced NO_X (Murray *et al.*, 2012; Pérez-Invernón *et al.*, 2025).

The first lightning parameterization computed lightning from convective cloud top height (**CTH**), a strong indicator of convective activity (Price and Rind, 1992). This approach built on theoretical and empirical studies (Williams, 1985; Vonnegut, 1963) suggesting a roughly fifth-power relationship between CTH and flash frequency. Using radar-based observations of continental thunderstorms in the United States, Price and Rind derived empirical power-law relationships between CTH and lightning flash rate. They also proposed an alternative parameterization linking lightning to peak updraft speed, though this formulation is less widely used in global models. To account for the large differences in hypothesized updraft velocities and lightning flash rates between land and oceanic storms, the authors proposed two separate equations for land and ocean grid boxes:

$$F_L = 3.44 \times 10^{-5}\ CTH^{4.9}$$

$$F_O = 6.40 \times 10^{-4}\ CTH^{1.73}$$

https://doi.org/10.5194/egusphere-2026-3212
Preprint. Discussion started: 13 July 2026

where F_L and F_O denote lightning flash rate per grid cell [flashes min^{-1}] and CTH is expressed in km above ground.

However, the ocean parameterization suffered from a scarcity of maritime lightning observations at that time and later turned out to substantially underestimate lightning over the oceans. The authors also proposed a spatial calibration factor to account for the fact that the CTH (which is computed as an average over the whole grid box) decreases exponentially with coarser spatial resolution (Price and Rind, 1994b). More recently, Stolz *et al.* (2021) proposed a method to account for the number of thunderstorms in the model grid box.

In follow-up work, Price and Rind (1993) came up with an equation to estimate the ratio z of intra-cloud lightning to CG lightning:

$$z = 63.09 - 36.54 \cdot CCD + 7.493 \cdot CCD^2 - 0.648 \cdot CCD^3 + 0.021 \cdot CCD^4$$

where CCD is the cold cloud depth in km, with no CG lightning assumed when CCD < 5.5 km.

Some studies adopted the CTH approach but updated the parameters to make it more consistent with theoretical expectations, storm updraft observations, and the observed land-ocean contrast in lightning activity (Boccippio, 2002; Michalon *et al.*, 1999; Luhar *et al.*, 2021). For instance, Michalon *et al.* (1999) took into account differences in cloud droplet concentrations (CDC) between land and ocean to modify the maritime equation (**CTH-CDC**):

$$F_O = CDC^{2/3}\ CTH^5 = 6.57 \times 10^{-6}\ CTH^{4.9}$$

where CDC in their study was not simulated by the model but prescribed using two standard values representing land and ocean conditions.

Many studies aimed to improve the representation of lightning by using additional or alternative proxy variables, arguing that the CTH approach has no direct physical link with the non-inductive charging mechanism and that its fifth-power relationship makes lightning frequency extremely sensitive to biases in simulated CTH. Grewe *et al.* (2001) built upon the CTH approach but included an indicator of the updraft strength (**US**):

$$F = 1.54 \times 10^{-5}\ (wd^{0.5})^{4.9}$$

where w is the updraft vertical velocity [m s^{-1}] and d the cloud thickness [m]. Note that the parameterization assumes differences in convection intensity between land and ocean are captured by the model, so no separate equations are required.

Meijer *et al.* (2001) found a simple linear relationship between convective rainfall and the number of CG lightning flashes (**CP_Linear**) for summer conditions over central Europe:

$$F_{CG} = 14700\ CP + 1.7$$

where CP is the accumulated convective precipitation [m] over a 6-hour period. While the authors did not provide a separate ocean equation, some global modelling studies assumed a 90% reduced flash rate over the oceans to account for the higher rain yields per flash (e.g. Boersma *et al.*, 2005; Finney *et al.*, 2014). If necessary, the predicted CG lightning can be converted to total lightning using the formula of Price and Rind (1993).

Allen and Pickering (2002), building upon earlier work (Allen *et al.*, 2000), proposed a fourth-order polynomial parameterization based on upward mass flux (**MFLUX**) to estimate the frequency of CG lightning:

https://doi.org/10.5194/egusphere-2026-3212
Preprint. Discussion started: 13 July 2026

$$F_{CG} = \frac{\Delta x \Delta y}{A}\left(-2.34 \times 10^{-2} + 3.08 \times 10^{-1}\, M - 7.19 \times 10^{-1}\, M^2 + 5.23 \times 10^{-1}\, M^3 - 3.71 \times 10^{-2}\, M^4\right)$$

where F_{CG} is the flash rate [flashes min^{-1}] within the 2.0°x2.5° grid cell, ΔxΔy is the cell area, A the area of a 2.0°×2.5° cell centred at 30°N (~53,500 km²), and M the upward cloud mass flux [kg m^{-2} min^{-1}] at an altitude of 0.44 sigma (~440 hPa). For M < 0 or M > 9.6, values are capped at the nearest bound. Given the low sensitivity to the surface type, no distinction is usually made between land and ocean grid boxes.

The authors also suggested an alternative polynomial parameterization based on convective precipitation (**CP_Poly**), which explicitly distinguishes between land and ocean:

$$F_{CG\_L} = \frac{\Delta x \Delta y}{A}\left(3.75 \times 10^{-2} - 4.76 \times 10^{-2}\, CP + 5.41 \times 10^{-3}\, CP^2 + 3.21 \times 10^{-4}\, CP^3 - 2.93 \times 10^{-6}\, CP^4\right)$$

$$F_{CG\_O} = \frac{\Delta x \Delta y}{A}\left(5.23 \times 10^{-2} - 4.80 \times 10^{-2}\, CP + 5.45 \times 10^{-3}\, CP^2 + 3.68 \times 10^{-5}\, CP^3 - 2.42 \times 10^{-7}\, CP^4\right)$$

where CP is the convective precipitation at the surface, set to 0 for precipitation rates less than 7 mm day^{-1} and capped at 90 mm day^{-1}. As a slight modification, Magi (2015) proposed fifth-order polynomial parameterizations of convective mass flux and convective precipitation to predict total lightsning.

Yoshida *et al.* (2009) addressed a critique of the CTH approach that cloud base height might also increase under warming, potentially resulting in constant cloud depths. To tackle this issue, they used cold cloud depth (**CCD**), defined as the vertical distance between cloud top and the 0 °C level, as a proxy for lightning. They derived empirical power-law relationships, including one for the Maritime Continent, of the form:

$$F_L = 1.58 \times 10^{-6}\, CCD^{4.9}$$

$$F_O = 1.26 \times 10^{-7}\, CCD^{5.1}$$

$$F_{MC} = 5.01 \times 10^{-7}\, CCD^{5.1}$$

where F is the lightning flash rate per grid cell [flashes min^{-1}] and CCD is in km.

