

# Dependence of Climate Sensitivity on the Given Distribution of Relative Humidity

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## Key Points:

- Climate sensitivity is sensitive to the assumed distribution of relative humidity.
- Different relative humidity profiles explain clear-sky climate sensitivity spread among models.
- Tropical relative humidity trend in reanalyses yields an increase in climate sensitivity.

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**Abstract**

We study how the vertical distribution of relative humidity (RH) affects climate sensitivity, even if it remains unchanged with warming. Using a radiative-convective equilibrium model, we show that the climate sensitivity depends on the shape of a fixed vertical distribution of humidity, tending to be higher for atmospheres with higher humidity. We interpret these effects in terms of the effective emission height of water vapor. Differences in the vertical distribution of RH are shown to explain a large part of the 10% to 30% differences in clear-sky sensitivity seen in climate and storm-resolving models. The results imply that convective aggregation reduces climate sensitivity, even when the degree of aggregation does not change with warming. Combining our findings with relative humidity trends in reanalysis data shows a tendency toward Earth becoming more sensitive to forcing over time. These trends and their height variation merit further study.

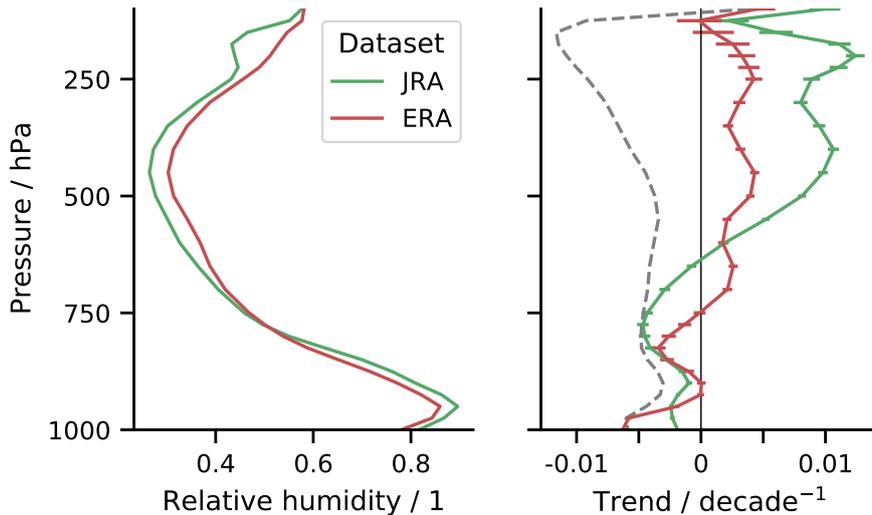
**Plain Language Summary**

Equilibrium Climate Sensitivity is the change in surface temperature in response to a doubling of atmospheric CO<sub>2</sub>. We study how the assumed vertical distribution of relative humidity affects this sensitivity. Theoretical considerations show that the more moist an atmosphere is, the more it warms as a response to an increase in CO<sub>2</sub>. Adding water vapor to the lower troposphere has the counter effect, lowering the sensitivity. We emphasize the importance of climate simulations taking humidity into account, as it is largely responsible for the difference in projections among models without clouds. We note surprising trends in humidity – with substantial drying of the lower troposphere over the ocean – in the last four decades as reported by two reanalyses of meteorological observations. Subject to the accuracy of these reconstructions, there appears to be a change with less moistening than expected, but with moistening/drying profiles which will condition Earth to become more sensitive to forcing over time. We stress the need for a study of observations to more critically evaluate these trends, and know better what models should aim for.

**1 Introduction**

The clear-sky response to an increase in greenhouse gases is a pillar of our understanding of global warming (Manabe & Wetherald, 1967; Charney et al., 1979). It is generally believed that this response is better described by an atmosphere whose relative, rather than absolute, humidity remains constant with warming. The distinction is crucial because in an atmosphere where RH is fixed, the response of surface temperature to radiative forcing (e.g., from changing CO<sub>2</sub>), is roughly twice as large as would be the case should absolute humidity be fixed. In an influential review of these matters, Held and Soden (2000) presented theoretical arguments and evidence from modelling in support of a constant relative humidity. At the time of their review, observations were insufficient to test this hypothesis, but Held and Soden concluded that “10 years may be adequate, and 20 years will very likely be sufficient, [...] to convincingly confirm or refute the predictions”. It is now twenty years later.

Taken at face value, two reanalyses of meteorological observations support this point of view, albeit less convincingly than we anticipated. This is shown in Fig. 1, where above 600 hPa RH is increasing with warming, at a rate of 1%/decade to 4%/decade. Rather than attempting to establish the reliability of the trends – a task for which we lack expertise – our aim is to estimate their implication for how Earth’s equilibrium climate sensitivity may be changing. How does a moister upper, or drier lower, troposphere make Earth more or less sensitive to forcing? Posing this question raises even more basic questions. For instance, to what extent does the given structure of the RH profile matter for the clear-sky climate sensitivity, even if it remains constant with warming?



