Uncertainty in hydrologic cycle intensification constrained by the solar absorption of atmospheric water vapor

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Hydrologic cycle intensification is a key dimension of climate change, with significant impacts on human and natural systems\textsuperscript{1,2}. A basic measure of hydrologic cycle intensification, the increase in global-mean precipitation per unit surface warming, varies by a factor of three in current-generation climate models (~1-3 \% K\textsuperscript{-1})\textsuperscript{3-5}. We show that much of this spread can be traced to intermodel variations in the atmospheric shortwave absorption response to greenhouse-gas-induced warming. As climate warms, increases in shortwave absorption suppress the precipitation increase by reducing the latent heating required to balance the atmospheric energy budget\textsuperscript{6,7}. Spread in the shortwave absorption response can be explained by differences in the sensitivity of solar absorption to variations in column precipitable water. An observational estimate suggests that in many models, this sensitivity is too small, and that the shortwave absorption response to warming is too weak. Spread in the simulated sensitivity of solar absorption to varying water vapor concentration is linked to differences in radiative transfer parameterizations. Attaining accurate shortwave absorption responses though radiative transfer scheme improvement would reduce spread in global precipitation increase per unit warming at the end of the 21\textsuperscript{st} century by \textasciitilde35\%, and produce an ensemble-mean increase that is almost 40\% smaller.

Projected global-mean precipitation changes are dictated by the atmospheric energy budget’s response to imposed radiative forcing and subsequent surface and atmospheric changes\textsuperscript{5-9}. On annual and longer timescales, net atmospheric longwave cooling to the surface and outer space (LW\textsubscript{cool}) is balanced by heating from shortwave absorption (SW\textsubscript{abs}), sensible
heating from the surface (SH), and latent heat release from precipitation (LP) according to the following\textsuperscript{10} (see also Fig. 1):

\begin{equation}
LW_{\text{cool}} = LP + SW_{\text{abs}} + SH
\end{equation}

When carbon dioxide (CO\textsubscript{2}) and other greenhouse gases increase, and the planet warms, these energy sources and sinks readjust due to a series of surface and atmospheric changes. Upon reaching equilibrium, the new balance is characterized by enhanced LW\textsubscript{cool}, increased SW\textsubscript{abs}, decreased SH from surface to atmosphere, and increased precipitation\textsuperscript{6,10-12} (Fig. 1). Climate model differences in the relative changes in the radiative and SH terms, per unit surface warming, produce different global-mean precipitation responses\textsuperscript{7,11,13}. While it is clear that SW\textsubscript{abs} increases mainly due to Clausius-Clapyeron-driven increases in atmospheric water vapor, previous studies have demonstrated that the SW\textsubscript{abs} response to warming has a notable spread across models\textsuperscript{4,7,11}. Moreover, the physical basis for this spread and extent to which it can explain spread in the precipitation response remains a topic of debate\textsuperscript{4,7,11}.

Global-mean precipitation responds to CO\textsubscript{2} forcing on two timescales\textsuperscript{8,14}, as illustrated by idealized experiments where CO\textsubscript{2} suddenly increases. Precipitation initially decreases due to a rapid increase in atmospheric static stability resulting from suppressed LW\textsubscript{cool} (the rapid adjustment)\textsuperscript{15,16}, then slowly increases with subsequent global-mean surface warming (the temperature-mediated response)\textsuperscript{17,18}. Previous studies investigating intermodel spread in global-mean precipitation response to increased CO\textsubscript{2} have either not considered rapid adjustments and temperature-mediated responses separately (i.e., they analyzed total precipitation changes)\textsuperscript{4,11}, or analyzed only a few models, undersampling the ensemble\textsuperscript{7}. These limitations have hindered understanding of the sources of spread in hydrologic cycle intensification, particularly regarding the role of SW\textsubscript{abs}\textsuperscript{4,7}. Here, we analyze rapid and temperature-mediated responses of global
precipitation to CO₂ forcing in 25 models participating in the Coupled Model Intercomparison Project Phase 5 (CMIP5) to understand the spread.

Rapid adjustments and temperature-mediated responses are separated by regressing globally-averaged annual anomalies in the atmospheric energy budget terms (Equation 1) against surface air temperature anomalies in simulations of instantaneous CO₂ quadrupling (Methods). For each term, the regression slope represents the temperature-mediated response and the intercept where ΔT=0 is the rapid adjustment\textsuperscript{19} (Extended Data Fig. 1). The temperature-mediated LP response exhibits substantial intermodel spread, with values ranging from ~1.8-2.7 W m\textsuperscript{-2} K\textsuperscript{-1} [2.0-3.2 % K\textsuperscript{-1}] (Fig. 2a). This would contribute a 4.5 W m\textsuperscript{-2} spread in total LP change, the difference between a 10\% and a 16\% increase, if all models were to warm by ~5 K (the multi-model mean warming averaged ~140-150 years after CO₂ quadrupling). The spread in total LP change resulting from the rapid adjustment from the same forcing is smaller (~3 W m\textsuperscript{-2}) (Extended Data Fig. 3). In this work, we focus on understanding spread in the temperature-mediated component.