Romps *et al.* (2014) found that CG lightning over the contiguous US can be largely predicted by the product of convective available potential energy (CAPE; a measure of atmospheric instability) and precipitation rate P (**CAPE×P**):

$$f_{CG} = \eta/E \times CAPE \times P$$

where f_{CG} is the CG lightning density [flashes m^{-2} s^{-1}], η/E is the constant of proportionality with a value of 1.3×10^{-11} J^{-1}, CAPE is in J kg^{-1} and P in kg m^{-2} s^{-1}. However, the approach later turned out to overestimate lightning over the tropical oceans (Romps, 2019). To solve this problem, Cheng *et al.* (2021) proposed to apply a CAPE threshold in oceanic regions to suppress lightning in low-CAPE environments but so far no global modelling study adopted this suggestion.

Finney *et al.* (2014) developed a lightning parameterization closely connected with the non-inductive charging mechanism based on the upward cloud ice flux in the mid-troposphere (at 440 hPa) where charge separation occurs (**IFLUX**):

$$f_L = 6.58 \times 10^{-7}\, q \times \Phi_{mass} / c$$

$$f_O = 9.08 \times 10^{-8}\, q \times \Phi_{mass} / c$$

https://doi.org/10.5194/egusphere-2026-3212
Preprint. Discussion started: 13 July 2026

where f is the flash density [flashes m^{-2} s^{-1}], q is the specific cloud ice water content at 440 hPa [kg ice per kg air], Φ_{mass} the updraft mass flux at 440 hPa [kg air m^{-2} s^{-1}], and c the fractional cloud cover at 440 hPa. Romps (2019) later modified this scheme by using the upward cloud ice flux at the 260 K isotherm (**IFLUX_T**) instead of the 440 hPa pressure level, arguing that this approach is more appropriate for climate change simulations, where the height of cloud charge separation can shift with warming.

Lopez (2016) developed a lightning parameterization for the European Centre for Medium-Range Weather Forecasts model that combines convective cloud base height (CBH), CAPE and a proxy representing the charging rate resulting from the collisions between graupel and other types of hydrometeors (Q_R) (**Q-CAPE-CBH**):

$$f = a\, Q_R\, CAPE^{0.5} \min(CBH, 1.8)^2$$

where f is the lightning density [flashes km^{-2} day^{-1}], a is a constant obtained after calibration against lightning observations, Q_R [kg m^{-2}] computed from the amounts of graupel, snow, and liquid water in the charge separation region between the 0° and -25°C isotherms, CAPE is in J kg^{-1}, and CBH in km. Notably, the parameterization partitions graupel and snow differently for land and ocean grid boxes.

He *et al.* (2022) modified this approach to compute lightning from CAPE and the column-integrated precipitating ice (cloud ice, snow, graupel) in the charging region (Q_{Ra}) based on findings from McCaul *et al.* (2009) (**Q-CAPE**):

$$f_L = a_1\, Q_{Ra}\, CAPE^{1.3}$$

$$f_O = a_2\, Q_{Ra}\, CAPE^{1.3}$$

where f is the lightning density [flashes m^{-2} s^{-1}], a_1 and a_2 are constants obtained after calibration against lightning observations, Q_{Ra} in kg m^{-2}, and CAPE in J kg^{-1}. More recently, Michibata (2024) extended this version further by including prognostic graupel, improving the representation of ice-phase processes in the charge separation region.

In recent years, several lightning parameterizations have been developed that rely on multiple large-scale environmental variables. Stolz *et al.* (2017) introduced a logarithmic multiple linear regression model with five predictors (**ENV**):

$$\log_{10}(f_L) = 1.037 + 0.171 \log_{10}(NCAPE) + 0.169 \log_{10}(CCN) - 0.723 \log_{10}(WCD) + 0.084 \log_{10}(SHEAR) - 0.623 \log_{10}(RH)$$

$$\log_{10}(f_O) = 3.413 + 0.300 \log_{10}(NCAPE) + 0.174 \log_{10}(CCN) - 1.521 \log_{10}(WCD) + 0.011 \log_{10}(SHEAR) - 0.352 \log_{10}(RH)$$

where f is the lightning density [flashes km^{-2} min^{-1}], NCAPE is normalised CAPE [J kg^{-1} m^{-1}], CCN the cloud condensation nuclei concentration [cm^{-3}], WCD the warm cloud depth [m], SHEAR the vertical wind shear [m s^{-1}], and RH the relative humanity [%].

A similar approach was followed by Etten-Bohm *et al.* (2021), who included up to seven environmental predictor variables and their interactions to compute lightning occurrence (**ENV_Int**). Verjans and Franzke (2025) used a tree-based regression approach, specifically Extreme Learning Machines (**ENV_ELM**), to predict lightning from nine atmospheric and geographic variables. It splits the input space of climatic conditions in seven separate regimes, for which lightning rates are simulated with specific single hidden layer neural networks. Notably, elevation >0.5 m is used for the second split, which effectively separates land and ocean grid boxes. Finally, Yin *et al.* (2026) showed

https://doi.org/10.5194/egusphere-2026-3212
Preprint. Discussion started: 13 July 2026

that CAPE alone can effectively predict lightning in a two-dimensional deep learning framework when spatial (non-local) information is included (**CAPE_NL**).

Presently, the CTH approach is still the most popular lightning parameterization (Fig. 2), maybe because CTH is a common variable in climate models and the parameterization is relatively robust across different models and convection schemes (Tost *et al.*, 2007). For instance, it was applied in 10 out of 12 models participating in the Atmospheric Chemistry and Climate Model Intercomparison Project (Finney *et al.*, 2016b) and in all Earth System Models participating in CMIP6 (Thornhill *et al.*, 2021). In recent years, the study by Romps *et al.* (2014) has also received a lot of attention (Fig. 2a), even though the CAPE×P approach proposed by the authors has seen more limited uptake in actual modelling studies (Fig. 2b, Table S1). In fact, 71% of all identified modelling studies after 2014 included the CTH parameterization, while only 20% used CAPE×P and 12% IFLUX (some studies applied multiple parameterizations).