**Figure 1.** Mean profile (left) and linear trend over 40 years (solid, right) for ERA5 and JRA-55 reanalysis data. Error bars show the standard deviation of the linear regression. The grey dashed line corresponds to what would be the trend in relative humidity for a constant absolute humidity considering ERA5 tropical temperature trend.

65 Questions such as these have not been the topic of much study. Past work has fo-  
 66 cused on cloud changes (Stevens et al., 2016; Sherwood et al., 2020), to a degree that  
 67 can give the impression that clouds alone stand in the way of a meaningful quantifica-  
 68 tion of how surface temperatures respond to radiative forcing. This impression is rein-  
 69 forced by observations showing that outgoing long-wave radiation (OLR) varies linearly  
 70 with temperature (Koll & Cronin, 2018), seeming to imply little role for RH. Looking  
 71 beyond the inability of present climate models to represent clouds with fidelity, it is well  
 72 known that: (i) water vapor strongly influences the radiation emitted from clear skies,  
 73 and (ii) uncertainty in the clear-sky climate sensitivity is not negligible. Regarding (i),  
 74 for the same thermal structure, OLR varies by more than  $50 \text{ W m}^{-2}$  with RH for present  
 75 day tropical surface temperatures (Pierrehumbert, 1995). As for (ii), Soden and Held  
 76 (2006) – the study often cited as being demonstrative of the constancy of clear-sky feed-  
 77 backs – reports a range of  $0.5 \text{ W m}^{-2} \text{ K}^{-1}$  in the combined water-vapor and lapse rate  
 78 feedbacks across CMIP3 models. CMIP5 models show a smaller, but still appreciable  
 79 ( $0.4 \text{ W m}^{-2} \text{ K}^{-1}$ ), spread (Vial et al., 2013). More disquieting are studies that isolate the  
 80 response of the tropical atmosphere to warming, as these suggest an even larger uncer-  
 81 tainty (Medeiros et al., 2008; Becker & Wing, 2020). Relatively little research has been  
 82 carried out to identify the origins of this uncertainty. Exceptional is the study by Po-  
 83 Chedley et al. (2018), who argue that changes in RH in the southern-hemisphere extra-  
 84 tropics are a large source of model spread; here we emphasize how and why such effects  
 85 are also substantial in the tropics.

86 The idea that the climate response is sensitive to the particular distribution of rela-  
 87 tive humidity being held fixed, can be thought of as a form of state dependence. Most  
 88 studies addressing this issue adopt a conceptual framework that only admit surface tem-  
 89 perature as a state variable (Meraner et al., 2013; Knutti et al., 2017). RH plays no role.  
 90 The limitation of such an assumption becomes obvious once one considers the climate  
 91 sensitivity of an atmosphere with  $\text{RH} = 0$ . Hence, neglecting humidity as a state vari-  
 92 able either implies that RH is known and constant, in which case the temperature might

only be a proximate cause of the change in climate sensitivity, or that the limit of a dry atmosphere is singular.

In the present article we report on our investigation of the influence of RH on climate sensitivity using a 1D radiative-convective equilibrium (RCE) model, and highlight a phenomenon we call humidity-dependence. Such a model is attractive for our purposes because it captures (often with surprising fidelity) the behavior of more elaborated descriptions of the climate system in a physically transparent manner. In §2 we describe the model and methods. In §3 we compute the relative impact of a perturbation in the profile at different levels, as a function of RH. In §4 we simulate less idealized profiles of RH to understand and better quantify their effect on the spread in clear-sky climate sensitivity produced by more elaborated models. In §5 we return to the trends in the reanalysis RH to quantify their implications for our understanding of the clear-sky climate sensitivity. We conclude in §6.

## 2 Model & Methods

Calculations were performed using the 1D-RCE model konrad (Kluft et al., 2019; Dacie et al., 2019). We adopt a configuration that uses the RRTMG radiative scheme (Mlawer et al., 1997) and a hard convective adjustment (Dacie, 2020) following the moist adiabatic lapse rate. Only clear-sky calculations are performed. In a subset of calculations discussed at the beginning of §3, we also used a uniform lapse rate. We used 500 pressure levels between 1000 hPa and 0.5 hPa. Following the prescription of the Radiative Convective Equilibrium Model Intercomparison Project, RCEMIP (Wing et al., 2018), the solar constant is set to  $551.58 \text{ W m}^{-2}$  and the zenith angle to  $42.05^\circ$ , resulting in an insolation of  $409.6 \text{ W m}^{-2}$ . The surface albedo is 0.2, and the ozone profile is coupled to the cold-point tropopause. The RH follows a prescribed vertical distribution up to the cold-point above which the specific humidity is kept uniform at its cold-point value. The RH is defined with respect to saturation over water above  $0^\circ\text{C}$  and with respect to saturation over ice below  $-23^\circ\text{C}$ . In between, a combination of both are used (ECMWF, 2018).

