Preconditioning, aerosols, and radiation control the temperature of glaciation in Amazonian clouds

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Glaciation in clouds is a fundamental phenomenon in determining Earth’s radiation fluxes, sensible and latent heat budgets in the atmosphere, the water cycle, cloud development and lifetime. Nevertheless, the main mechanisms that govern the temperature of glaciation in clouds have not been fully identified. Here we present an analysis of 15 years (2000-2014) of satellite, sunphotometer, and reanalysis datasets over the Amazon. We find that the temperature of glaciation in convective clouds is controlled by preconditioning dynamics, natural and anthropic aerosols, and radiation. In a moist atmospheric column, prone to deep convection, increasing the amount of aerosols leads to a delay in the onset of glaciation, reducing the glaciation temperature. For a dry column, radiative extinction by biomass burning smoke leads to atmospheric stabilization and an increase in the glaciation temperature. Our results offer observational benchmarks that can help a more precise description of glaciation in convective cloud models.

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Microphysical interactions between aerosol particles and cloud droplets can lead to a delay in total glaciation in deep convective clouds, according to results from modeling and observational studies. Cloud development and lifetime, and their response to radiation and aerosols remain some of the most important issues that need to be improved in climate modeling. Glaciation is a fundamental ingredient controlling cloud lifetime and precipitation, hence understanding further how it can be influenced by aerosols, radiation, and dynamics constitutes an important piece of this puzzle.

The temperature of total glaciation (\(T_g^\ast\)) can be defined as the warmest section of the glaciated phase in clouds, considering the accuracy and spatial resolution of the instrumentation in use. \(T_g\) can be anywhere between a few degrees below 0 °C and –38 °C, and it is regulated by complex in-cloud physical processes. For instance, the magnitude of updraft speed in a mixed-phase section of a convective cloud can modulate the local vapor supersaturation, which controls whether droplets and/or ice particles can grow, depending on the number concentration and size distribution of water droplets and ice particles. These glaciation-controlling interactions between cloud microphysics and dynamics cannot be fully represented in global climate models.

Even though \(T_g^\ast\) is critical to define the mixed-phase cloud section in equilibrium climate sensitivity studies, we have limited observational knowledge of this variable, and it remains to be determined whether it could be used to circumscribe climate modeling scenarios.

Here we distinguish \(T_g^\ast\) (i.e., a temperature that can be measured in situ) from \(T_g\), a proxy estimate of \(T_g^\ast\), derived from indirect measurements. Although past studies have observed how properties, such as cloud top temperature, respond to dynamics and aerosols in the atmosphere, there have been few in situ measurements of \(T_g^\ast\) itself. Some observational analyses, from space or ground-based remote sensing, have shown how \(T_g\) can be retrieved for single maritime or continental clouds, or how \(T_g\) can correlate with aerosols from dust and forest fire events. Notice all these previous estimates of \(T_g^\ast\) correspond to particular case studies, not accounting for long-term meteorological variability or site-specific aerosol properties. We still lack robust statistics based on basic observational evidence to understand how dynamical forcing, radiation, and aerosols influence \(T_g^\ast\), particularly in deep tropical clouds. For instance, deep convective clouds in the Amazon are periodically subjected to heavily polluted atmospheric conditions that occur yearly, from August to October, due to the prevalent use of fire as a land-clearing tool. This situation induces micro- and macrophysical changes that have been observed in Amazonian clouds but the effect of biomass burning smoke on \(T_g^\ast\), coupled with other drivers of cloud dynamics, remains uncertain.

The challenge here is to understand the relative role of key players that control \(T_g^\ast\) in the Amazon. The association of intense solar heating and abundant humidity, with weak vertical wind shear, in this region leads to frequent atmospheric instability. Large scale convergence and mesoscale organization modulate the vertical transport of moisture. Dynamics determine the local atmospheric humidity profile that defines a fundamental feedback pathway for the preconditioning effect and the development of deep convection. When a parcel ascends through a moist column, a smaller humidity gradient implies that less of its water content is eroded by the surrounding drier environment, favoring the development of deeper convection cells. Strong updrafts can push the total glaciation level upward, decreasing \(T_g\) and driving deep convection up to the upper troposphere, where changes in lapse rate and vertical pressure gradient cause cloud detrainment. This contributes to humidifying the vicinity of cloud tops, preconditioning the surrounding environmental air to the formation and growth of other convective cells. From the microphysical point of view, aerosols can decrease \(T_g\) by delaying droplet freezing. In the warm phase, aerosols acting as cloud condensation nuclei reduce droplet effective radii, and the efficiency of collision-coalescence processes, in favor of diffusional growth. Increased vapor diffusion boosts the release of latent heat of condensation, which in turn leads to increased buoyancy and updrafts. As a consequence, more droplets, with smaller average sizes, are taken aloft to temperatures below the 0 °C isotherm. These smaller supercooled droplets result in less efficient heterogeneous freezing, hence glaciation occurs higher in the atmosphere, at a lower \(T_g\).