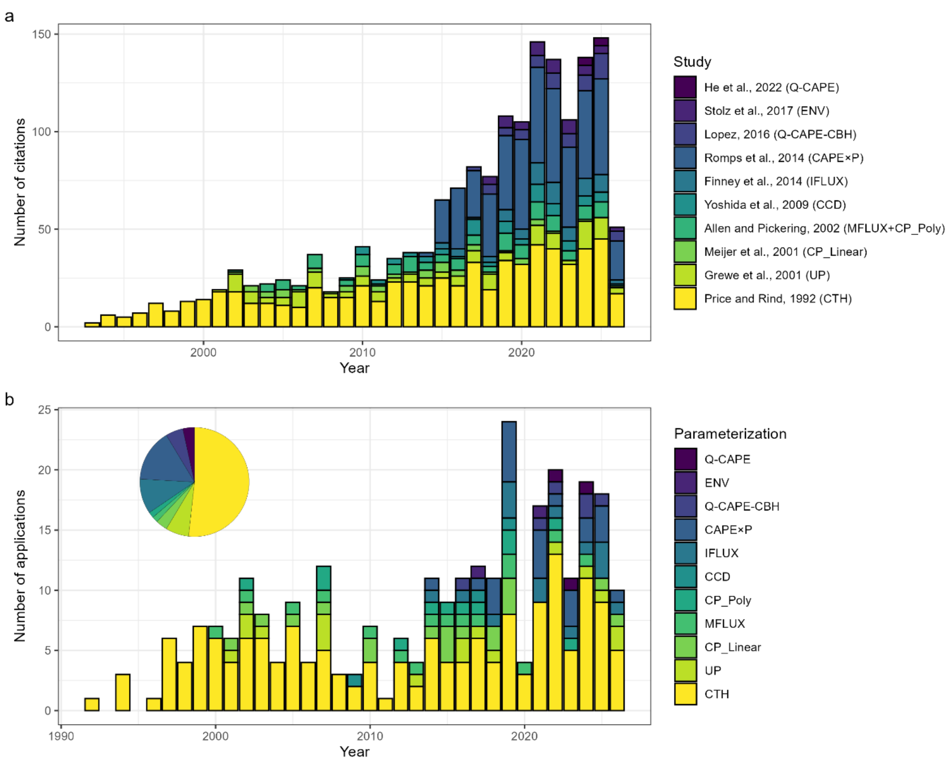

Fig. 2: Popularity of different lightning parameterizations. Number of citations per year for the main reference of the parameterizations according to Web of Science (a) and number of applications of the parameterizations in actual modelling studies (b). Only parameterizations developed before 2023 are shown to enhance clarity. The pie chart indicates the fractional share of different parameterizations since 2023.

https://doi.org/10.5194/egusphere-2026-3212
Preprint. Discussion started: 13 July 2026

It should be noted that numerous additional lightning parameterizations exist in numerical models, many of which more directly represent the microphysical processes of cloud electrification. These are typically applied in high-resolution, cloud-resolving models that explicitly represent convection (McCaul *et al.*, 2009; Yair *et al.*, 2010; Cummings *et al.*, 2024; Fierro *et al.*, 2013). However, while computational power increased significantly in recent years, these models are still computationally not suited for large-scale, long-term climate simulations (Field *et al.*, 2018). An alternative is so-called superparameterization, in which a two-dimensional cloud-resolving model is embedded within each grid column of a conventional climate model (Charn and Parishani, 2021). Nevertheless, summarizing all existing lightning parameterizations is beyond the scope of this review. Instead, we focus here on schemes that have been applied and evaluated in global-scale modelling studies.

3 Evaluation of parameterizations

3.1 Lightning datasets

For model evaluation, simulated lightning densities are typically compared against ground-based observations, such as those from WWLLN (Kaplan and Lau, 2022), the Earth Networks Total Lightning Network (Zhu *et al.*, 2022), or the Flash Location Aggregation from Strokes into a High-resolution Multi-scale Analysis Product (Qu *et al.*, 2026), or – more commonly – satellite-based products like the Optical Transient Detector (OTD) on board of the Orbview-1 satellite and the Lightning Imaging Sensor (LIS) on the Tropical Rainfall Measurement Mission (TRMM) satellite. OTD provided near-global coverage but was only operational from April 1995 to March 2000. In contrast, LIS only covered regions between ±38° but was active for a longer period (12/1997-04/2015). LIS also achieved a higher detection efficiency (DE), recently estimated at 59-71%, compared to 22-52% for OTD (Cecil *et al.*, 2026a). Data from both sensors are included in the joint OTD/LIS products, which are consequently more robust in the tropics. A few newer studies also evaluated against the “successor” of TRMM LIS, ISS LIS, which was hosted on the International Space Station (ISS) and covered regions up to ±55° during 03/2017-11/2023 (Cecil *et al.*, 2026a). Both OTD and LIS were Low Earth Orbit (LEO) missions that sampled a given region only occasionally. As a result, robust estimates of lightning density generally require temporal and/or spatial smoothing to compensate for sparse sampling. The DE of each lightning detection system, as well as its sensitivity to CG or IC lightning flashes, or even the definition of a flash based on measured raw data, can significantly influence both the development of parameterization and its subsequent evaluation. Ground-based Lightning Location Systems (LLS) typically detect radio waveforms emitted by lightning in the Very Low Frequency (VLF) and Low Frequency (LF) ranges, using the Time of Arrival (TOA) method to identify strokes produced by lightning (Nag *et al.*, 2015). Subsequently, they apply various clustering criteria to group strokes into flashes. LLS generally exhibit a much higher DE for CG lightning than for IC lightning, particularly in datasets spanning decades. On the other hand, space-based optical instruments such as LIS or geostationary sensors detect optical events (pixel brightness) associated with lightning from space (Blakeslee *et al.*, 2020; Cecil *et al.*, 2026b). These events are then clustered into groups and flashes using different spatiotemporal criteria. The DE of space-based optical instruments tends to be high for both CG and IC lightning but depends on factors such as cloud thickness or discharge altitude (Blakeslee *et al.*, 2020).

Besides the challenges inherent to observing lightning, additional issues arise when these observations are used to benchmark lightning parameterizations. When CG parameterizations such as CP_Linear, CP_Poly or CAPE×P are compared with total lightning observations from space, the predicted CG lightning is usually scaled by an estimated CG fraction within each grid cell, which can distort evaluation metrics. Additionally, evaluations are not always fully independent as

https://doi.org/10.5194/egusphere-2026-3212
Preprint. Discussion started: 13 July 2026

parameterizations which were calibrated using a specific lightning product might have inherited its sampling biases during training, which can influence their apparent performance in subsequent assessments when compared to different datasets. Finally, the evaluation metrics might not only reflect the performance of the parameterization itself but also the model's ability in simulating the predictor variables. For instance, the spatial correlation coefficient dropped from 0.92 to 0.77 when Verjans and Franzke (2025) applied their parameterization in a climate model compared to the reanalysis data the model was originally trained on. Given the short time period of lightning observations, evaluations are typically conducted with respect to lightning climatologies, inter-annual variability, seasonality, or the diurnal cycle rather than long-term trends.

3.2 Spatial evaluation

The CTH approach is still the most common lightning parameterization and is often used as a benchmark for newer schemes (Fig. 3). Maybe unsurprisingly, newly developed parameterizations usually outperform older approaches in the studies that introduce them, but their skill is less consistent when later implemented by other groups and models. Some schemes, including CTH and IFLUX, generally capture the spatial patterns of observed lightning densities well ($r > 0.7$), whereas others like MFLUX and CP_Poly perform relatively poorly ($r < 0.6$), or show mixed performance (UP, CAPE×P) (Fig. 3a). Interestingly, Tost *et al.* (2007) reported that CTH not only had the highest correlation compared to UP, MFLUX, and CP_Poly, but was also the most robust to the underlying convection scheme. However, CTH tends to overestimate spatial variability (Fig. 3b), largely due to a strong exaggeration of the land-ocean contrast in lightning activity (Fig. 3c). In contrast, most other parameterizations, including the "aerosol variant" CTH-CDC, underestimate both spatial variability and the land-ocean contrast, even those parameterizations that use separate equations for land and ocean cells (Fig. 3b+c). The exception is ENV_Int, which, despite not explicitly separating land and ocean grid boxes, reproduces the land-ocean contrast relatively well.