While LW\textsubscript{cool} is the key driver of the temperature-mediated LP response in the multi-model mean, the spread in temperature-mediated response of both LW\textsubscript{cool} and SW\textsubscript{abs} is large and correlated (|r|>0.60) with the LP response across models (Extended Data Fig. 2). The anti-correlation between the temperature-mediated SW\textsubscript{abs} and LP responses is somewhat larger in magnitude and occurs in both all-sky (r=-0.64) and clear-sky (r=-0.73) (Fig. 2a). This suggests clouds play a negligible role in the relationship\textsuperscript{7,9}. An anti-correlation arises because SW\textsubscript{abs} and LP compete to balance enhanced LW\textsubscript{cool} in a warmer climate (Fig. 1). Thus models with a larger SW\textsubscript{abs} increase tend to have a smaller LP increase, per unit surface warming. The importance of SW\textsubscript{abs} for model spread in the global-mean precipitation response to increased CO₂ was also
demonstrated by ref. [7]; however, we find the importance of $SW_{abs}$ stems mainly from the temperature-mediated component of the change, inconsistent with their findings (Supplementary Discussion). Based on our results, the temperature-mediated $SW_{abs}$ response is a key source of model spread in hydrologic cycle intensification, analogous to the importance of cloud feedbacks for model uncertainty in climate sensitivity.

What generates the spread in the temperature-mediated $SW_{abs}$ response? Under greenhouse-gas induced warming, $SW_{abs}$ increases mainly due to enhanced solar absorption by water vapor (WV) in a warmer and moister atmosphere $^{7,11}$. Thus, model spread in the $SW_{abs}$ response arises from differences in WV absorption. This is supported by the large anti-correlation between the temperature-mediated LP and clear-sky $SW_{abs}$ ($SW_{clrabs}$) responses (Fig. 2b). Previous studies have proposed two potential sources of model disagreement in the simulated increase of $SW_{abs}$: 1) different increases in global-mean column WV and/or different vertical/horizontal patterns of WV change for the same surface warming $^{7}$; 2) differences in the sensitivity of $SW_{abs}$ to a unit change in atmospheric WV content, related to radiative transfer parameterizations $^{11}$. In this paper, we seek to determine which source is more important and better understand its physical basis.

Does model spread in the temperature-mediated $SW_{abs}$ response come from the first source, i.e., differences in the WV response for the same surface warming? Cross-model correlations between globally-averaged temperature-mediated WV responses (both column-integrated and at individual levels) and the temperature-mediated $SW_{clrabs}$ response are weak and statistically insignificant, suggesting it does not (Supplementary Discussion, Extended Data Fig. 4). To substantiate this further and examine the role of horizontal variability in WV changes, we estimate temperature-mediated $SW_{abs}$ responses using radiative kernels, i.e., linear
approximations of radiative flux sensitivity to perturbations in atmospheric state (Methods). As the kernels are developed with a single radiative transfer code\textsuperscript{13}, model spread in kernel-derived responses mainly reflects intermodel differences in the WV response to surface warming\textsuperscript{13}. If the WV response were causing most of the spread in temperature-mediated $SW_{\text{abs}}$ response, the kernel-derived responses and actual responses computed from model-produced fluxes should be highly correlated, with a similar spread. However, the kernel-derived responses have approximately half the spread and are uncorrelated with the model-produced responses (Fig. 2a). Thus variations in the models’ temperature-mediated $SW_{\text{abs}}$ response are unaccounted for by the total WV increase or subtle differences in the vertical/horizontal structure of WV increase among models. This is consistent with the findings of ref. [11]. Instead, the main source of intermodel variability in the temperature-mediated $SW_{\text{abs}}$ response would appear to be the sensitivity of $SW_{\text{abs}}$ to a unit change in atmospheric WV.

The sensitivity of solar absorption to a change in WV concentration is estimated in each model by binning $SW_{\text{clrabs}}$ based on local-monthly total precipitable water (TPW) in the control climate and computing the regression slope of bin-averaged $SW_{\text{clrabs}}$ against TPW (Methods). Fig. 3a shows sensitivity curves for the two models having the largest and smallest sensitivities. The sensitivities range from 0.03 to 0.11 %/[$kg$ $m^{-2}$] across models (Fig. 3), with much of the difference arising from absorption under moist conditions (Extended Data Fig. 5). The sensitivities are almost perfectly correlated with the temperature-mediated $SW_{\text{clrabs}}$ responses ($r=0.93$, Fig. 3b). This confirms that the sensitivity of $SW_{\text{clrabs}}$ to a change in atmospheric moisture is the principle source of spread in the temperature-mediated $SW_{\text{clrabs}}$ response.