The delayed freezing releases latent heat higher in the atmosphere, which fuels buoyancy and strengthens updrafts, bringing more moisture from lower levels, and favors the formation of deeper clouds. On the other hand, some types of aerosols can also act as ice-forming nuclei, inducing glaciation in clouds, under heavily polluted conditions. The extinction of sunlight by the aerosol layer in cloud-free areas can change the vertical temperature profile and alter surface heat fluxes. This in turn can curtail convection patterns locally, reduce updraft motion, and hence influence the development of deep convective clouds and the onset of glaciation.

Here we show how \(T_g\) in Amazonian deep convective clouds responds to the aerosol load in the atmosphere, depending on the preconditioned state of the upper troposphere. By combining 15 years of satellite, ground-based sunphotometer, and reanalysis data, we confirm the pivotal part humidity represents as a dynamical forcing controlling deep convection in the Amazon, and reveal the complexity of interactions between aerosol microphysics, radiative effects, and the humidification of the atmospheric column. The retrieved \(T_g\) patterns are consistent with direct measurements reported in previous studies, and with microphysical mechanisms affecting glaciation. \(T_g\) can also be controlled by the combined influence of dynamics and aerosol radiative effects originated from severe biomass burning pollution.

**Results and discussion**

We mark \(T_g\) as an estimator of \(T_g^\ast\) derived from satellite data using a ratio between the reflectance at two wavelengths that are sensitive to the thermodynamic phase (cf. Methods). This allows for a good approximation for the temperature at which most of the hydrometeors are in the solid phase. Comparisons between \(T_g\) and in situ measurements are examined further ahead.

**A proxy for the local dynamical forcing.** In order to define a proxy for the dynamical forcing, one needs to find a set of meteorological variables that show the highest absolute correlation with \(T_g\) (\(R_{T_g}\) in Table 1), while being nearly independent of the microphysical forcing represented by the aerosol optical depth \(\tau_a\) with the lowest absolute correlation \(R_{\tau_a}\), a procedure that has been used in other studies. A large number of meteorological and surface parameters in reanalysis datasets were investigated to that end, in four synoptic times from 0 to 18 UTC. The top results are shown in Table 1 (correlation \(R\) values all under 0.05).

The first three variables in Table 1 are specific and relative humidity at high levels in the troposphere, for which \(R_{T_g}\) varies from about –0.25 to –0.18, while \(R_{\tau_a}\) ranges between –0.03 and –0.04. The absolute values of \(R_{T_g}\) are expected to be small compared to unity, since it is probable different sources of random events may act during the long 15 y timeframe used in this study. The identification of humidity at high levels in association with the dynamical forcing is consistent
with a moistened (preconditioned) upper layer that favors convection and colder $T_g$ (hence the negative correlation). The photosynthetically active radiation at the surface ($R_{T_g} = -0.17$) was also listed in Table 1, compatible with surface radiative warming in cloud-free areas generating atmospheric instability necessary for convective initiation. Also cloud cover at 150 hPa ($R_{T_g} = -0.15$) is consistent with an increased detrainment in the upper troposphere for conditions that favor deep convection. Humidity at lower to mid levels (1000-650 hPa) showed negligible or non-significant correlations with $T_g$ and $T_a$.

In principle, the reanalysis variables shown in Table 1 can be combined to define a proxy that represents the local dynamical forcing over $T_g$ variability. We opted for simply considering the specific humidity at 225 hPa ($q_{225}$) as this index, which is used here just for segregating the data. More specifically, the tertiles in the distribution of $q_{225}$ values were used to classify $T_g$ and $T_a$ data in three subsets, corresponding to drier than average ($D$), average ($A$), and more moist than average ($M$) specific humidity classes in the upper troposphere, due to a varying degree of atmospheric preconditioning. Implicitly we are recognizing the upper tropospheric humidity as the most consequential dynamical parameter related to the development of deep convection in the Amazon, due to the moistening of the atmospheric column, as seen before27−29 (cf. preconditioning analysis in SI). Other methodologies were tested to build a dynamical forcing index, using combinations of $q_{225}$, vertical wind shear, and the convective available potential energy, with no significant impact on our main results.

The $T_g$ relation to aerosols per preconditioning state. The relation between average $T_g$ and $T_a$ observed in southern Amazon is shown in Fig. 1. For a very clean atmosphere with $T_a < 0.1$, $T_g$ is typically between about −12 and −16 °C. These are equivalent to a natural or background range for $T_g$ since $T_a$ corresponds to the average aerosol load in the rainy season in southern Amazon ($T_a = -0.1-0.2$). The more moist the upper troposphere, the colder $T_g$ as the preconditioning effect favors deeper convection27−29. At the relative low aerosol content range, with $T_a < 0.4$, the intercepts of the $T_g$ vs. $T_a$ relation define the expected maximum average glaciation temperature (at $T_a = 0$), ranging from −10.1 ± 0.5 °C ($D$ conditions) to −15.2 ± 0.7 °C ($M$). In these conditions the aerosol microphysical effect (cf. discussion ahead) is represented by the similar slopes found for the $T_g$ vs. $T_a$ relation: about −12.6 °C/unit $T_a$, −12.1 °C/unit $T_a$, and −13.6 °C/unit $T_a$, respectively for $D$, $A$, and $M$ conditions. Assuming these three estimates represent the same microphysical phenomenon we calculate the average slope as $-12.6 ± 1.7 °C/unit T_a$ for $T_a < 0.4$.