A common bias across many schemes, including CTH, is the overestimation of lightning in the tropics and underestimation in sub- and extratropical regions (Finney *et al.*, 2014; He *et al.*, 2022; Ghosh *et al.*, 2025). This is related to overestimations over the Amazon and the Maritime Continent, while lightning over Central Africa is underestimated by all parameterizations. While this is also the case for **CTH**, it still captures the maximum over the Congo Basin better than others (Lopez, 2016), although not all convection schemes reproduce this maximum (Tost *et al.*, 2007). CTH also underestimates lightning in Europe, Central and North America, and Argentina, while overestimating it in Amazonia, Southeast Asia, the Maritime Continent, and northern Australia (Tost *et al.*, 2007; Murray *et al.*, 2012; Finney *et al.*, 2016a; Lopez, 2016; Clark *et al.*, 2017; Verjans and Franzke, 2025; Krause *et al.*, 2014; Finney *et al.*, 2014). Additionally, it simulates too few low and high flash frequencies and too many intermedia values (Finney *et al.*, 2014; Wong *et al.*, 2013). The **UP** parameterization also overestimates lightning over the Amazon and – for some convection schemes – the oceans and underestimates it over Central Africa (Tost *et al.*, 2007; Lopez, 2016). Spatial variability is sometimes captured accurately, but for some configurations exceeds observed values by a factor of more than two (Fig. 3b). **CP_Linear** produces too much lightning over the Amazon, the Maritime Continent, and tropical oceans, while underestimating lightning over Central Africa, Northern Argentina, North America, and western India (Lopez, 2016; Finney *et al.*, 2014). However, it captures extratropical lightning better than CTH (Flemming *et al.*, 2015). **MFLUX** greatly overestimates lightning over the oceans, in particular over the western tropical Pacific, while underestimating it in the extratropics and, in particular, Central Africa (Finney *et al.*, 2014; Tost *et al.*, 2007; Murray *et al.*, 2012; Gordillo-Vázquez *et al.*, 2019; Allen and Pickering, 2002). In contrast to most other parameterizations, MFLUX tends to simulate the correct or even too low magnitude over the Amazon and the Maritime

https://doi.org/10.5194/egusphere-2026-3212
Preprint. Discussion started: 13 July 2026

Continent (Tost *et al.*, 2007; Finney *et al.*, 2014; Murray *et al.*, 2012), which is likely related to the general underestimation of continental lightning. **CP_Poly** behaves similar to MFLUX, with overestimations over tropical oceans and tropical South America, and underestimations in Central Africa and extratropical land areas (Tost *et al.*, 2007; Murray *et al.*, 2012; Finney *et al.*, 2014; Lopez, 2016; Gordillo-Vázquez *et al.*, 2019; Clark *et al.*, 2017). **CCD** resembles CTH but with a smaller land-ocean contrast (Clark *et al.*, 2017). **IFLUX** has been used in numerous comparative studies of lightning schemes and demonstrates a similar or better ability to predict spatial patterns as CTH (with the exception of Ghosh *et al.* (2025)). It improves the tropics-subtropics ratio in lightning activity (Finney *et al.*, 2014) but underestimates lightning in Central Africa, India, Australia, and southern US, while overestimating it over tropical oceans, the Maritime Continent, the Amazon, western North America, Central Asia, and boreal regions (Finney *et al.*, 2016a; Stolz *et al.*, 2021; Charn and Parishani, 2021; He *et al.*, 2022; Verjans and Franzke, 2025; Finney *et al.*, 2014). The **CAPE×P** approach, initially shown to be an excellent predictor for lightning in the continental US (Romps *et al.*, 2014), clearly loses skill at global scale, despite a high correlation between lightning and CAPE times precipitation over land (Romps *et al.*, 2018). This might be related to using the same equation for land and ocean grid boxes (note that Charn and Parishani (2021) applied separate scaling factors over land and oceans, which likely explains the higher correlation relative to other studies shown in Fig. 3). CAPE×P overestimates lightning particularly over tropical oceans (Romps *et al.*, 2018; Yin *et al.*, 2026), but also over the Amazon and Southeast Asia, while underestimating it in mid-latitude land areas and also over mid-latitude oceanic regions east of the continents (Gordillo-Vázquez *et al.*, 2019; Charn and Parishani, 2021; Pérez-Invernón *et al.*, 2019). **Q-CAPE-CBH** improves lightning distribution in South Asia, the US, and over the oceans relative to CTH, but underestimates lightning particularly in Central Africa and also in Colombia, Ural Mountains, and some ocean regions near continents (Lopez, 2016; He *et al.*, 2022). The Central African underestimation also occurs in the modified **Q-CAPE** scheme (He *et al.*, 2022). **ENV** produces too much lightning over tropical oceans and too little over (sub)tropical land (Stolz *et al.*, 2021). **ENV_Int** overestimates lightning over the western coasts of North and South America, mountains, South Africa, and Australia, while underestimating it over the eastern half of North and South America, India, Central and North Africa (Whaley *et al.*, 2024). **ENV_ELM** substantially reduced the Central African bias but still overestimates tropical ocean and eastern African lightning, while underestimating it in Southeastern South America and North America (Verjans and Franzke, 2025). **CAPE-NL** captures spatial patterns even better and avoids the overestimation of ENV_ELM over tropical oceans, but underestimates lightning in high latitudes (Yin *et al.*, 2026).

https://doi.org/10.5194/egusphere-2026-3212
Preprint. Discussion started: 13 July 2026