We estimate the real atmosphere’s $SW_{\text{clrabs}}$ sensitivity by combining radiative fluxes from the Clouds and the Earth’s Radiant Energy System Energy Balance and Filled products
with TPW measurements from three sources (Methods). SWclr\textsubscript{abs} sensitivities obtained from CERES-EBAF and all three WV sources (~0.11-0.13 %/[kg m\textsuperscript{-2}]) are on the upper end of the CMIP5 range (Fig. 3), implying that SWclr\textsubscript{abs} sensitivity is too weak in most models. This is consistent with studies showing a general underestimation of solar absorption in climate models\textsuperscript{22,23}. Thus the temperature-mediated SWclr\textsubscript{abs} response is underestimated by many models. Models with SWclr\textsubscript{abs} sensitivity within observational uncertainty have temperature-mediated SWclr\textsubscript{abs} responses ranging from 0.95-1.09 W m\textsuperscript{-2} K\textsuperscript{-1}, i.e. the upper 25% of the full spread of 0.52-1.09 W m\textsuperscript{-2} K\textsuperscript{-1} (Fig. 3b). Given the strong anti-correlation between the temperature-mediated SWclr\textsubscript{abs} and LP responses (Fig. 2b), this further implies that many models *overestimate* the temperature-mediated increase in global-mean precipitation, assuming no compensating errors in other energy budget terms. The latter may not be true, however, as models possibly underestimate LW\textsubscript{cool} due to a missing iris effect\textsuperscript{24}, contributing an *underestimation* in precipitation increase independent of the SWclr\textsubscript{abs} response.

What is the physical basis for the model spread in SWclr\textsubscript{abs} sensitivity to varying atmospheric WV? Simulated solar absorption for a given atmospheric WV concentration is determined by radiative transfer algorithms that approximate complex spectral absorption by WV molecules and other constituents. We examine the influence of these algorithms on the simulated SWclr\textsubscript{abs} sensitivities by categorizing the SW parameterization scheme in each model based on its treatment of clear-sky solar absorption by WV (Fig. 3c). The schemes vary considerably among models and their characteristics have a strong correspondence with SWclr\textsubscript{abs} sensitivity. In general, models that implement more modern approaches and/or use a larger number of mathematical terms (\(N\) in Fig. 3c) to approximate the complex dependency of SW transmission on wavelength, tend to have larger and more realistic SWclr\textsubscript{abs} sensitivities (see also...
Supplementary Discussion). It is important to note that a commonly used observational product, the International Satellite Cloud Climatology flux dataset (ISCCP-FD)\textsuperscript{25}, exhibits a large bias in SW\textsubscript{clr\textsubscript{abs}} sensitivity (Fig. 3c). This product generates fluxes with a radiative transfer algorithm nearly identical to that used in the GISS-E2-H and GISS-E2-R models (Supplementary Discussion), and as a consequence yields the same SW\textsubscript{clr\textsubscript{abs}} sensitivity as those models (Fig. 3c). Thus, extreme caution should be taken when treating ISCCP-FD radiative fluxes as observations.

Intermodel variability in the accuracy of SW parameterization schemes likely results from model developers’ ongoing challenge of balancing the need for accurate radiative transfer calculations against considerations of computational efficiency and realistic simulation of other climate system components\textsuperscript{23}. As computational capabilities have grown, improvement in LW schemes and other model components seem to have taken precedence over parameterization of SW gaseous absorption, with many modeling institutions continuing to implement outdated schemes for the latter\textsuperscript{23,26} (Extended Data Fig. 6). This is understandable considering the importance of LW fluxes and cloud feedbacks for climate sensitivity, but here we show that atmospheric solar absorption is equally important for hydrologic cycle intensification. Based on a simple calculation (Methods), we estimate that if the temperature-mediated SW\textsubscript{clr\textsubscript{abs}} response to CO\textsubscript{2} forcing were perfectly constrained in the current generation of models, the spread in total precipitation increase per unit warming predicted at the end of the 21\textsuperscript{st} century under the Representative Concentration Pathway scenario 8.5 (RCP8.5)\textsuperscript{27} would be reduced by ~35%, and the ensemble-mean precipitation increase per unit warming would decrease by nearly 40% (Extended Data Fig. 7). Even for the total precipitation change (i.e. not normalized by surface warming), a spread reduction of ~25% and reduction in ensemble-mean increase of ~25% could
be obtained. Clearly, improvements in clear-sky SW radiative transfer parameterizations should have high priority in future model development.