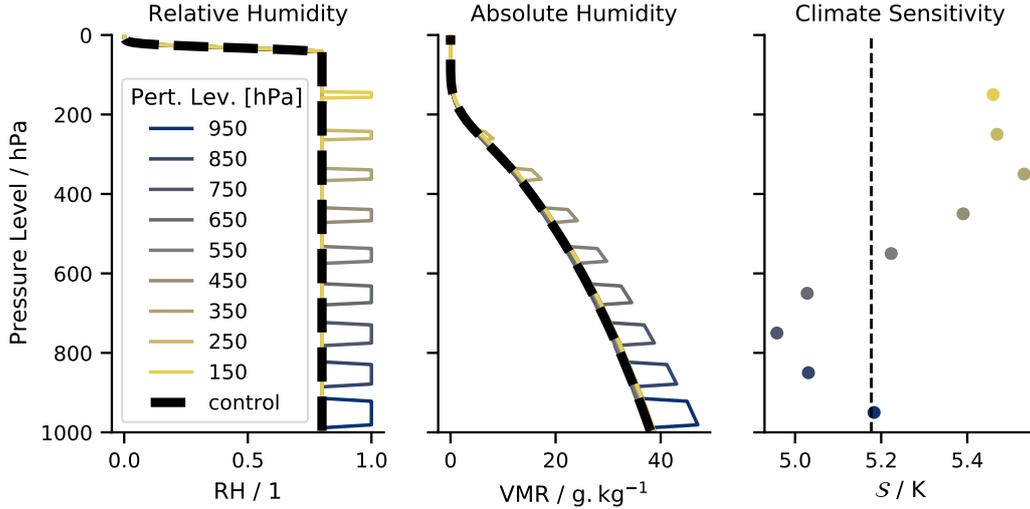
A *run* is defined by its RH profile. It is composed of two equilibrium computations: (i) a spin-up with a constant surface temperature  $T_0 = 300 \text{ K}$ , (ii) a new equilibrium after applying a sudden doubling of the  $\text{CO}_2$  concentration. In (ii) the surface has no longer a fixed temperature but a fixed enthalpy sink, whose value is the top of the atmosphere radiative imbalance at the end of the spin-up, as Kluft (2020) argues to be best practice. The Equilibrium Climate Sensitivity,  $\mathcal{S}$  of our model is defined as the difference between the second equilibrium surface temperature and  $T_0$ .

In §3, we discuss *perturbation runs*. In these, the tropospheric RH profile is uniform except for a 600 m thick layer, where the RH is increased or decreased (the perturbation). A perturbation run is thus defined by a base RH, a perturbation pressure, and a perturbation intensity  $\delta_{\text{RH}}$ . The corresponding 'run' without perturbation is called a *control run*. This is illustrated in Fig. 2.

As a measure of the impact of a perturbation, we define the amplification factor  $a$  as the ratio of the  $\mathcal{S}$  in the perturbation run,  $\mathcal{S}_p$ , to the  $\mathcal{S}$  in the corresponding control run,  $\mathcal{S}_c$ :

$$a = \frac{\mathcal{S}_p}{\mathcal{S}_c} - 1. \quad (1)$$

In reanalysis data, see Fig. 1, the RH profiles peak in the boundary layer and in the upper-troposphere and show a distinct minimum in the mid-troposphere. For this reason, we call such a profile *C-shaped*. In order to simulate a C-shaped RH profile, we developed the following piecewise model, in pressure coordinates (shown in Fig. 4):



**Figure 2.** Illustration of the *perturbation runs* method. The control run, with a base RH of 0.8, is shown in dashed black. Each color corresponds to a run with a perturbation  $\delta_{RH} = 0.2$  at a different level. The two left panels show the relative and absolute humidity profiles. The right panel shows  $\mathcal{S}$  for each *perturbation run* as a function of perturbation pressure alongside the value of  $\mathcal{S}$  for the control run (dashed vertical line).

- 140 – Linear in the boundary layer, from the surface to the lower-tropospheric peak (low
- 141 point);
- 142 – Quadratic in the mid-troposphere, defined by 3 points: the two peaks and the hu-
- 143 midity at 500 hPa (mid point);
- 144 – Linear above the upper-tropospheric peak, defined by the upper-tropospheric peak
- 145 (top point) and the cold-point.

146 The advantages of such an RH profile is that it is defined by only 5 points, corre-

147 sponding to parameters that are straightforward to interpret, and it catches the main

148 feature of a realistic profile better than a uniform profile. Moreover, these parameters

149 give us enough degrees of liberty to fit well AMIP and RCEMIP data, as detailed in §4.

### 150 3 Humidity–Dependence of $\mathcal{S}$

151 As a first set of experiments, we perform runs with different uniform tropospheric

152 RH profiles, and for uniform and moist adiabatic lapse rates. Values of  $\mathcal{S}$  for these runs

153 are plotted in Fig. 3 (top panel). We find a robust increase in  $\mathcal{S}$  with a moister tropo-

154 sphere. We decomposed  $\mathcal{S}$  into contributions from the forcing and the feedback follow-

155 ing Gregory et al. (2004). This shows that changes in  $\mathcal{S}$  arise from changes in feedback

156 as the forcing tends to be much smaller and of the opposite sign.