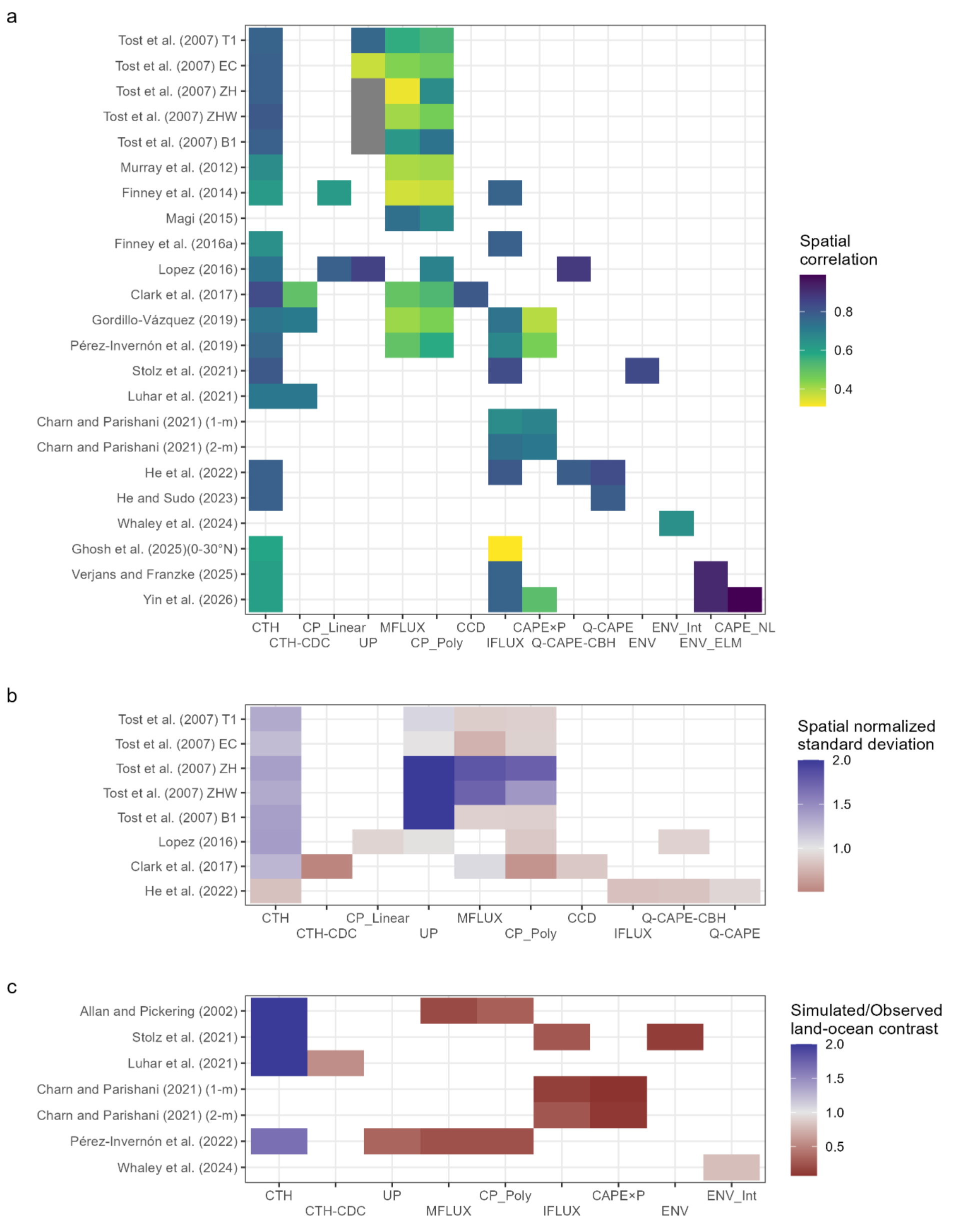

Fig. 3: Evaluation of different lightning parameterizations in reproducing the spatial patterns of observed lightning climatologies as extracted from the literature. Panels show: (a) correlation, (b) normalized standard deviation, and (c) land-ocean contrast relative to observations (capped at 2.0 to enhance visibility). Higher values in a) indicate better reproduction of mean lightning spatial patterns. Blue colours in b) indicate overestimation of spatial variability, while red indicates underestimation. Similarly, blue colours in c) indicate overestimation of the land-ocean contrast in lightning activity. Note that evaluation methods differ across studies (e.g. Clark *et al.* (2017) evaluated against LIS/OTD observations within ±38°, whereas Tost *et al.* (2007) used ±60°, see Table S2) so direct comparison

https://doi.org/10.5194/egusphere-2026-3212
Preprint. Discussion started: 13 July 2026

across studies should be made cautiously. Murray *et al.* (2012) included a seasonal dimension, reflecting spatiotemporal performance. Some values were estimated from graphs (https://plotdigitizer.com/app) when not directly reported. Grey boxes show parameterizations included in the comparison but with unknown values because symbols fell outside the plotting range. The individual values for each study and parameterization can be extracted from Table S2.

3.3 Temporal evaluation

Most temporal evaluations of lightning parameterizations have focused on the seasonal cycle, while the diurnal cycle and inter-annual variability have received far less attention (Fig. 4).

Seasonal cycle: Lightning activity generally follows the shift of the intertropical convergence zone, resulting in peak global lightning activity during Northern Hemisphere (NH) summer, as lightning is concentrated over land areas. Consequently, the parameterizations' ability to reproduce seasonality partly depends on their ability to simulate the land-ocean contrast, which is facilitated by the use of separate equations for land and ocean grid boxes. All parameterizations struggle to reproduce the observed annual cycle of global lightning, with sometimes even negative correlations (Fig. 4a). Correlations improve when evaluations are conducted for each hemisphere individually, especially when the observations include extratropical regions (i.e. are not only based on TRMM LIS). However, even for these cases the amplitude of the seasonal cycle is typically underestimated, at least for the NH (Fig. 4b). Noteworthy, many parameterizations simulate a secondary maximum during NH winter when global lightning activity according to LIS/OTD is low (Gordillo-Vázquez *et al.*, 2019; Tost *et al.*, 2007). The **CTH** approach generally captures the month of peak lightning in most regions, apart from Equatorial South America and parts of South Asia (Krause *et al.*, 2014). Timing accuracy varies: while Tost *et al.* (2007) reported that CTH simulates the boreal summer maximum about 20 days too early, Stolz *et al.* (2021) found a delay of two months. CTH-CDC also captures seasonality in most tropical regions, apart from NH South America (Clark *et al.*, 2017). **CP_Linear** simulates the maximum roughly one month too late (Finney *et al.*, 2014). **UP** has great difficulties to simulate the seasonal cycle and shows high variability across different convection schemes (Tost *et al.*, 2007). Allen and Pickering (2002) found that **MFLUX** represented the 1996 seasonal cycle more accurately than CTH and **CP_Poly**. In contrast, Tost *et al.* (2007) reported that neither MFLUX nor CP_Poly captured the seasonal cycle of global lightning activity, while Gordillo-Vázquez *et al.* (2019) noted that MFLUX performed better than CP_Poly. **IFLUX** captures seasonality reasonably well but typically peaks 1-2 months later than observed (Finney *et al.*, 2014; Gordillo-Vázquez *et al.*, 2019; Stolz *et al.*, 2021). **CAPE×P**'s global lightning activity tends to peak about one month earlier than observed and also overestimates global lightning occurrence during the NH winter (Gordillo-Vázquez *et al.*, 2019). At the hemispheric scale, however, a delayed peak and an overestimation of seasonal variability have been reported (Yin *et al.*, 2026). **ENV** predicts the peak in both hemispheres two months too late (Stolz *et al.*, 2021), while **ENV_ELM** and **CAPE_NL** simulate the seasonal cycle very accurately (Verjans and Franzke, 2025; Yin *et al.*, 2026).

Inter-annual variability: Verjans and Franzke (2025) and Yin *et al.* (2026) both evaluated inter-annual variability using the same set of test years, selected from a 27-year period (with lightning data only partly available for some years). They reported good prediction skill for **IFLUX** and **ENV_ELM**, especially for the NH, while **CTH**, **CAPE×P**, and **CAPE_NL** performed worse (Fig. 4). However, this assessment relied on only six years of data, which limits its robustness.

Monthly time-series: Monthly time-series combine seasonality and inter-annual variability. Clark *et al.* (2017), analysing five parameterizations, found that only the **CTH-CDC** approach reproduced this

https://doi.org/10.5194/egusphere-2026-3212
Preprint. Discussion started: 13 July 2026

variability to some extent (Fig. 4), but given its poor spatial performance pointed out that this may result from error cancellation across regions.