The slope in the $T_g$ vs. $T_a$ relation is nearly negligible for the 0.4 < $T_a$ < 0.8 section in Fig. 1. $T_g$ is roughly independent of the aerosol signal, and related to the level of preconditioning, with $T_g$ between −15 and −17 °C in $D$ conditions, −18 and −20 °C ($A$), and −20 and −19 °C in $M$ conditions.

Under heavy pollution ($T_a > 0.8$) there are marked differences in $T_g$ patterns. Under $D$ and $A$ preconditioning states, $T_g$ gets warmer with $T_a$, i.e., glaciation occurs earlier during the vertical development of convective clouds as the atmospheric smoke loading increases. At the highest $T_a ~1.4$ level the glaciation temperature for $D$ and $A$ conditions averages between about −15 and −16 °C, the same range observed for the very clean aerosol range when $T_a < 0.4$. To our knowledge, this is the first time this effect is observed. Notice that under $M$ conditions $T_g$ shows a sharp transition for $T_a > 0.8$, reaching about −31 °C on average for the most polluted conditions, in general agreement with individual observations of deep convective clouds approaching the limit for homogeneous glaciation12,13,20. These results are subsequently discussed.

**Table 1.** Top correlations in the period 2000-2014, between ECMWF reanalysis variables and $T_g$ ($R_{T_g}$), and between reanalysis variables and $T_a$ ($R_{T_a}$).

| Dataset | Variable | Level      | $R_{T_g}$ | p value | $R_{T_a}$ | p value |
|---------|----------|------------|-----------|---------|-----------|---------|
| PL      | Specific humidity | 225 hPa | −0.2547   | <10$^{-10}$ | −0.0338   | 0.0030   |
| PL      | Relative humidity | 300 hPa | −0.2274   | <10$^{-10}$ | −0.0315   | 0.0058   |
| PL      | Relative humidity | 350 hPa | −0.1798   | <10$^{-10}$ | −0.0402   | 0.0004   |
| SF      | Clear sky photosynthetically active radiation | Surface | −0.1730   | <10$^{-10}$ | +0.0491   | 0.0001   |
| PL      | Cloud cover | 150 hPa | −0.1525   | <10$^{-10}$ | −0.0305   | 0.0075   |
| PL      | Divergence | 175 hPa | −0.1344   | <10$^{-10}$ | +0.0245   | 0.0318   |
| PL      | U component of wind | 70 hPa | +0.1336   | <10$^{-10}$ | +0.0392   | 0.0006   |
| PL      | Cloud cover | 250 hPa | −0.1330   | <10$^{-10}$ | −0.0350   | 0.0021   |
| PL      | Geopotential | 825 hPa | +0.1202   | <10$^{-10}$ | +0.0330   | 0.0039   |
| PL      | U component of wind | 125 hPa | +0.1192   | <10$^{-10}$ | +0.0335   | 0.0034   |

(1) ECMWF datasets used in the analyses: ERA-Interim Pressure Levels (PL), Era-Interim Surface39 (SF), and Era-Interim/Land40.

**Fig. 1.** Glaciation temperature ($T_g$) in Amazonian convective clouds, from 2000 to 2014, as a function of the columnar aerosol optical depth ($T_a$), according to classes of atmospheric preconditioning. Red, black, and blue coloring correspond to lower, mid, and upper tertiles, respectively, in the distribution of $q_{225}$, a proxy for the convective preconditioning effect. Aerosol data was obtained from daily averages of level 2.0 AERONET38 measurements at 5 sites in the Amazon Basin. $T_a$ was inferred from GOES satellite imagery acquired in 100 x 100 km boxes around the AERONET sites between 17:00 and 18:00 UTC (13:00-14:00 LT). Error bars correspond to the standard error of the mean, $q_{225}$ was obtained from daily 1° gridded ECMWF Era-Interim reanalysis data49 at 18:00 UTC.
Cloud fraction, cloud base updraft relation to aerosols, and preconditioning. To better understand how $T_g$ may respond to preeminent local drivers of convection in the Amazon, estimates for the cloud fraction ($f_c$) and the updraft at cloud base ($w$) were also studied, in relation to aerosols and the preconditioning state. Figure 2 shows that in general, the more moisture present in the upper troposphere, the larger the cloud fraction, which is likely to be an expression of the preconditioning feedback effect itself. Under M conditions $f_c$ ranges from 0.80 to 0.92, showing a slight increase with $T_a$. For A conditions $f_c$ oscillates with no clear dependence on the aerosol signal, varying between 0.68 and 0.75. The pattern is clearly nonmonotonic for D conditions, showing an average $f_c$ of 0.51 for a very clean atmosphere ($T_a$ ~0.1), peaking at 0.62 for $T_a$ ~0.8, then decreasing to 0.40~0.45 when 1.6 < $T_a$ < 1.8. Note that for the cleaner subset with $T_a$ < 0.4, $f_c$ increases with $T_a$ for any preconditioning state, considering the small error bars in this part of Fig. 2.