157 Let us use the effective emission height concept for the interpretation of our calcu-

158 lations. Let  $\Phi_e$  be Earth’s infrared irradiance at the top of the atmosphere. It can be

159 associated with radiant power emitted by a black body at a temperature,  $T_e$ , such that

160  $\Phi_e = \sigma T_e^4$ , where  $\sigma$  is the Stefan-Boltzmann constant. We define the *effective emission*

161 *height* to be the altitude  $z_e$  such that  $T(z_e) = T_e$ . These ideas can be generalized to

162 allow for spectrally specific effective emission heights (Seeley & Jeevanjee, 2021), i.e.,  $z_{e,\lambda}$

163 with  $\lambda$  denoting some wavelength or spectral interval.

164 To help understand the water vapor feedback, we first apply this concept to a case  
 165 with a uniform lapse rate,  $dT/dz = -\Gamma$ , and grey radiation characterized by a single  
 166 emission height. If an initial (positive) perturbation in  $\text{CO}_2$  causes an increase in the emis-  
 167 sion height  $\delta z_{e,i} > 0$ , it would lead to a decrease in the emission temperature,  $\delta T_{e,i} =$   
 168  $-\Gamma \delta z_{e,i}$ . This leads to a deficit in the  $\Phi_e$ , and hence a positive radiative forcing. To bal-  
 169 ance the reduced emission, the troposphere (and surface) warms until the temperature  
 170 at  $z_e + \delta z_e$  adjusts to the value it previously had at  $z_e$ . As a reaction to this warming,  
 171 if RH is to remain fixed, the absolute humidity must increase following the Clausius-  
 172 Clapeyron law. The increase in  $e$  will in turn lead to a further change in  $z_e$ , which must  
 173 be balanced by further warming, increasing humidity, and so on.  $\mathcal{S}$ , is the sum of the  
 174 response from the initial forcing, plus this water vapor feedback.

175 Clausius-Clapeyron implies that

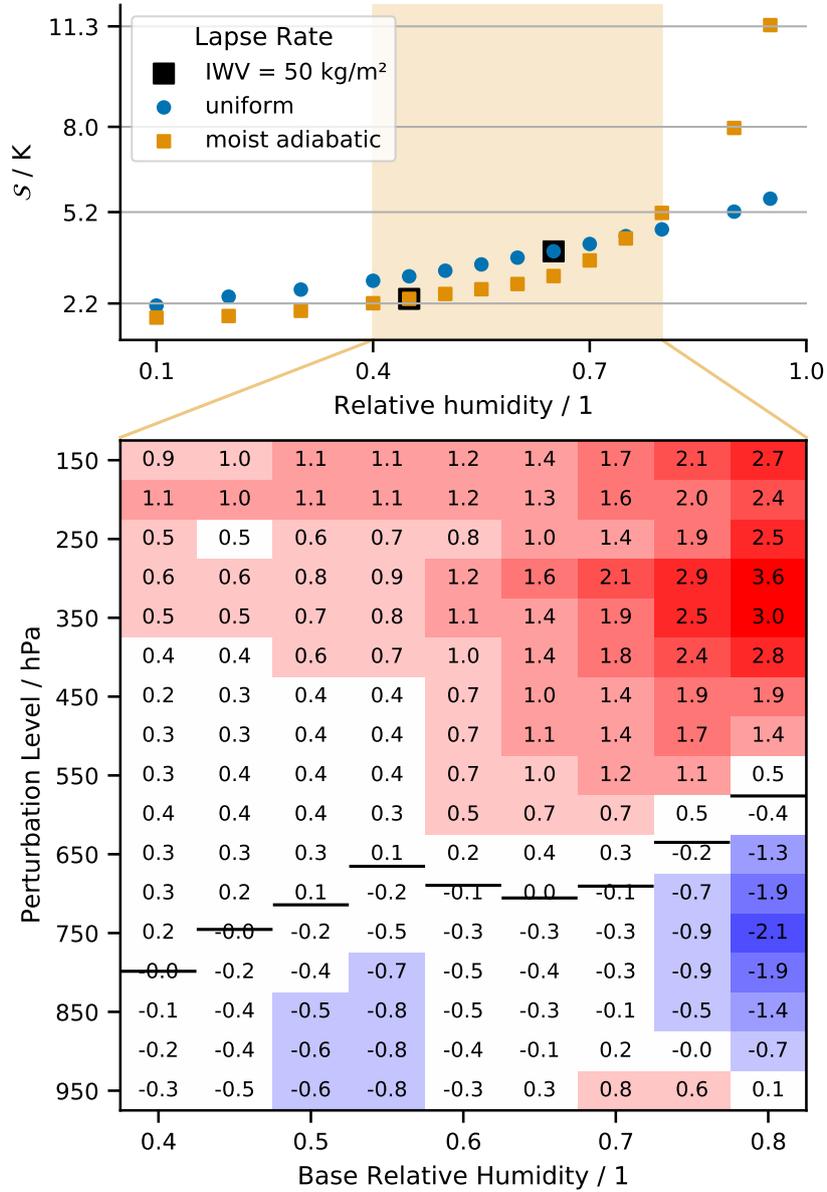
$$\delta e = RH \frac{\ell_v e_s}{R_v T^2} \delta T, \quad (2)$$

176 where  $\ell_v$  is the vaporization enthalpy, an  $R_v$  the water vapor gas constant. Eq. (2) shows  
 177 that  $\delta e \propto RH$ , which explains the linear relation between the  $\mathcal{S}$  and the tropospheric  
 178 RH for a given initial forcing ( $2 \times \text{CO}_2$ ), e.g., as displayed by the blue points in Fig. 3.