**Methods**

**CMIP5 models.** The CMIP5 models analyzed here are listed in Extended Data Table 1, with corresponding references. We use one ensemble member (r1i1p1) from 25 models that had available monthly output of atmospheric temperature and humidity, precipitation, and energy fluxes for the pre-industrial control (piControl) and abrupt quadrupled CO₂ (abrupt4xCO₂) experiments at time of analysis.

**Computing rapid adjustments and temperature-mediated responses.** The Gregory method is employed using each model’s piControl and abrupt4xCO₂ run. For each year of the abrupt4xCO₂ run, the global-mean abrupt4xCO₂ anomaly of a physical quantity (e.g., LP) relative to the piControl simulation is paired against the corresponding anomaly of 2-m air temperature, generating a scatterplot (Extended Data Fig. 1). To compute the annual anomalies, the piControl 21-year mean, centered on the corresponding year of the abrupt4xCO₂ simulation, is subtracted from each abrupt4xCO₂ 1-year mean. Subtracting by this running mean removes possible influences of climate drift on the anomalies. The scatterplots are generated using 150 years of the abrupt4xCO₂ simulation, when available. A linear regression is then applied to each scatterplot, with the slope and y-intercept of the fit representing the temperature-mediated and rapid responses to CO₂ forcing, respectively.
The Gregory methodology is displayed visually for the GFDL-CM3 model in Extended Data Fig. 1. It shows the yearly evolution of globally-averaged LW\textsubscript{cool}, SW\textsubscript{abs}, SH, and LP changes after a quadrupling of atmospheric carbon dioxide (CO\textsubscript{2}). The physical interpretation of these changes has been thoroughly discussed in numerous studies\textsuperscript{6,11,15,17,28-30}. The high degree of linearity of the scatterplots demonstrates the reliability of this approach for separating temperature-mediated responses and rapid adjustments.

Calculating temperature-mediated SW\textsubscript{abs} responses with radiative kernels. Radiative kernels were developed using an offline version of the MPI-ECHAM5 radiation code and represent the sensitivity of top-of-atmosphere (TOA) and surface SW radiative fluxes to small perturbations in atmospheric specific humidity and surface albedo\textsuperscript{13}. SW\textsubscript{abs} responses due to WV are computed as follows: 1) Temperature-mediated responses in the logarithm of specific humidity at all months, locations, and pressure levels are multiplied by the SW specific humidity atmospheric (TOA minus surface) kernel, for all-sky and clear-sky. Specific humidity responses are computed as the difference in abrupt4xCO\textsubscript{2}-piControl anomalies averaged over years 121-150 and 1-30 of the abrupt4xCO\textsubscript{2} simulation, normalized by the corresponding difference in 2-m air temperature. 2) The result is integrated over the depth of the troposphere (defined as all levels between the surface and a tropopause height that varies linearly with latitude from 100 hPa on the Equator to 300 hPa at the poles), and then averaged over all months and locations. The SW\textsubscript{abs} responses due to surface albedo are computed in similar fashion but with surface albedo kernels and temperature-mediated responses. The final SW\textsubscript{abs} response for each model (Fig. 2a) is the sum of the WV and surface albedo components of the response, with the WV component dominating\textsuperscript{13}. 
Estimating the sensitivity of $SWclr_{abs}$ to a unit WV change. $SWclr_{abs}$ sensitivity to WV variability is computed based on local and temporal variations of TPW in the control climate. All grid cells and months from 150 years of a model’s piControl simulation over the tropical oceans are aggregated into one sample to compute the sensitivity. The years 2001-2009 and 1984-2009 are used for estimates based on CERES-EBAF and ISCCP-FD, respectively. Tropical oceans are defined as grid cells with centers between 30°S and 30°N and with land fraction less than 0.50. All model output is regridded to 2.5° x 2.5° lat-lon prior to performing calculations. To compute the sensitivity, the $SWclr_{abs}$ at each grid cell and for each month is normalized by incoming solar radiation, then binned according to TPW with equal bin size of 2 kg m$^{-2}$. $SWclr_{abs}$ is averaged within each TPW bin and plotted against the bin center value (Fig. 3a). Only bins with at least 20 data values in every model and observational source are considered, resulting in a common TPW range of 12-58 kg m$^{-2}$. The linear regression slope of the scatterplot represents the $SWclr_{abs}$ sensitivity to varying TPW for a particular model.