Reanalysis data were combined with satellite temperature retrievals to derive $w$, using a validated methodology for Amazonian convective clouds. The method employs the temperature difference observed between the surface and cloud base, assuming a dry adiabatic lapse rate between the two reference levels. Therefore $w$ can also be seen as an instability proxy in the boundary layer. As shown in Fig. 3, the preconditioning effect corresponds to increased $w$ the more moist the upper troposphere, with $w$ averages ranging from a maximum of ~0.69 m s$^{-1}$ under M pristine conditions, to ~0.11 m s$^{-1}$ for D polluted conditions. In general, $w$ decreases nearly monotonically with increasing $T_a$. In particular, for D and A conditions, respectively, about 53 and 48% of reduction are observed in the range $T_a$<0.40.

Observations of $T_g$. Under clean conditions, Amazonian “green ocean” continental clouds can have liquid water content profiles and droplet size distributions that resemble maritime clouds. Hence, we compare our $T_g$ retrievals for Amazon clouds first with pristine conditions over the ocean or land, then in other situations. Reported direct measurements of $T_g$ show results such as −10 °C for maritime pristine clouds, or −15 °C for “less maritime” cases (i.e., with smaller droplet sizes). In another work, a $T_g$ of about −15 °C in maritime tropical clouds was estimated from in situ measurements showing a rapid decrease in vertical profiles of supercooled water droplet concentrations, as most of the precipitate mass freezes at the border between mixed and glaciated phases. These previous results for pristine cases agree with the intercept in Fig. 1 for M conditions, showing a $T_g$ of −15.2 ± 0.7 °C. In particular, Stith et al.14 performed in situ cloud penetration experiments over one of the Amazonian sites used in this work, and found a $T_g$ of −17°C for measurements in February during the wet season, when the atmosphere in the region is usually pristine, frequently under a moistened preconditioned state with intense convective activity. This matches well Fig. 1 results for $T_a$<2.0, when the average $T_g$ ranges from −16 °C to −18 °C under M conditions. In addition, our results also show how $T_g$ varies in cleaner subset conditions according to the state of atmospheric humidification. We propose here observational constraints for the preconditioning effect in Amazonian clouds at $T_a$ ~0, in which $T_g$ ranges from −10.1 ± 0.5 °C in D conditions to −15.2 ± 0.7 °C in M conditions. The aerosol microphysical effect manifested itself as an average slope of −12.6 ± 1.7 °C/unit $T_a$ in this pristine atmosphere limit. These figures can be tested or used in future observational, experimental, or modeling works.

Direct measurements of $T_g$ near −38 °C have been reported previously, which coincide with our coldest individual (i.e., nonaveraged) $T_g$ retrievals under M conditions. Note Fig. 1 shows matched-up cloud and aerosol data, resulting in more limited statistics in the final result than in the full database. Measurements of $T_g$ ~−38 °C in cumulus clouds have been linked to the availability of abundant cloud condensation nuclei aerosols, which activate smaller droplets that can stay in a supercooled state up to the homogeneous glaciation limit. Our results, however, show that when a large amount of aerosols is available, $T_g$ can either approach the −38 °C limit, or remain much lower in the atmosphere, depending on how dynamics primes the atmospheric column for convective activity.

From cloud formation to glaciation. For the cleaner subset, with $T_a$<0.4, cloud droplets will form under an aerosol-limited activation regime, when the cloud droplet number concentration is mostly determined by $T_a$, and nearly independent of $w$. Therefore the marked reduction of up to ~53% in $w$ (Fig. 3) should not have a significant impact on the initial droplet number concentration at the cloud base. In general the bigger $T_a$, the more
numerous cloud droplets are formed at cloud base. We interpret the linear decrease of $T_g$ with $\tau_g$ (Fig. 1), as a consequence of cloud invigoration due to the aerosol microphysical effect, leading to a delay in the occurrence of full glaciation and deeper convective clouds. The dynamical forcing linked to the preconditioning state also affects $T_g$, since the more humidified the column, the colder the observed $T_g$. In these conditions, the radiative extinction effect of aerosols is at its relative minimum. $f_c$ increases by $\sim$4–9% (Fig. 2), indicating a more horizontally spread out cloud field on average, increased shading at the surface, and a more stable boundary layer evidenced by the 34–53% reduction in the magnitude of $w$ (Fig. 3). Nevertheless, since in this regime the cloud droplet population is mostly sensitive to the number of aerosol particles, we conclude ultimately the dynamics-microphysics coupling prevails over radiative effects in determining $T_g$ for the cleaner subset.