179 A non-uniform lapse rate – as is the case for the moist adiabat, whereby  $\Gamma$  is a mono-  
 180 tonically increasing function of  $T$  – gives rise to additional effects. One is the well known  
 181 lapse rate feedback. Another is a moister atmosphere: a troposphere whose surface and  
 182 cold point temperatures are spanned by a moist adiabatic, rather than a uniform, lapse  
 183 rate, will be warmer everywhere, and hence moister for the same RH. A further effect  
 184 is that the vertical distribution of absolute humidity will be more bottom heavy, falling  
 185 off less with height in the lower troposphere, where the moist adiabat is less than its mean  
 186 value, and more with height, where the moist adiabat is greater than its mean value. The  
 187 ability of an atmosphere with a moist adiabatic temperature profile to sample higher ab-  
 188 solute humidities results in a strong increase in the water vapor feedback at high RH.  
 189 This effect is particularly strong in our example because at the given value of  $T_0$  the at-  
 190 mospheric window loses its transparency (Koll & Cronin, 2018) at high humidities, a  
 191 self-amplifying affect that explains the sharp increase in  $\mathcal{S}$  as RH increases for the moist  
 192 adiabatic versus the uniform lapse rate runs (Fig. 3). Repeating our calculations with  
 193 a smaller  $T_0$  reduces the sensitivity to RH (not shown). For most values of RH, however,  
 194 the moist adiabatic runs have a smaller  $\mathcal{S}$ , even more so if one uses the integrated wa-  
 195 ter vapor (IWV) as the control variable, as shown by the points highlighted in on Fig. 3.  
 196 This is mostly indicative of the importance of the lapse rate feedback. Calculations (not  
 197 shown) that use a ‘fixed’ moist adiabatic lapse rate, i.e., one not allowed to change with  
 198 surface warming, also have a slightly reduced  $\mathcal{S}$  as compared to calculations adopting  
 199 a uniform lapse rate with the same value of IWV. This suggests that the shape of the  
 200 humidity profile also influences  $\mathcal{S}$ .

201 To assess how the shape of the RH profile influences  $\mathcal{S}$  we perform perturbation  
 202 runs as described in §2 (see also Fig. 2). Perturbation runs are performed with  $\delta_{\text{RH}} =$   
 203  $-0.1, 0.1, 0.2$ . From these the amplification factor,  $a$  per Eq. 1, is related to  $\delta_{\text{RH}}$  through  
 204 linear regression. Fig. 3 plots  $a$  from its regressed slope multiplied by  $\delta_{\text{RH}} = 0.1$ . Val-  
 205 ues are calculated for RH perturbations applied every 50 hPa to an otherwise constant  
 206 RH profile. This sequence of height varying perturbation runs is computed for  $0.4 \leq \text{RH} \leq$   
 207  $0.8$ . The impact of a positive RH perturbation is small, but discernibly positive (increas-  
 208 ing  $\mathcal{S}$ ) in the upper troposphere, and negative (decreasing  $\mathcal{S}$ ) in the lower troposphere.  
 209 The higher the base RH, the stronger is the sensitivity to the humidity perturbation. More-  
 210 over, the level of sign change rises with base RH.

211 The perturbation runs are consistent with our earlier discussion, but not especially  
 212 intuitive. To understand them, and test their robustness, we performed line-by-line ra-  
 213 diative transfer using the ARTS model (not shown) (Buehler et al., 2018). We find two



**Figure 3.** (Upper panel)  $S$  for different uniform tropospheric RH, and for experiments with a uniform tropospheric lapse rate of  $6.5 \text{ K km}^{-1}$  or with a moist adiabatic lapse rate. Black squared points correspond to experiments where integrated water vapor (IWV) was the closest to  $50 \text{ kg m}^{-2}$ . (Lower panel) Amplification factor  $a$  (in percent) for 0.1 RH perturbation for different humidities and different perturbation levels. Blue and red colors for changes larger than 0.5% in magnitude are indicative of the value's range. Black lines represent the mid-tropospheric level at which  $a$  changes sign.