We consider only tropical oceans when computing $SWclr_{abs}$ sensitivity due to the relatively small variability of surface albedo and solar zenith angle within this region, better isolating the effect of TWP on $SWclr_{abs}$ (see Supplementary Discussion). Sensitivities are nearly invariant to the simulation (e.g. piControl, abrupt4xCO2, historical, RCP8.5) or numbers of years from which they are calculated (not shown). Furthermore, sensitivities computed from various percentiles of the $SWclr_{abs}$ distribution within each TPW bin (ranging from the 10$^{th}$ to 90$^{th}$ percentile) are very similar to those computed with the $SWclr_{abs}$ bin mean (not shown). This demonstrates that the methodology robustly quantifies the dependency of $SWclr_{abs}$ on atmospheric moisture.
Observations. The CERES-EBAF dataset provides clear-sky radiative fluxes at the TOA and surface on a grid comparable to climate models and has global coverage. TOA fluxes are based on satellite measurements, and surface fluxes are generated with a radiative transfer model constrained by the TOA fluxes\(^{21}\). Although the surface fluxes are model produced, they are computed with a radiative transfer algorithm that is arguably more advanced and physically-based than that used in most climate models (Supplementary Discussion), and they are in good agreement with point observations\(^{21,31-33}\). To compute CERES-EBAF SW\(_{\text{clr abs}}\) sensitivities to varying TPW, WV is taken from three sources: 1) the Special Sensor Microwave Imager (SSM/I)\(^{34}\); 2) a product developed by Remote Sensing Systems (RSS) that combines measurements from various instruments, including SSM/I, the Special Sensor Microwave Imager Sounder (SSMIS), the Advanced Microwave Scanning Radiometer (AMSR-E), and the WindSat Polarimetric Radiometer\(^{35}\); 3) the Television Infrared Observation Satellite Operational Vertical Sounder (TOVS)\(^{36}\). ISCCP-FD SW\(_{\text{clr abs}}\) sensitivity is based on TOVS WV, which was used in development of the flux dataset\(^{25}\).

Constraining late 21\(^{\text{st}}\) century precipitation changes. We exploit the strong model relationships among SW\(_{\text{clr abs}}\) and LP under CO\(_2\) forcing (Extended Data Figs. 7a-b) to compute a hypothetical change in LP that may occur at the end of the 21\(^{\text{st}}\) century under realistic climate forcing if the true temperature-mediated SW\(_{\text{clr abs}}\) response to CO\(_2\) forcing were perfectly known. The “true” temperature-mediated SW\(_{\text{clr abs}}\) response is approximated from the model relationship between the SW\(_{\text{clr abs}}\) sensitivity to varying TPW and temperature-mediated SW\(_{\text{clr abs}}\) response, using the observed value of SW\(_{\text{clr abs}}\) sensitivity based on CERES-EBAF (Extended Data Fig.
7a). The resulting true value of the SWclr$_{abs}$ response is then used with the model relationship between the temperature-mediated LP and SWclr$_{abs}$ response to estimate a “bias” in LP response that originates from a bias in the SWclr$_{abs}$ response (Extended Data Fig. 7b). The bias for each model is then removed from the predicted precipitation change at the end of the 21$^{st}$ century in the RCP8.5 scenario relative to the piControl according to:

\[
\frac{\Delta LP}{\Delta T_{cons}} = \frac{\Delta LP_{RCP8.5} - bias * \Delta T_{RCP8.5}}{\Delta T_{RCP8.5}}
\]  

(2)

where $\frac{\Delta LP}{\Delta T_{cons}}$ is the constrained total change in LP normalized by surface warming with the bias removed, $\Delta LP_{RCP8.5}$ is the total late 21$^{st}$ century LP change (mean of years 2081-2100 in RCP8.5 minus mean of years 131-150 in piControl), bias is the bias in temperature-mediated LP response due to the bias in SWclr$_{abs}$ response to CO$_2$ forcing (Extended Data Fig. 7b), and $\Delta T_{RCP8.5}$ is the late 21$^{st}$ century 2-m air temperature change computed similarly to $\Delta LP_{RCP8.5}$.

The above procedure makes several assumptions, including: 1) the middle of the range in CERES-EBAF-computed SWclr$_{abs}$ sensitivity to varying TPW is most representative of the real atmosphere, 2) the best “true” value of temperature-mediated SWclr$_{abs}$ response (Extended Data Fig. 7a, blue star) and LP response (Extended Data Fig. 7b, black horizontal line) occurs at the linear regression line to the cross-model scatterplots, and 3) the temperature-mediated LP response contributes linearly (with $\Delta T$) to the total late 21$^{st}$ century change in LP computed from RCP8.5, as depicted in Equation 2.

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Additional references in Methods


Additional references in Extended Data Tables and Figures


Supplementary Information is included with this manuscript.