Diurnal cycle: Only one study has compared multiple parameterizations against the observed diurnal cycle of global lightning (Tost *et al.*, 2007; Fig. 4). Locally, lightning activity over land areas usually peaks in the late afternoon. The **CTH** scheme captures the first global maximum at 14:00 UTC (corresponding to the African afternoon peak), but underestimates the second maximum in the Americas. **CP_Poly** reproduces the general diurnal pattern but also fails to capture the second maximum. The performance of **UP** and **MFLUX** is overall worse and depends more on the convection scheme (Tost *et al.*, 2007).

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Preprint. Discussion started: 13 July 2026

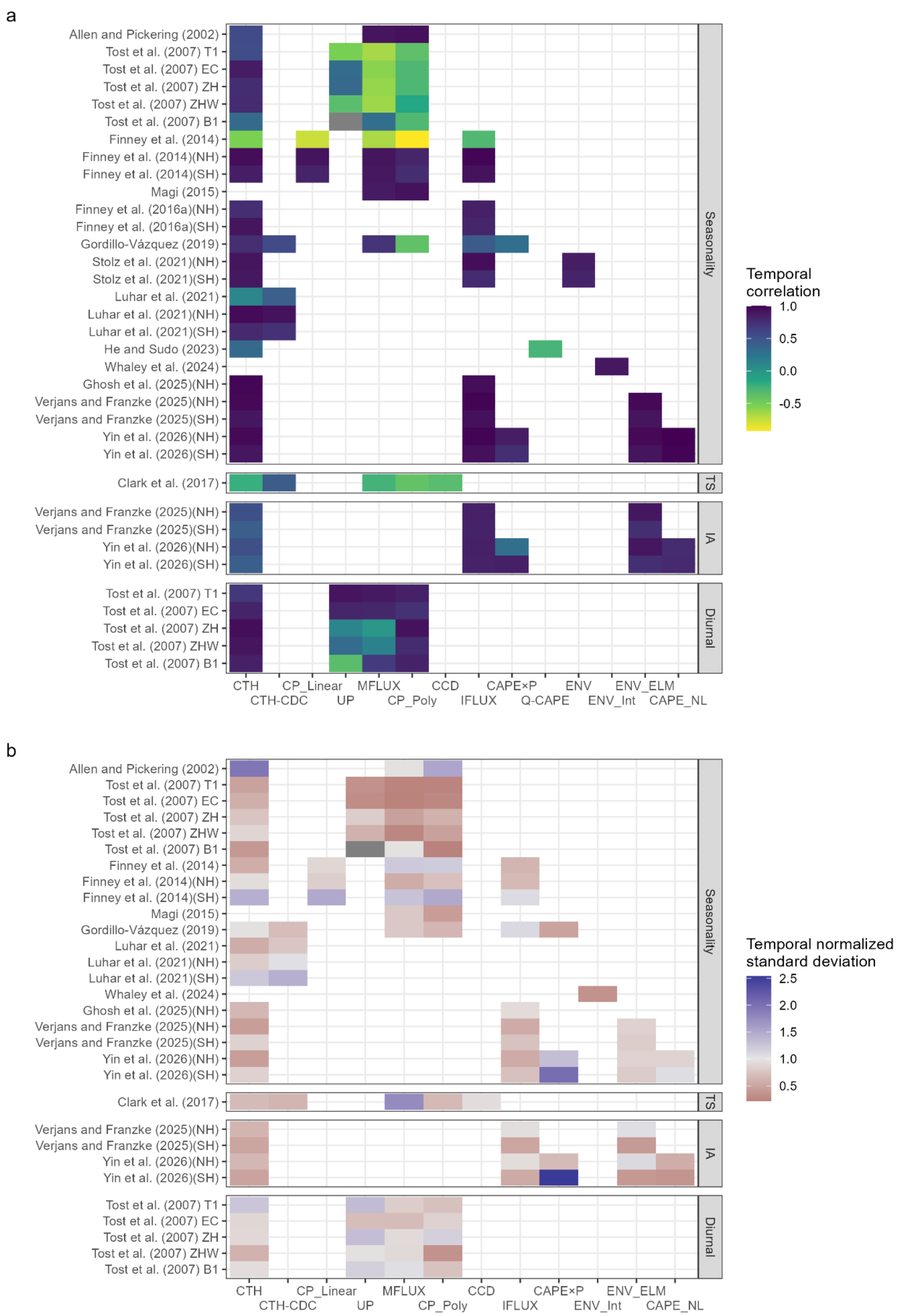

Fig. 4: Assessment of different lightning parameterizations in reproducing temporal variations of observed lightning across multiple time scales: seasonal, monthly time-series (TS), inter-annual (IA),

https://doi.org/10.5194/egusphere-2026-3212
Preprint. Discussion started: 13 July 2026

and diurnal. Some studies split the evaluation between Northern Hemisphere (NH) and Southern Hemisphere (SH). In panel (a), darker colours in the correlation indicate better performance in capturing the timing of lightning activity. In panel (b), blue shades in the normalized standard deviation represent overestimation, while red shades indicate underestimation of the amplitude of variations. The individual values for each study and parameterization can be extracted from Table S3.

3.4 Reliability beyond statistical metrics

Being able to reproduce observed lightning patterns is a necessary but not sufficient condition for making reliable lightning projections under novel climate conditions. The fact that most parameterizations require separate equations for land and ocean further suggests that important processes or variables are still not adequately represented. Recently, data-driven machine learning approaches achieved impressive statistical performance when evaluated against observations, with the test years explicitly excluded from the training data (Verjans and Franzke, 2025; Yin *et al.*, 2026). However, the key question is whether these highly flexible models, especially those that receive information from other grid cells, truly capture the fundamental features underlying charge separation, or whether they merely learn to reconstruct the training data effectively. We illustrate this issue using the FLASHMAP lightning dataset by predicting, for each grid cell and month of the test year, the corresponding monthly mean from all other years. This simple approach achieves high correlation coefficients at both spatial and seasonal scales (Fig. 5), but would obviously be insensitive to changing environmental conditions. Therefore, reproducing inter-annual variability in the test years would provide an important benchmark for model evaluation. However, this is hindered by the short record length of consistently available lightning data. For instance, Verjans and Franzke (2025) and Yin *et al.* (2026) used six test years (including one incomplete year), assembled from lightning observations from three separate missions, each with uncertain detection efficiencies and varying spatial coverage.