214 opposing effects. In spectral regions where  $z_{e,\lambda}$  is near the height of the RH perturba-  
 215 tion, the change in  $z_{e,\lambda}$  as water-vapor adjusts to warming is lessened. It is as if the fixed  
 216 perturbation height helps anchor  $z_{e,\lambda}$ . In spectral regions where the effective emission  
 217 height is well below the RH perturbation, the change in  $z_{e,\lambda}$  as water-vapor adjusts to  
 218 warming is heightened – increasing the strength of the water vapor feedback. The first  
 219 (damping) effect explains the reduction in  $\mathcal{S}$  associated with RH perturbations in the  
 220 lower troposphere. It is also apparent at strongly absorbing wave numbers (rotational  
 221 and ro-vibrational bands) for the perturbations in the upper troposphere. But for the  
 222 latter case this reduction in the water-vapor feedback by the perturbation is more than  
 223 offset by the second (amplifying) effect whereby the perturbation in the upper atmosphere  
 224 increases the changes in  $z_{e,\lambda}$  in parts of the window-region ( $400\text{ cm}^{-1} < \lambda < 1200\text{ cm}^{-1}$ )  
 225 where  $\text{CO}_2$  does not dominate.

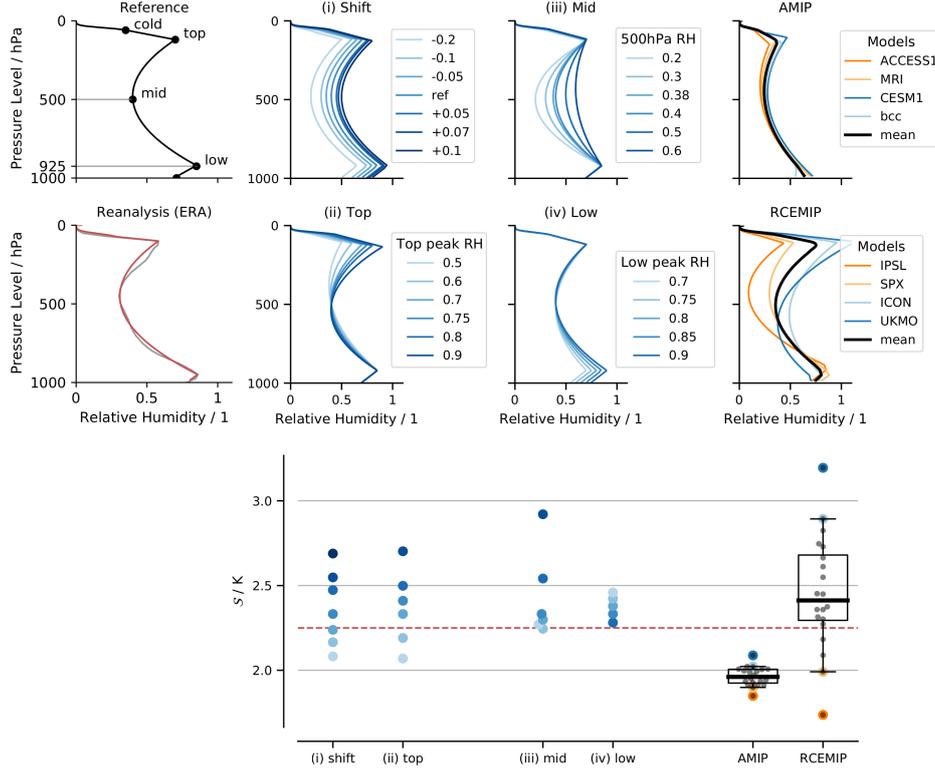
#### 226 4 Implications for Model-Based Estimates of ECS

227 Given the non-linearity of these effects, generalization is not automatic. Here we  
 228 check whether results of the previous section can also be identified for less idealized per-  
 229 turbations to RH profiles more similar to those observed and simulated by climate mod-  
 230 els. For this purpose we use C-shaped RH profiles as defined in §2. To reduce their de-  
 231 grees of liberty we additionally fix the low point to 925 hPa and set the slopes below the  
 232 low point, and above the high point, to  $2.0 \times 10^{-5}\text{ Pa}^{-1}$  and  $-5.8 \times 10^{-5}\text{ Pa}^{-1}$  respec-  
 233 tively. These values are the mean of the parameters when fitting to RCEMIP profiles  
 234 (see following paragraphs). We additionally set the RH at the cold-point to be half its  
 235 peak (upper-troposphere) value, the level of this cold-point being computed by konrad.  
 236 Calculations (runs) were then performed to quantify the impact of changing the remain-  
 237 ing parameters: Starting from a 0.7/0.4/0.85 (top/mid/low) profile, we: (i) shifted the  
 238 whole profile; (ii) changed only the RH at the top of the atmosphere; (iii) changed only  
 239 the humidity at 500 hPa; (iv) changed only the humidity in the lower atmosphere. Hu-  
 240 midity profiles and resulting changes in  $\mathcal{S}$  are presented in Fig. 4. Qualitatively the re-  
 241 sponse to these perturbations agrees well with what was learned from the response to  
 242 more idealized perturbations: (i & ii)  $\mathcal{S}$  increases with an increase in the upper tropo-  
 243 spheric RH, also when this is part of a general moistening; (iv)  $\mathcal{S}$  decreases if RH increases  
 244 are confined to the lower troposphere; and (iii) increases in RH in the middle troposphere  
 245 lead to little change in  $\mathcal{S}$ , until a critical RH is reached at which point  $\mathcal{S}$  increases markedly.