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National Climatic Data Center (http://www.ncdc.noaa.gov/oa/rsad/ssmi/gridded/index.php), and the RSS data obtained from Remote Sensing Systems (http://www.remss.com/measurements/atmospheric-water-vapor/tpw-1-deg-product). We thank Michael Previdi for providing the radiative kernels. Finally, we thank Stephen A. Klein, Karl E. Taylor, Peter M. Caldwell, and Andrew A. Lacis for discussion on the topic.

Author Contributions

A.M.D., X.Q., and A.H. designed the methodology. A.M.D. performed the analysis and wrote the paper. M.D.Z. provided the kernel-derived temperature-mediated SW$_{abs}$ response estimates. All authors discussed the results and edited the manuscript.

Author Information

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Figure 1. Schematic of the atmospheric energy budget. The atmosphere is depicted as a box with its key sources and sinks of energy displayed as arrows. Sources: shortwave absorption (SW\textsubscript{abs}), sensible heat flux from the surface (SH), and latent heat release from precipitation (LP: the latent heat of vaporization, L, multiplied by the precipitation rate). Sinks: net longwave cooling (LW\textsubscript{cool}: the difference between outgoing LW flux at the top-of-atmosphere and net upward LW flux at the surface). Black arrows are for the current climate and blue arrows are for a hypothetical equilibrium climate with increased atmospheric carbon dioxide (CO\textsubscript{2}). Arrow lengths are qualitative and are not drawn exactly to scale. Note that LW\textsubscript{cool} and SW\textsubscript{abs} are drawn at the top-of-atmosphere, although these terms include both top-of-atmosphere and surface contributions.
Figure 2. Relationship between the temperature-mediated LP and SW$_{abs}$ response. (a) The temperature-mediated response of LP and SW$_{abs}$ for all-sky (SW$_{abs}$) and clear-sky (SW$_{clr \, abs}$) computed using model-produced fluxes or with radiative kernels [indicated with (ker)]. Individual CMIP5 models are shown as blue circles. The numbers above the abscissa are the cross-model correlations between the respective SW$_{abs}$ responses and the LP response. Numbers in parentheses are correlations between the model-produced and kernel-derived temperature-mediated SW$_{abs}$ responses, for all- and clear-sky. (b) Scatterplot of the model-produced temperature-mediated LP vs. SW$_{clr \, abs}$ response for the 25 models. The gray line represents a relationship with slope = -1. Model numbers are defined in Extended Data Table 1.
Figure 3. The sensitivity of solar absorption to varying atmospheric water vapor (WV). (a) SWclr_{abs} normalized by incoming solar flux versus total precipitable water (TPW) for selected models and CERES-EBAF estimates with three WV sources (see Methods). The slope of the curve represents the sensitivity of SWclr_{abs} to varying TPW (s, [%/[kg m^{-2}]]). (b) Scatterplot of the temperature-mediated SWclr_{abs} response (Fig. 2b abscissa) versus SWclr_{abs} sensitivity (panel...
a) for the 25 models. (c) The relationship between SWclr_{abs} sensitivity and characteristics of the parameterization scheme for solar absorption by WV in a cloud-free atmosphere, with colors for each model referring to different types of parameterizations as described in the legend ($N$ refers to the number of exponential terms representing WV absorption). References and further discussion for panel (c) are given in Extended Data Table 1 and Supplementary Discussion, respectively. Model numbers are identified in panel (c). In (b) and (c), the width of the horizontal shading for each model represents the 95% confidence interval (CI) of the regression slope to the SWclr_{abs} versus TPW curve. The 95% CI encompassing CERES-EBAF estimates from all water vapor sources (obs) and for ISCCP-FD is represented with vertical dashed lines.
Extended Data Table 1. **CMIP5 models analyzed in this paper.** The numbers used to identify models throughout the paper are given in the first column. General references and references documenting the details of the shortwave parameterization schemes, particularly with regard to the treatment of gaseous absorption, are listed in the rightmost columns. Additional information about the BCC-CSM1.1 models may be found at the webpage given under the modeling institution.

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<td>Norwegian Climate Centre, Norway</td>
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Extended Data Figure 1. Demonstration of the Gregory method for the GFDL-CM3.

Global-annual-mean anomalies (abrupt4xCO₂-piControl) in atmospheric energy budget terms (latent heat release from precipitation [LP], net longwave cooling [LW\text{cool}], shortwave absorption [SW\text{abs}], and sensible heating [SH]) are regressed against those in 2-m air temperature (see Methods). For LP, precipitation anomalies are multiplied by the latent heat of vaporization, L.

The statistics of the linear regression (slope [temperature-mediated response, W m⁻² K⁻¹], y-intercept [rapid adjustment, W m⁻²], and correlation coefficient, r) are displayed in the legend.
Extended Data Figure 2. Summary of model spread in temperature-mediated responses.