For the higher pollution subset ($0.4 < \tau_g < 0.8$) the main forcings act simultaneously. As $\tau_g$ increases, the average $f_c$ in $D$ conditions grows from about 0.55 to 0.62, a 13% increase (Fig. 2), while in $M$ conditions $f_c$ stays relatively high at about 0.84 within a $\sim$1% variation. This points to a relatively weak importance of the aerosol radiative effect in cloud-free areas, since $f_c$ is either already high or increases with $\tau_g$. Considering the aerosol microphysical effect, as $\tau_g$ increases in this polluted conditions range, so does the number concentration of cloud droplets formed initially at cloud base. However, the droplet activation regime undergoes a transition in which $w$ becomes increasingly more important, while its magnitude decreases in general (Fig. 3). These constitute two opposing trends for the number of activated droplets at cloud base, which is critical in determining $T_g$. $M$ conditions see a reduction of about 42% in the average magnitude of $w$ when $0.4 < \tau_g < 0.8$, while for $D$ conditions the reduction is about 24%; for the average $T_g$ the equivalent changes are about +3.4% and $\sim$10% (Fig. 1, $M$ and $D$ conditions, respectively). We cogitate that the sharper relative reduction in $w$ can be the main factor in defining the small increase in $T_g$ for $M$ conditions due to a relative decrease in the concentration of active droplets. In $D$ conditions, the smaller reduction in $w$ and simultaneous increase in $\tau_g$ can be possibly associated with an increase in the number of droplets, and hence this could explain the observed reduction in $T_g$. Therefore we conclude that for these polluted conditions, the dynamics-microphysics coupling probably dominates the observed variations in $T_g$ as compared to radiative effects.

Under heavy smoke pollution with $\tau_g > 0.8$, aerosol particles are activated at cloud base in a $w$-limited activation regime, when the number of cloud droplets is mostly sensitive to variations in $w$ and roughly independent of $\tau_g$. Since $w$ is consistently stronger in a moistened column (Fig. 3), denser cloud droplet concentrations occur under $M$ conditions when compared to $A$ or $D$ conditions. Therefore a delay in glaciation is observed (Fig. 1, $M$ conditions), when a premoistened column sustains the deep convection outset. It is possible secondary ice production processes play a central role in controlling the total concentration of ice particles, related to the observed sudden change in $T_g$. In parallel, as the highest $f_c$ above 0.90 are observed under the same $M$ conditions (Fig. 2), solar radiation extinction by boundary layer aerosols is less prevalent due to more frequent surface shading by clouds, hence the aerosol radiative effect and boundary layer stabilization are relatively less important. For $D$ conditions the smallest observed $f_c$ $\sim$0.40–0.45 results in more frequent mixing between the cloud and external drier air, and also in a relative maximum for aerosol radiative extinction in cloud-free areas. This helps to stabilizing the boundary layer, a drastic reduction in $f_c$ with increasing $\tau_g$ (Fig. 2). In particular, the boundary layer stabilization is evidenced by the smallest $w$ observed under $D$ conditions of $\sim$0.11 m s$^{-1}$ (Fig. 3). In theory, a parcel ascending through a mixed-phase cloud under drier, subsaturated environmental conditions, with large number concentrations of hydrometeors, and with small in-cloud updraft velocities tends to experience evaporation of liquid droplets and growth of ice particles from water vapor deposition (Wegener–Bergeron–Findeisen process). This is analogous to $D$ conditions in Figs. 1–3 for $\tau_g > 0.8$ (although note Fig. 3 shows the updraft at cloud base, not in-cloud updrafts). Therefore we consider this phenomenon as a possible explanation for the physical process behind the $T_g$ warming with increasing $\tau_g$, with the depletion of liquid droplets and accretion of ice mass at this limit of a driest atmospheric column, more stable boundary layer associated with the smallest $w$ estimates, and heavy pollution. We conclude the relatively warmer $T_g$ of about $\sim$13 to $\sim$15°C for $D$ conditions (Fig. 1) is determined by the coupling between the aerosol radiative effect and dynamics set to a drier atmospheric column, unfavorable to deep convection. Conversely, for $A$ conditions the observed $T_g$ below $\sim$30°C is determined by the coupling between modified preconditioning dynamics and the aerosol microphysical effect.

We showed that $T_g$ in convective clouds in the Amazon is controlled by three main players, with coupled interactions: a) dynamics, represented by the atmospheric preconditioning state; b) aerosol particles, introducing cloud condensation and ice nuclei at cloud base; and c) the radiation field in the boundary layer and surface, which modulates local atmospheric stability and convection initiation. We identify couplings between: i) dynamics and microphysical aerosol effects; and ii) dynamics and radiative aerosol effects. These results provide observational process-informed constraints for deep convection studies in the tropics. They could be used, for instance, to model the depth of the mixed-phase section in convective clouds in a variety of dynamical, microphysical, and radiative scenarios, leading to a more precise description of glaciation in cloud models, with potential developments for climate research.