246 In a second step, we performed runs with RH profiles set to fit RCEMIP simula-  
 247 tions using storm-resolving and general circulation models (Except for UKMO-CASIM  
 248 whose humidity profile led to a runaway) on large domains with an SST of 300 K (Wing  
 249 et al., 2020) and CMIP5 AMIP ensembles. The fit is done by retrieving the pressure and  
 250 humidity of the five points defining our C-shaped profile. In particular, the low and top  
 251 points coincide with the local maxima and the cold-point pressure is retrieved from the  
 252 temperature profile. The mid point remains fixed at 500 hPa and the surface is taken as  
 253 the lowest point available. This enables us to assess the effect of the humidity profile alone,  
 254 all other things being equal.

255 With RCEMIP RH profiles, we find a  $\pm 26\%$  variation around the mean  $\mathcal{S}$  value.  
 256 The spread in feedback is  $-1.25\text{ W m}^{-2}\text{ K}^{-1}$  to  $-3\text{ W m}^{-2}\text{ K}^{-1}$ , slightly smaller but com-  
 257 parable to what is found by Becker and Wing (2020). We thus explain the surprisingly  
 258 large spread in clear-sky sensitivity in RCEMIP as being in large part a response to dif-  
 259 ferent RH profiles simulated by the models. Becker and Wing (2020) attribute this inter-  
 260 model spread in RH to different degrees of convective self-aggregation, hence our work  
 261 suggests that different degrees of convective self-aggregation can influence the climate  
 262 sensitivity, even if the convective self-aggregation does not change with warming.

263 From CMIP5 AMIP output, we retrieved mean profiles over the tropical oceans (equa-  
 264 torward of  $30^\circ$ ) averaged over the entire simulated period. As compared to RCEMIP RH



**Figure 4.** (Upper two rows) C-shaped RH profiles: Reference 0.7/0.4/0.85 (top/mid/low) profile (top-left); ERA5 profile as computed for §5 (grey), and corresponding C-shaped fit (red) (bottom-left). Four central panels correspond to the idealized experiments described in the first paragraph of §4. Two right-most panels display the mean and extreme profiles of the AMIP (top-right) and RCEMIP (bottom-right) datasets. (Lower panel)  $\mathcal{S}$  for the idealized experiments and for the experiments with a profile fitted to the AMIP or RCEMIP ensembles. Boxplots’ whiskers are set to display the 5th and 95th percentiles. On this graph and for statistics, only one point per model ”family” (i.e. issued by the same institute) is used, corresponding to the average of all this family’s models. Red dashed line correspond to the  $\mathcal{S}$  computed with ERA5 C-shaped fit RH profile above.

265 profiles, those from the AMIP simulations are on average dryer, and thereby associated  
 266 with a smaller  $\mathcal{S}$ . The drier AMIP profiles are indicative of large-scale circulations driven  
 267 by differences in surface temperatures, i.e., Hadley and Walker cells which give rise to  
 268 the dry tropics. The AMIP simulations differ less in their humidity profiles and likewise  
 269 show less spread in  $\mathcal{S}$ , but even so differences approaching 10% are evident

270 Given observations of the RH profiles in the atmosphere, it should be possible to  
 271 correct model estimates of climate sensitivity using calculations such as ours. From a  
 272 comparison of Fig. 1 and Fig. 4, we note that the RCE models tend to be moister than  
 273 the observations, the AMIP simulations are drier. Fitting the C-shaped humidity profile  
 274 to the observations yields an  $\mathcal{S}$  of about 2.25 K; this is smaller than that of most RCE  
 275 models, but larger than for the AMIP models. Likewise, ECS estimates in early calcu-  
 276 lations following the RH humidity profile used by Manabe and Wetherald (1967), would,  
 277 due to an unrealistically dry upper atmosphere, be biased too low. However, for the lower  
 278 humidities and temperatures used in that study, the fixed lapse assumption actually over

279 compensates, leading to a larger sensitivity as seen in Kluft et al. (2019). This, along  
 280 with the upper panel of Fig. 3, is illustrative of how the lapse rate feedback depends on  
 281 the base state RH.

## 282 5 Impact of RH Trends in Reanalysis Data

283 Based on the above analysis we return to our initial question, which is how to inter-  
 284 pret RH trends in the reanalysis products. The profiles presented in Fig. 1 are from  
 285 the ERA5 (Hersbach et al., 2020), and the JRA-55 (Kobayashi et al., 2015) reanalyses  
 286 of the past forty years (1979-2019) of meteorological observations. Relative and abso-  
 287 lute humidity, as well as temperature, are averaged over tropical oceans (equatorward  
 288 of  $30^\circ$ ). Trends regressed from monthly data are significant at several levels and consis-  
 289 tent across both reanalyses. They are also evident in the difference between the mean  
 290 profile in the first and last decade (not shown). We were surprised that RH at low lev-  
 291 els was robustly decreasing – something that merits further investigation – even if av-  
 292 eraged over height  $\delta RH \approx 0$ . Our analysis does not tell us how strongly these trends  
 293 influence the expected warming over the past forty years, but it does tell us that the pat-  
 294 tern of change, with moistening aloft and drying in the lower middle troposphere is con-  
 295 ditioning the climate system toward greater sensitivity.