Among the conventional parameterizations, ice-based schemes like IFLUX and Q-CAPE are generally considered to have the strongest physical connection to lightning generation because they explicitly represent the microphysical charging processes occurring within thunderstorms (Cheng, 2021). These schemes more directly capture the collisions between graupel, snow, and ice crystals in mixed-phase cloud regions where electrification occurs. However, uncertainties remain in how models simulate cloud microphysics, as well as in the evaluation of simulated ice fluxes, because the concentration of ice particles in clouds is difficult to observe (Ghosh *et al.*, 2025). Convective intensity approaches such as CAPE×P also have a relatively strong physical basis because strong updrafts play a critical role in transporting and separating charged ice particles within deep convective clouds. In contrast, size-based parameterizations such as CTH are more empirical and only indirectly linked to the charging process. Although larger and deeper storms tend to produce more lightning, these schemes mainly rely on statistical relationships and do not explicitly represent the underlying cloud microphysics responsible for electrification.

https://doi.org/10.5194/egusphere-2026-3212
Preprint. Discussion started: 13 July 2026

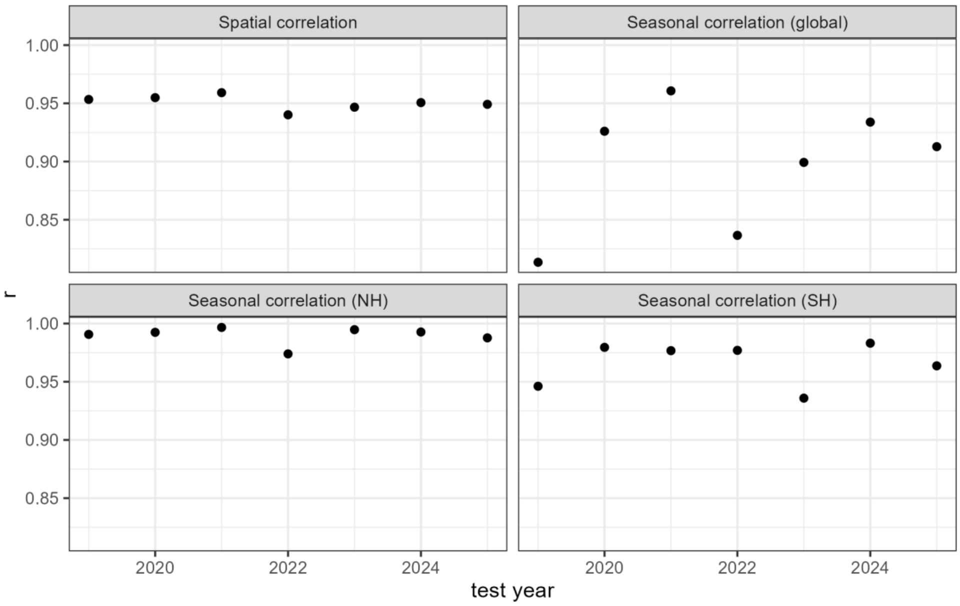

Fig. 5: Correlation between observed (FLASHMAP) and predicted lightning densities when for each month and grid cell simply predicting the monthly mean of all other years.

4 Lightning projections

4.1 Global sensitivity

The CTH approach is by far the most common one to project changes in lightning activity (Fig. 6). Most studies looked at total lightning, while projections on CG lightning are rare and in some cases it is not even clear which of both was reported. Whether CG lightning reacts more sensitive than total lightning is uncertain as the few studies that reported changes for both lightning types (all computing CG lightning from CTH-derived total lightning multiplied by the CCD-derived CG fraction) came to different conclusions: Price and Rind (1994c) reported a 30% increase in total lightning and noted that the increase was larger for CG lightning. However, in a follow-up paper they referred to a 30% increase in CG lightning (Price and Rind, 1994a). Two other studies found that CG lightning was roughly 33% less sensitive to climate change than total lightning (Pérez-Invernón *et al.*, 2023; Krause *et al.*, 2014). Several studies did not report changes in lightning flash frequency but instead changes in lightning NO_x production. While older studies often assumed CG lightning to be much more potent in generating NO_x than intra-cloud lightning (Price *et al.*, 1997), recent research suggests their NO_x production efficiency are similar (He *et al.*, 2022). Depending on this assumption, changes in NO_x production are thus rather indicative for changes in CG lightning or total lightning. Averaged over all three variables (total lightning, CG lightning, lightning NO_x production) and parameterizations (i.e. one mean value per parameterization), lightning increases by 4.4±7.6% per degree global warming. Averaged over all projections the lightning sensitivity is higher at 7.5±7.9% K^{-1}. This is due to the large overrepresentation of CTH, with 61% of the projections applying CTH. Interestingly, the **CTH** approach yields relatively similar lightning sensitivities in different climate models and scenarios (9.8±6.1% K^{-1}), despite the fifth-power relationship making lightning very sensitive to simulated changes in cloud height. There is one outlier by Lamarque *et al.* (2005) that has the highest lightning

https://doi.org/10.5194/egusphere-2026-3212
Preprint. Discussion started: 13 July 2026

sensitivity across all projections (~44% K^{-1}), however note that the associated global temperature increase was not reported and had to be estimated (Schumann and Huntrieser (2007) computed an even higher value of 60% K^{-1} but their assumed 2000-2100 temperature increase of 2 K seems too low for the A2 scenario). The variant of CTH, **CTH-CDC**, has a substantially lower sensitivity (3.4±4.7% K^{-1}). **UP**, **CP_Poly**, and **CCD** have similar sensitivities (2.8% K^{-1}, 2.2±3.1% K^{-1} and 3.2±0.7% K^{-1}, respectively), but all of these are based on only one model. **MFLUX** has a negative sensitivity (-3.5±6.8% K^{-1}), including the lowest value across all projections (-11% K^{-1}; Finney *et al.*, 2016b). The original **IFLUX** parameterization also predicts a decrease in lightning frequency under warming (-4.5±3.9% K^{-1}), but its variant, **IFLUX_T**, on average assumes a slight increase (0.8±4.7% K^{-1}). (Note that 4/6 IFLUX_T projections are from Charn and Parishani (2021) who scaled land and ocean lightning to match OTD/LIS; as ocean lightning in their study increased more than land lightning this reduced the projected increase in global lightning). **CAPE×P** has a sensitivity of 3.7±2.7% K^{-1}. Again, this value is based on simulations from a single climate model and the uncertainty in this case chiefly arises from how CAPE is computed (Charn and Parishani, 2021). **Q-CAPE-CBH** has a high sensitivity of 24.2±15.6% K^{-1}, including one of the highest values across all projections (35% K^{-1}), however, this is solely based on short-term projections (2001-2020) from one model and may be subject to substantial inter-annual variability (He *et al.*, 2022). **Q-CAPE** has a value of 13.6±11.5% K^{-1}, with three out of four projections from a single model and for the historical period. **ENV_Int** and **ENV_ELM** (apparently using more predictors than in the original parameterization) are almost insensitive (0.09±0.2% K^{-1} and 1.6% K^{-1}, respectively) but once again lack robustness as only having been applied in one model (Whaley *et al.*, 2024; Verjans *et al.*, 2025). No projections are presently available from **CP_Linear**, **ENV**, and **CAPE_NL**.