The temperature-mediated response of each atmospheric energy budget term is shown for each model as blue circles and the model mean as a red cross. Clear-sky LW<sub>cool</sub> and SW<sub>abs</sub> (LW<sub>clr</sub><sub>cool</sub> and SW<sub>clr</sub><sub>abs</sub>, respectively) are shown in the rightmost columns. The numbers above the abscissa are the cross-model correlations between the responses of those energy budget terms and LP.
Extended Data Figure 3. Total changes and rapid adjustments for LP and SWclr abs. (a) The total change in LP per unit warming (mean over years 131-150 of the abrupt4xCO2 simulation minus the corresponding mean of the piControl simulation, normalized by 2-m air temperature change) versus total change in SWclrabs per unit warming.  (b) The rapid adjustment of LP versus rapid adjustment of SWclrabs.
Extended Data Figure 4. Contributions of water vapor (WV) change to model spread in temperature-mediated SWclr_{abs} response. (a) The Gregory method (Methods) is applied to anomalies of globally-averaged specific humidity (q) at standard atmospheric levels, total precipitable water (TPW), and upper tropospheric precipitable water (UPW, computed by vertically integrating q between 500 and 200 mb) to quantify the temperature-mediated response of atmospheric WV for each model. The natural log was applied before computing annual anomalies. For each quantity, the symbols (circle, diamond, square) represent the model mean and the whiskers represent the full model spread. The globally-averaged SWclr_{abs} q kernel (Methods) is overlaid (blue curve). (b) The cross-model correlation between the responses of water vapor in panel (a) and the temperature-mediated SWclr_{abs} response. No correlations in (b) are statistically significant at the 5% level, with degrees of freedom corresponding to the number of participating modeling institutions (14) within the 25 model ensemble.
Extended Data Figure 5. The SWclr\textsubscript{abs} sensitivity curve for each model. Normalized bin-mean SWclr\textsubscript{abs} versus TPW and corresponding linear fit (as in Fig. 3a) are displayed for each model (black dots/line), with models sorted from (top left) smallest sensitivity (s, %/[kg m\textsuperscript{-2}]) to (bottom right) largest sensitivity. Dashed lines depict the 10\textsuperscript{th}-90\textsuperscript{th} percentile spread of SWclr\textsubscript{abs}. 

12. GISS-E2-H
13. GISS-E2-R
18. IPSL-CM5B-LR
17. IPSL-CM5A-MR
16. IPSL-CM5A-LR
15. INM-CM4
24. MRI-CGCM3
4. BCC-CSM1.1(m)
7. CNRM-CM5
3. BCC-CSM1.1
8. CNRM-CM5-2
25. NorESM1-M
6. CCSM4
11. GFDL-ESM2M
10. GFDL-ESM2G
21. MPI-ESM-LR
22. MPI-ESM-MR
23. MPI-ESM-P
20. MIROC5
5. CanESM2
19. MIROC-ESM
1. ACCESS1.0
9. GFDL-CM3
2. ACCESS1.3
14. HadGEM2-ES
within each TPW bin, demonstrating the tight constraint TPW places on SWclr_{abs}. Numbers next
to model names are those from Extended Data Table 1. On every panel, the SWclr_{abs} sensitivity
curve and linear fit based on CERES-EBAF fluxes and SSM/I water vapor are also shown (blue
triangles/line); the 10^{th}-90^{th} percentile spread is shown only on the second panel for visual
clarity.
Extended Data Figure 6. Methodology for parameterizing solar absorption by WV. The relationship between SWclr\textsubscript{abs} sensitivity to varying TPW and methodology used to parameterize SW absorption by WV in a cloud-free atmosphere, with colors for each model referring to different parameterization procedures as documented in the references listed in the legend (see also Extended Data Table 1). Boxes outlined in black indicate that WV continuum absorption in the SW is accounted for in the parameterization. Model numbers are defined. The width of the horizontal shading for each model represents the 95% confidence interval (CI) of the regression slope to the SWclr\textsubscript{abs} (bin mean) versus TPW curve (shown in Extended Data Figure 5).
95% CI encompassing CERES-EBAF estimates from all water vapor sources (obs) and for ISCCP-FD is represented with vertical dashed lines.
Extended Data Figure 7. Constraining the spread in late 21st century precipitation change. 