## 296 6 Conclusions

297 The response of the atmosphere to radiative forcing as a function of the assumed  
 298 profile of relative humidity (RH) is explored using a one-dimensional radiative-convective  
 299 equilibrium model. For profiles chosen to sample the range produced by state of the art  
 300 climate and storm-resolving models run under idealized conditions, the calculated equi-  
 301 librium climate sensitivity of our model ( $\mathcal{S}$ ) varies between 2 K to 3 K, depending on the  
 302 RH profile, highlighting a humidity-dependence of the climate sensitivity: Moister at-  
 303 mospheres were shown to have a larger  $\mathcal{S}$ , increasingly so with warmer temperature, con-  
 304 sistent with understanding of how water vapor influences the transmissivity of the at-  
 305 mospheric window (Nakajima et al., 1992; Koll & Cronin, 2018; Seeley & Jeevanjee, 2021).  
 306  $\mathcal{S}$  is further shown to increase with increasing humidity in the upper troposphere, but  
 307 decreases with increases in humidity in the lower mid-troposphere.

308 The use of a simple physical model, konrad, makes it easier to understand the ba-  
 309 sic physics determining the outcome of our calculations. For instance, with the chosen  
 310 framework it is possible to show how the the lapse rate’s influence on the total amount  
 311 and vertical distribution of humidity for a given profile of RH influences  $\mathcal{S}$ . We could also  
 312 investigate how  $\mathcal{S}$  depends on the shape of the RH profile, which expresses competing  
 313 effects, whereby perturbations to the humidity can both reduce or increase the change  
 314 in the emission height associated with changes in absolute humidity to maintain a con-  
 315 stant relative humidity with warming. The former effect dominates when the humidity  
 316 perturbation is near the emission height resulting in a slight reduction in  $\mathcal{S}$  for bottom  
 317 heavy humidity profiles.

318 Our work emphasizes the importance of realistically representing the relative humi-  
 319 dity profile when calculating climate sensitivity. Models that are too humid, particu-  
 320 larly in the mid- and upper-troposphere will have larger sensitivities, an effect which  
 321 will amplify with increased warming. Convective self-aggregation modifies the mean re-  
 322 lative humidity profile, thereby reducing ECS, even if the degree of convective aggrega-  
 323 tion itself does not change with warming. In this context, our study also encourages the  
 324 use of RH as metric for the fidelity of the moist physics in climate models. To the ex-  
 325 tent climate models are unable to realistically represent the observed distribution of RH,  
 326 our methods may make it possible to estimate the quantitative effect of these biases.

Humidity profiles over tropical oceans as represented in reanalysis products, tend to be moister than those produced by models forced with observed SSTs, implying a larger clear-sky sensitivity. Three dimensional radiative convective equilibrium models, which are more physical – but less constrained by large-scale sea-surface temperature gradients – tend to be more humid, but also have more divergent humidity profiles.

Surprisingly large changes in RH are reported by the reanalysis products over the last forty years, changes which our calculations suggest will condition the climate system to be more sensitive to forcing in the future. This finding adds an additional dimension to Knutti and Rugenstein’s (2015) statement that the feedback parameter is not constant, and that non-linearity in the system may be important when assessing Earth’s equilibrium climate sensitivity. The surprising trends in the reanalysis humidity products, particularly the drying in the tropical lower troposphere, reminds us of Held and Soden’s plea to be attentive to this issue, and merits the renewed attention of experts.

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- Primary data including simulation scripts and code for reproducing the figures are available on Zenodo through <https://doi.org/10.5281/zenodo.4423268>.
- konradv0.8.1 is available at [github.com/atmtools/konrad](https://github.com/atmtools/konrad), and latest sources are available at <https://doi.org/10.5281/zenodo.4434837>.
- ERA5 data is available on the Copernicus Climate Change Service Climate Data Store (CDS, <https://cds.climate.copernicus.eu/cdsapp#!/dataset/reanalysis-era5-pressure-levels-monthly-means?tab=overview>).
- JRA-55 data were retrieve from [https://jra.kishou.go.jp/JRA-55/index\\_en.html](https://jra.kishou.go.jp/JRA-55/index_en.html).
- The German Climate Computing Center (DKRZ) hosts the standardized RCEMIP and CMIP5-AMIP output ([https://cera-www.dkrz.de/WDCC/ui/ceraresearch/info?site=RCEMIP\\_DS](https://cera-www.dkrz.de/WDCC/ui/ceraresearch/info?site=RCEMIP_DS)).

The authors declare no conflict of interest.

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