**Methods**

**Derivation of $T_g$**

Calibrated radiances measured at three wavelengths (0.03, 3.90, and 11.0 µm) by National Oceanic and Atmospheric Administration’s (NOAA) satellites GOES-8, –12, and –13 were analysed in a latitude/longitude box over the Amazon Basin defined between [$\sim$2° to $\sim$16°N; $\sim$49° to $\sim$70°W], with daily acquisitions between 17:00 and 18:00 UTC (13:00–14:00 LT), from 2000 to 2014. Radiance measurements at 11.0 µm were converted to brightness temperatures ($T_b$) via the blackbody radiation emission of clouds in this channel, and its partial absorption in the atmospheric column. Cloudy pixels were defined as having $T_b < \sim$10°C and $\rho_{6.3} > 0.15$, at 4 km spatial resolution. In the Amazon, it is possible to have warm clouds forming at temperatures above $\sim$10°C or having thin cirrus clouds with reflectance below 0.15. Thus, potentially many warm cloud pixels are not counted in the resulting data set, and with these thresholds ensure exclusion of shadows, river patches, and vegetated or degraded surface pixels. We tested the influence of adopting different numerical values for the $T_g$ and $\rho_{6.3}$ thresholds, and they had no impact over our main findings. These thresholds definitions are therefore suitable for the goals in this study; that focus only on cold top clouds, and do not account for other cloud types. $\rho_{6.3}$ and $\rho_{3.0}$ were analysed in 100 x 100 km boxes centered around five National Aeronautics and Space Administration (NASA) Aerosol Robotic Network (AERONET) sites: Alta Floresta (AF, $\sim$9.87°N, $\sim$56.10°E), Abracos Hill (AH, $\sim$10.76°N, $\sim$62.36°E), Cuiabá (CB, $\sim$15.73°N, $\sim$60.02°W), Il Paraná (IP, $\sim$10.93°N, $\sim$61.84°W), and Rio Branco (RB, $\sim$9.96°N, $\sim$67.87°W). The ratio $\rho$ between $\rho_{6.3}$ and $\rho_{3.0}$ for cloudy pixels over each site was analysed according to the thermodynamic phase and season of the year. This was done considering that cloudy pixels with $T_b > 0°C$ corresponded exclusively to liquid phase droplets, while cloudy pixels with $T_b < \sim$38°C contained only solid phase particles. Supplementary Fig. 1 shows the histogram of $\rho$ for each season and thermodynamic phase, for all the ice-only and water-only cloudy pixels used in this study. This corresponds to a total of $\sim$4.6 million pixels, of which $\sim$3.7 million were...
observed during the wet season (November to May), and ~0.93 million are from the dry season (June to October). The difference between the number of pixels in each subset reflects the seasonal differences of cloud formation in the Amazon Basin. Supplementary Fig. 1 shows the marked contrast of R values according to the thermodynamic phase of the cloudy pixels, due to differential absorptivity properties of visible and mid-infrared wavelengths by water and ice particles. Notice that a fully fledged thermodynamic phase detection algorithm is not under discussion here; we rather consider simply that there is a striking distinction in the pattern of the ratio R between liquid-only and solid-only phases. By empirical inspection of Supplementary Fig. 1 the lower limits for the R value of ice particles were defined as 7.62 and 9.63 in the dry and wet seasons, respectively. These R limits effectively allowed the discrimination of ice particles, in the sense that less than 0.40% of water-only pixels in each season showed R values above the ice thresholds. For mixed-phase pixels, the retrieved R is intermediate between the distributions in Supplementary Fig. 1. In this case, the method detects when the prevalent thermodynamic phase matches the ice spectral signature. Dataset retrieved R values showed no significant dependence with r_p. Because deep convective cells in the Amazon often span several hundreds of kilometers in the horizontal scale (i.e. corresponding to Mesoscale Convective Systems, MCS), the observation of large 3D cloud structures from a geostationary satellite point of view usually spans not only cloud tops but also cloud sides (cf. T_p assessment from satellite imagery in SI, and Supplementary Fig. 2). This concept is key to the algorithm since it allows vertical profiling of optical properties in a cloud field, including the total glaciation level. The selection of R values above the ice threshold, therefore, covers the total extent of the glaciated phase, from the coldest pixels near the very top of clouds, down to the warmest pixels at temperature T_p still identified as ice due to their prevalent R spectral signature. The selected pixels were then ranked according to their brightness temperature. The median temperature of the 5% hottest glaciated pixels in 100 km boxes was defined as representing the spatial variability of T_p, thus avoiding high numerical fluctuations associated with extreme values in statistical distributions. This allows accommodating horizontal and vertical variations for the retrieved T_p values over MCS spatial scales, when comparing with r_p temporal averages. Uncertainty was estimated by circular block bootstrapping by analyzing the monthly T_p time series for each site, using 10,000 replications and a block size of 20 data points (~10 days). Results from all sites were averaged to derive monthly estimates, resulting in uncertainties of 0.6 °C for wet season months (October to April), and 1.1 °C for the dry season (May to September). The different uncertainty levels are mainly due to the more frequent occurrence of clouds in the wet season. Additionally this technique allows identifying the cloud thermodynamic phase. Supplementary Fig. 2 shows an example, where the ice phase (blue) corresponds to pixels colder than T_p, the mixed phase (green) to pixels between 0 °C and T_p, and water clouds (red) correspond to pixels above 0 °C. This methodology relies only on simple thermodynamic and radiative properties of ice and water in the atmosphere, making it robust for long-term studies, and allows a simple comparison strategy with future works. See additional Methods for a complete description of aerosol, atmospheric preconiditoning state, and cloud properties, and the use of European Centre for Medium-Range Weather Forecasts (ECMWF) reanalysis datasets in this study.