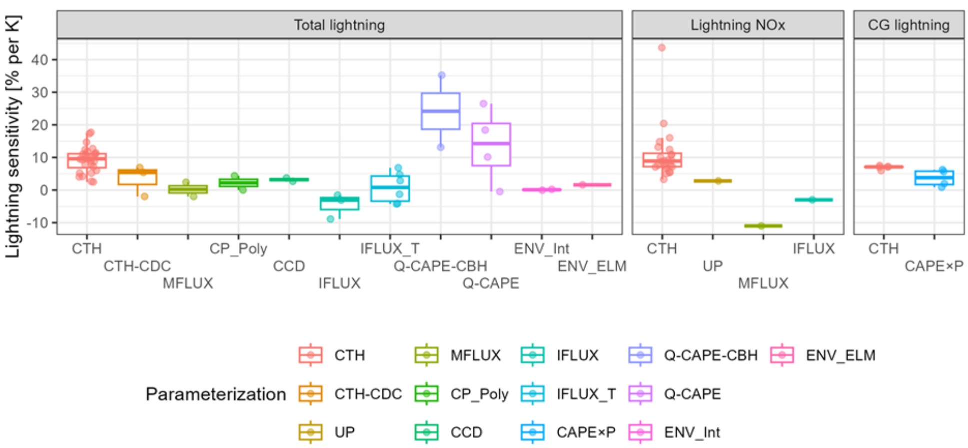

Fig. 6: Change in global lightning frequency per degree global warming for different lightning parameterizations. If a study conducted multiple projections for the same parameterization (e.g. using different model setups or emission scenarios) each projection is plotted separately. The individual values for each projection can be extracted from Table S4.

4.2 Spatial patterns of projected lightning changes

At regional scale, lightning projections tend to increase more in high latitudes relative to the tropics, where some parameterizations assume decreasing lightning activity. This contradicts earlier

https://doi.org/10.5194/egusphere-2026-3212
Preprint. Discussion started: 13 July 2026

observation-based findings that lightning in the tropics reacts much more sensitive to changes in wet bulb temperature (Williams, 1994) but supports the findings of Reeve and Toumi (1999) who found no correlation between lightning and temperature in the tropics. The **CTH** approach generally projects larger increases over land than over the oceans where lightning in some models decreases (Price and Rind, 1994c; Krause *et al.*, 2014; Clark *et al.*, 2017; Finney *et al.*, 2016b). Over land, decreases are sometimes projected over Northeastern South America, while increases are simulated for Central Africa, the Maritime Continent, and in high latitudes (Price and Rind, 1994c; Krause *et al.*, 2014; Pérez-Invernón *et al.*, 2023; Finney *et al.*, 2016b; Guryanov *et al.*, 2024). **UP** projects increases in the Eastern US and Russia but decreases in Africa and Australia (Finney *et al.*, 2016b). **MFLUX** results in larger increases (or less decreases) over land than over the ocean, while for **CTH-CDC**, **CP_Poly**, and **CCD** this depends on the emission scenario (Clark *et al.*, 2017). Over land, lightning decreases under **MFLUX** mainly occur in the (sub)tropics, while increases are found in northern Asia (Finney *et al.*, 2016b). **IFLUX** also projects lightning decreases in the tropics but increases or non-significant changes in mid and high latitudes (Finney *et al.*, 2018). For **IFLUX_T**, Charn and Parishani (2021) showed large decreases in future lightning almost everywhere on Earth when using a 1-moment microphysics scheme, while the picture looked heterogeneous for a – presumably more realistic – 2-moment scheme. For the latter, lightning decreased over most of Africa, Southern Europe, the Middle East, India, and Australia but increased over most of the Americas, Eastern Europe, Russia, China, and the Maritime Continent. Under both microphysics schemes the increase (decrease) was higher (lower) over the oceans than over land (Charn and Parishani, 2021). For **CAPE×P**, global projections are only available from the same study which, however, not only tested the effect of a 1-moment vs. 2-moment microphysics scheme but also two alternative ways to compute CAPE (Charn and Parishani, 2021). These simulations suggest increasing lightning over the Maritime Continent, the oceans, and in mid and high latitudes, decreasing lightning in subtropical Africa, and contrasting projections in Central Africa and tropical South America depending on the model setup. These global modelling outcomes are broadly consistent with regional CAPE×P projections over the contiguous US (Romps *et al.*, 2014; Romps, 2019), Germany (Brisson *et al.*, 2021), the Arctic (Chen *et al.*, 2021), and the tropical ocean (Romps, 2019). Interestingly, the cloud-resolving simulations by Romps (2019) revealed the same increase for CAPE×P and IFLUX_T in the US, but a very different response over the tropical ocean (increase vs. decrease). Charn and Parishani (2021), comparing the same two parameterizations, also noted large differences under the 1-moment scheme but found that both approaches are broadly in agreement (lightning decreasing over Africa but increasing in high latitudes and over the oceans) when using the more complex 2-moment scheme. **Q-CAPE** with prognostic graupel projects increases in Eastern Africa and most of the Americas, Eurasia, and the oceans, but decreases over most of Australia and other parts of Africa (Michibata, 2024). **ENV_Int** predicts more lightning in mid-latitudes, particularly in Siberia, the western US, and Australia (Whaley *et al.*, 2024). In contrast, lightning is projected to slightly decrease over tropical land and the Arctic. **ENV_ELM** projects increases in Eastern Africa, East and Southeast Asia, Eastern North America, and southern South America, and decreases in the Amazon, Central America, and the Maritime Continent (Verjans *et al.*, 2025).

5 Conclusions and outlook

Many parameterizations have been developed to simulate lightning in global chemistry-climate models and to project how lightning activity might change in a warmer world. CTH and IFLUX capture spatial patterns of present-day lightning activity relatively well, while MFLUX, CAPE×P, and convective precipitation-based approaches typically perform worse. Some newer approaches, such as Q-CAPE-CBH, Q-CAPE, and ENV_ELM have also shown promising results, but they need to be

https://doi.org/10.5194/egusphere-2026-3212
Preprint. Discussion started: 13 July 2026

confirmed by other studies. Simulating the magnitude of spatial and temporal variability remains challenging and is typically underestimated. CTH, CAPE×P, and IFLUX are currently the most popular approaches, however, there is a lack of consensus across parameterizations about how lightning responses to climate change. In particular, convection- versus cloud-ice-driven parameterizations predict opposite trends, as atmospheric instability and convection strength are expected to increase whereas cloud ice is expected to decrease (Romps, 2019). Additionally, even if a parameterization in principle captures the key factors influencing lightning, the accuracy of climate model projections depends on the ability to realistically simulate deep convection. While advances in computational capacity, such as cloud-resolved simulations for specific regions (Finney *et al.*, 2020; Brisson *et al.*, 2021; Kahraman *et al.*, 2022; Kawazoe *et al.*, 2025), hold promise for improving the representation of lightning in models, current computational resources are insufficient for global, century-scale simulations. In the meantime, extending existing lightning observations by new satellite products such as ISS-LIS (Blakeslee *et al.*, 2020; Cecil *et al.*, 2026b) and continued monitoring from ground-based networks will allow to compare earlier projections with actual changes in lightning frequency. This will aid in identifying the most reliable approaches for predicting lightning under future climate conditions.

Code and data availability

No new data was generated in this research. Identified modelling studies, evaluation scores, and lightning sensitivities can be found in files S1-S4.

Author contributions

AK led the analysis and wrote the first manuscript draft. All authors contributed to the writing and discussion.

Competing interests

The authors declare that none of the authors has any competing interests.

Acknowledgements

We thank David Romps for his feedback. We used ChatGPT to improve the wording and clarity of selected sections of the manuscript.

Financial Support

This work was funded by Deutsche Forschungsgemeinschaft (German Research Foundation) via the FlashForest project (flashforest.eu; project number 536753546).

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