# Supplementary Information: Minimal recipes for global cloudiness

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## 1 Table of fields

For convenience, in Table 1 we list all fields used in our study.

| Symbol | Description | Reference |
|---|---|---|
| $C$ | Energetically consistent effective cloud albedo | Datseris and Stevens (2021) |
| $L$ | Longwave cloud radiative effect | Loeb et al. (2018) |
| $\omega_{500}$ | Pressure velocity at 500hPa | Grise and Kelleher (2021) |
| $\omega_{\text{std}}$ | Standard deviation of $\omega_{500}$ within a month | Norris and Iacobellis (2005) |
| $\omega_{\text{up}}$ | Fraction of updrafts of $\omega_{500}$ within a month | Bony et al. (1997) |
| $V_{\text{sfc}}$ | 10-meter wind speed | Brueck et al. (2015) |
| SST | Sea surface temperature (SST) | Qu et al. (2015) |
| $q_{\text{tot}}$ | Total column water vapor | - |
| $q_{700}$ | Specific humidity at 700hPa | Myers and Norris (2016) |
| EIS | Estimated inversion strength | Wood and Bretherton (2006) |
| CTE | Estimated cloud top entrainment index | Kawai et al. (2017) |

**Table 1.** Fields to-be-predicted $(C, L)$ and predictors considered in this study. An indicative reference for each is given as well. We multiply $\omega_{500}$ with $-1$ in this study, so that $\omega_{500} > 0$ means upwards motion.

## 2 Data pre-processing

All predictors, with the exception of $\omega_{\text{std}}$, $\omega_{\text{up}}$, are obtained from monthly-mean ERA5 data. The standard deviation $\omega_{\text{std}}$, and fraction of updrafts $\omega_{\text{up}}$, of $\omega_{500}$, are derived from hourly $\omega_{500}$ data, aggregated over monthly periods. Using up to 6-hourly sampled data yields little quantitative difference in $\omega_{\text{std}}, \omega_{\text{up}}$.

All data, including the CERES EBAF monthly-mean data, have been transformed into an equal area grid of cell size $\approx 250$km, from their standard orthogonal longitude-latitude grids. This is very important, otherwise statistical weights need to be used in the nonlinear least squares optimization process. Additionally, only data over ocean (a spatiotemporal mask is defined when CERES auxiliary ocean fraction is $> 50\%$) are considered, as, favoring simplicity, we would like to derive minimal models that do not deal with the complexities of including a land type contribution. Data were also limited to $\pm$ 70$^{\text{o}}$, to avoid potential CERES measurement artifacts near the poles.

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## 3 Comparison with Cloud Controlling Factors Framework

At a fundamental level, our methodological approach (described in Sect. 2.3 of main text) is similar with the well-known Cloud Controlling Factors Framework (CCFF) (Stevens & Brenguier, 2009; Klein et al., 2017). We are fitting some measure of cloudiness using a function of predictors. However, there are some key differences worth highlighting in more detail.

The first is that the data used here are not anomalies. This means that the mean value of $Y$, and its seasonal cycle, must be captured by the fit. The importance of capturing the mean value and mean seasonal cycle is further enforced by the fact that the inter-annual variability of cloudiness is small in decadal timescales (Stevens & Schwartz, 2012; Stephens et al., 2015), and hence the mean seasonal cycle captures the majority of the signal (e.g., for hemispherically averaged all-sky reflected shortwave radiation, 99% of the variability (Datseris & Stevens, 2021)). Since the cloud fitting function is expected to capture the mean, it can be a nonlinear function (and if it is linear, then it must have intercept 0 by force). Another argument behind allowing nonlinear functions is that, generally speaking, a theory of cloudiness should be able to predict cloudiness over a broad range of different climatic states, not just small deviations from a reference climate (which justifies using a linear framework).

A second difference with typical CCFF studies is that we fit across all available space and time without any restrictions to special regions of space or cloud types (i.e., $f$ does not depend on space). Typically in CCFF the fitted parameters (which are linear coefficients) are either aggregated over some specific region of Earth (e.g., subtropical subsidence regions like in Myers and Norris (2016)), or are fitted for each spatial point of the planet (e.g., like in Grise and Kelleher (2021)), or the focus is exclusively on a specific cloud type (e.g., low clouds like in Myers et al. (2021)). A third difference is that the cloud fraction (or cloud cover) is never considered as a quantifier of cloudiness, while the majority of CCFF studies use cloud fraction as the predictive field. Cloud fraction however does not have any energetic meaning, and cannot be used to connect clouds to the energy balance, and as a consequence, also cannot be used in a conceptual energy balance model.

## 4 Potential connection with energy balance models

In the introduction of the main text we discussed the benefits of including cloudiness in an energy balance model. There are two steps in achieving this in practice. First, express cloudiness as a function of simpler physical quantities. Second, represent these quantities in an energy balance model. In this work we achieved the first step. To accomplish the second step, one would have to express predictors $\omega_{500}, \omega_{\text{std}}, \text{CTE}$ as functions of temperature, or temperature differences (which are the typical state variables of energy balance models). While this task is certainly a subject of future research on its own right, the choice of predictors was such that there are physically sensible qualitative connections to start from. The discussion of this section may help guide future work on the subject.

The theory behind the baroclinic instability (Charney, 1947; Eady, 1949; Pierrehumbert & Swanson, 1995) states that midlatitude storms are driven by the equator-to-pole temperature gradient. Hence, larger temperature gradient would lead to stronger storms, reflected by a larger $\omega_{\text{std}}$ in the midlatitudes. The mean circulation in the Ferrel cell (represented by $\omega_{500}$) will likely also increase due to continuity and the increased momentum carried by the storms. In the tropics, the Held-Hou model (Held & Hou, 1980) establishes a proportionality between the strength of the Hadley circulation $\omega_{500}$ and gradients in potential temperature, which in first approximation can be taken as the surface temperature. We have noticed that in the tropics the spatial structure of $\omega_{500}$ and $\omega_{\mathrm{std}}$ are very similar, but why this is the case is not obvious.

The estimated cloud top entrainment index CTE is harder to express in terms of temperatures. Measures like CTE (or EIS or the Lower Stratospheric Stability) capture the temperature inversion magnitude between the boundary layer and surface (Wood & Bretherton, 2006). In the tropical subsidence regions, this inversion strength can be conceptually tied to temperature gradient between the warm equator and colder ocean of subtropics as follows: The free tropospheric temperature is, to a first approximation, homogenized by gravity waves to the value in the convecting regions (weak temperature gradient approximation (Sobel et al., 2001)). Surface temperature in the tropical subsidence regions however reflects the colder ocean temperature. The connection of EIS with the underlying ocean temperature in the case of midlatitudes is less clear. Conceptually, a temperature inversion can occur in cyclonic storms due to kinematic (or alternatively, mechanical) reasons: warm air masses from the midlatitudes are forced on top of the cold polar fronts, creating a temperature inversion scenario. However, more research on the subject is necessary to make more concrete claims.

Given these considerations, it seems that a promising way to express these predictors (and hence cloudiness) in an energy balance model is via the equator-to-pole temperature gradient. Future research should focus on validating this claim in more detail, but also make the qualitative connections we drew here quantitative by providing clear functional forms that connect, e.g., mean $\omega_{500}$ or $\omega_{\mathrm{std}}$ with equator-to-pole temperature gradient.

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