Data availability
All datasets used in this work are freely available in public repositories. NOAA satellite data can be accessed from the GOES Imager GVAR_Img product page at https://www.arl.noaa.gov/rao/products/search?sub_id=8&datatype_family=GVAR_Img. NASA aerosol data is available from https://aeronet.gsfc.nasa.gov/cgi-bin/webtool_aod_v3?stage=2&place_code=10&region=South_America&state=Brazil. Reanalysis datasets are available from ECMWF at https://www.ecmwf.int/en/forecasts/dataset/ecmwf-reanalysis-v5.

Code availability
The Python code used for processing the dataset sources used in this study is available from the corresponding author upon request.

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References
1. Rosenfeld, D. et al. Global observations of aerosol-cloud-precipitation-climate interactions: aerosol-cloud–climate interactions. Rev. Geophys. 52, 750–808 (2014).
2. Altaratz, O., Koren, I., Remer, L. A. & Hirsch, E. Review: cloud invigoration by aerosols—Coupling between microphysics and dynamics. Atmos. Res. 140–141, 38–60 (2014).
3. Seinfeld, J. H. et al. Improving our fundamental understanding of the role of aerosol–cloud interactions in the climate system. Proc. Natl. Acad. Sci. 113, 5781–5790 (2016).
4. Lohmann, U. & Neubauer, D. The importance of mixed-phase and ice clouds for climate sensitivity in the global aerosol–climate model ECHAM6–HAM2. Atmos. Chem. Phys. 18, 8807–8828 (2018).
5. Tan, I., Storelvmo, T. & Zelinka, M. D. Observational constraints on mixed-phase clouds imply higher climate sensitivity. Science. 352, 224–227 (2016).
6. Mülmenstädt, J., Sourdeval, O., Delanoë, J. & Quaas, J. Frequency of occurrence of rain from liquid-, mixed-, and ice-phase clouds derived from A-Train satellite retrievals. Geophys. Res. Lett. 42, 6502–6509 (2015).
7. Rosenfeld, D. & Lensky, I. M. Satellite-based insights into precipitation formation processes in continental and maritime convective clouds. Bull. Am. Meteorol. Soc. 79, 2457–2476 (1998).
8. Korolev, A. et al. Mixed-Phase Clouds: Progress and Challenges. Meteorol. Monogr. 58, 5.1–5.50 (2017).
9. Tabazadeh, A., Dijkstr, S. Y. & Reiss, H. Surface crystallization of supercooled water in clouds. Proc. Natl. Acad. Sci. 99, 15873–15878 (2002).
10. Li, Z. et al. Long-term impacts of aerosols on the vertical development of clouds and precipitation. Nat. Geosci. 4, 888–894 (2011).
11. Rosenfeld, D., Woodley, W. L., Lerner, A., Kelman, G. & Lindsey, D. T. Satellite detection of severe convective storms by their retrieved vertical profiles of cloud particle effective radius and thermodynamic phase. J. Geophys. Res. 113, D04208 (2008).
12. Rosenfeld, D. & Woodley, W. L. Deep convective clouds with sustained supercooled liquid water down to ~375 °C. Nature. 405, 440–442 (2000).
13. Rosenfeld, D., Woodley, W. L., Krauss, T. W. & Makitov, V. Aircraft microphysical documentation from cloud base to anvils of hailstorm feeder clouds in Argentina. J. Appl. Meteorol. Climatol. 45, 1261–1281 (2006).
14. Paller, L., Hagerty, J. A., Heymsfield, A. & Grainger, C. A. Microphysical characteristics of tropical updrafts in clean conditions. J. Appl. Meteorol. 43, 779–794 (2004).
15. Lawson, R. P., Woods, S. & Morrison, H. The microphysics of ice and precipitation development in tropical cumulus clouds. J. Atmos. Sci. 72, 2429–2445 (2015).
16. Yuan, T., Martins, J. V., Li, Z. & Remer, L. A. Estimating glaciation temperature of deep convective clouds with remote sensing data. Geophys. Res. Lett. 37, L08808 (2010).
17. Martins, J. V. et al. Remote sensing the vertical profile of cloud droplet effective radius, thermodynamic phase, and temperature. Atmos. Chem. Phys. 11, 9485–9501 (2011).
18. Rosenfeld, D. et al. Glaciation temperatures of convective clouds ingesting desert dust, air pollution and smoke from forest fires. Geophys. Res. Lett. 38, L21804 (2011).
19. Ten Hoeve, J. E., Remer, L. A., Correia, A. L. & Jacobson, M. Z. Recent shift from forest to savanna burning in the Amazon Basin observed by satellite. Environ. Res. Lett. 7, 024020 (2012).
20. Andreae, M. O. Smogging rain clouds over the Amazon. Sci. 303, 1337–1342 (2004).
21. Kaufman, Y. J. & Nakajima, T. Effect of Amazon smoke on cloud microphysical and albedo analysis from satellite imagery. J. Appl. Meteorol. 32, 729–744 (1993).
22. Koren, I. Measurement of the effect of Amazon smoke on inhibition of cloud formation. Sci. 303, 1342–1345 (2004).
23. Schiro, K. A., Neelin, J. D., Adams, D. K. & Lintner, B. R. Deep convection and column water vapor over tropical land versus tropical ocean: a comparison between the Amazon and the tropical western Pacific. J. Atmos. Sci. 73, 4043–4063 (2016).
24. Malhi, Y., Pegoraro, E., Nobre, A. D., Pereira, M. G. P. & Grace, J. Energy and water dynamics of a central Amazonian rain forest. J. Geophys. Res. 107, 8061 (2002).
25. Zhuang, Y., Fu, R., Marengo, J. A. & Wang, H. Seasonal variation of shallow-to-deep convection transition and its link to the environmental conditions over the Central Amazon. J. Geophys. Res. 122, 2649–2666 (2017).
26. Silva Dias, M. A. F. et al. Cloud and rain processes in a biosphere-atmosphere interaction context in the Amazon Region. J. Geophys. Res. 107, 8072 (2002).
27. Brown, R. G. & Zhang, C. Variability of midtropospheric moisture and its effect on cloud-top height distribution during TOGA COARE. J. Atmos. Sci. 54, 15 (1997).
28. Wurtele, M. L. & Khouider, B. The deepening of tropical convection by congestus preconditioning. J. Atmos. Sci. 67, 2601–2615 (2010).
29. Holloway, C. E. & Neelin, J. D. Moisture vertical structure, column water vapor, and tropical deep convection. J. Atmos. Sci. 66, 1665–1683 (2009).
30. Korolev, A. Limitations of the Wegener–Bergeron–Findeisen mechanism in the description of mixed-phase clouds. J. Atmos. Sci. 64, 3372–3375 (2007).
31. Petersen, W. A. & Rutledge, S. A. Regional variability in tropical convection: observations from TRMM. Journal of Climate. 14, 3566–3586 (2001).
32. Blyth, A. M. Entrainment in Cumulus Clouds. J. Appl. Meteorol. 32, 626–641 (2003).
33. Chen, Q. et al. How do changes in warm-phase microphysics affect deep convective clouds? Atmos. Chem. Phys. 17, 9585–9598 (2017).
34. Koren, I., Dagan, G. & Altaratz, O. From aerosol-limited to invigoration of warm convective clouds. Science. 344, 1143–1146 (2014).
35. McCluskey, C. S. et al. Characteristics of atmospheric ice nucleating particles associated with prescribed burns and wildfires. J. Geophys. Res. Atmos. 119, 10458–10470 (2014).
36. Lohmann, U. A glaciation indirect aerosol effect caused by soot aerosols. Geophys. Res. Lett. 29, 1052 (2002).
37. Hansen, J., Sato, M. & Ruedy, R. Radiative forcing and climate response. J. Geophys. Res. 102, 6831–6864 (1997).
38. Holben, B. N. et al. AERONET—a federated instrument network and data archive for aerosol characterization. Remote Sens. Environ. 66, 1–16 (1998).
39. Berrisford, P. et al. Atmospheric conservation properties in ERA-Interim. Q. J. R. Meteorol. Soc. 137, 1381–1399 (2011).
40. Balsamo, G. et al. ERA-Interim/Land: a global land surface reanalysis data set. Geophys. Res. Lett. 42, 6485–6491 (2015).
41. Reutter, P. et al. Aerosol- and updraft-limited regimes of cloud droplet formation: influence of particle number, size, and hygroscopicity on the activation of cloud condensation nuclei (CCN). Atmos. Chem. Phys. 9, 7067–7080 (2009).
42. Andreade, M. O. Correlation between cloud condensation nuclei concentration and aerosol optical thickness in remote and polluted regions. Atmos. Chem. Phys. 9, 543–556 (2009).
43. Tao, W.-K., Chen, J.-P., Li, Z., Wang, C. & Zhang, C. Impact of aerosols on convective clouds and precipitation. Rev. Geophys. 50, RG2001 (2012).
44. Stevens, B. & Feingold, G. Untangling aerosol effects on clouds and precipitation in a buffered system. Nature. 461, 607–613 (2009).
45. Ladino, L. A. et al. On the role of ice-nucleating aerosol in the formation of ice particles in tropical mesoscale convective systems. Geophys. Res. Lett. 44, 1574–1582 (2017).
46. Ackerman, A. S. et al. Reduction of tropical cloudiness by soot. Science. 288, 1042–1047 (2000).
47. Riedi, J. et al. Cloud thermodynamic phase inferred from merged POLDER and MODIS data. Atmos. Chem. Phys. 10, 11851–11865 (2010).
48. Hoelzemann, J. J. et al. Regional representativity of AERONET observation sites during the biomass burning season in South America determined by correlation studies with MODIS Aerosol Optical Depth. J. Geophys. Res. 114, D13301 (2009).
49. Marchand, R., Beagley, N., Thompson, S. E., Ackerman, T. P. & Schultz, D. M. A bootstrap technique for testing the relationship between local-scale radar observations of cloud occurrence and large-scale atmospheric fields. J. Atmos. Sci. 63, 2813–2830 (2006).

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Author contributions
A.L.C. initiated the study, analysed the data, and wrote the paper. E.T.S. participated in the analysis and interpretation of data, and contributed to the writing. M.A.F.S.D. and I.K. participated in science discussions and analyses, and contributed to the writing.

Competing interests
The authors declare no competing interests.

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