(a) The relationship between temperature-mediated SW$c_{\text{abs}}$ response and SW$c_{\text{abs}}$ sensitivity to varying TPW (as in Fig. 3b) showing an estimate of the “true” SW$c_{\text{abs}}$ response (blue line/star), and how it is quantified. (b) The temperature-mediated LP versus SW$c_{\text{abs}}$ response (as in Fig. 2b) showing how the “true” SW$c_{\text{abs}}$ response in (a) is used to quantify a bias in temperature-
mediated LP response originating from a bias in SWclr_abs response; the bias for an example model (#13: GISS-E2-R) is displayed.  (c) The full (abscissa) versus constrained (with bias in panel [b] removed, ordinate) total change in LP per unit 2-m warming at the end of the 21st century under RCP8.5 (see Methods and Equation 2). (d) As in (c) but for total LP change not normalized by warming. Model numbers are defined in Extended Data Table 1. Two models (#8: CNRM-CM5-2 and #23: MPI-ESP-P) are excluded from panels (c) and (d) due to unavailable RCP8.5 output.
Supplementary Discussion

Uncertainty in hydrologic cycle intensification constrained by the solar absorption of atmospheric water vapor

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Discussion of the spread in hydrologic cycle intensification

As shown in this paper, model spread in the temperature-mediated shortwave absorption (SWabs) response to carbon dioxide (CO₂) forcing, particularly for clear-sky (SWclrabs), substantially contributes to the spread in temperature-mediated precipitation (LP) response. The total change in LP per unit warming (including the temperature-mediated response and rapid adjustment), however, is not correlated with the total change in SWclrabs across models (Extended Data Fig. 3a). This may be the consequence of large scatter in the rapid adjustment of LP, which is not strongly related to that of SWclrabs (Extended Data Fig. 3b). Ref. [9] found the opposite result using 8 CMIP3 models: that the temperature-mediated responses of latent heating and solar absorption are not correlated, but that total changes at a warming of 2 K are anti-correlated (r=-0.66). The differences between their results and ours likely originates from different analysis methods and sampling. For one, they use only 8 models from CMIP3 while we use 25 from CMIP5. Additionally, they combine different types of CO₂ forcing scenarios (e.g., 1% increase to CO₂ doubling or quadrupling and instantaneous CO₂ doubling) and base their temperature-mediated estimates on scatterplots of only a few (5-10) data points from each
simulation. It is shown in their analysis that quite different slopes may be obtained from
different forcing simulations even with the same model. We argue that our results are more
robust. In addition to using many more models, we base our temperature-mediated estimates on
a large number of data points (140-150) from a single forcing scenario (instantaneous CO₂
quadrupling). Furthermore, our findings are consistent with ref. [4] who also found that total
changes in LP (per unit warming) are not correlated with those in SW_{abs} under doubled CO₂
using a larger sample of CMIP3 models (14) than ref. [9].

We show that removing the bias in temperature-mediated LP response due to a bias in the
SW_{clr} response reduces the spread in predicted precipitation change per unit warming at the
end of the 21st century under RCP8.5 by 36%, and reduces the ensemble mean increase by 38%
(Extended Data Fig. 7c). Even if we do not normalize by differences in surface warming ΔT,
which is the main driver of the spread in total precipitation change ΔLP, a discernible reduction
in spread by 27% and ensemble mean increase by 25% can be achieved (Extended Data Fig. 7d).
The spread reduction is substantial considering the numerous factors in addition to the
temperature-mediated SW_{abs} response to CO₂ forcing potentially contributing to model scatter in
RCP8.5 projections. These include temperature-mediated responses of other energy budget
components (Extended Data Fig. 2), greenhouse gas forcing other than CO₂, aerosols, and the
rapid LP adjustments to all forcings. For instance, ref. [4] demonstrated the potent role of black
carbon forcing for CMIP3 spread in simulated global precipitation change under a realistic
climate change scenario. That we obtain a 36% reduction in ΔLP/ΔT under RCP8.5 by only
constraining the temperature-mediated component of SW_{clr} change under pure CO₂ forcing
(and only a somewhat larger reduction by 45% when repeating the same exercise with the
quadrupled CO₂ runs, not shown) suggests that the role of black carbon forcing on the spread
may be reduced in CMIP5 relative to CMIP3. This is an interesting possibility worthy of further analysis.

How may uncertainty in late 21st century precipitation change be reduced further? As discussed above, a realistic climate change scenario includes greenhouse gas forcing (from CO2 and other gases), aerosol forcing, and rapid adjustments to these forcings. A better understanding of all these factors is therefore critical, including of the rapid adjustment to CO2 forcing. This factor has a non-negligible spread (Extended Data Fig. 3b) and is not strongly correlated with the corresponding intermodel variations in temperature-mediated response (r= -0.23, not shown). Additionally, the spread in the temperature-mediated LP response to CO2 forcing is not only driven by the SWclrabs component, as indicated by residual scatter in Fig. 2b. Extended Data Fig. 2 shows that the net atmospheric longwave cooling (LWcool) response also has a large spread that is correlated with the LP response. The SWabs and LWcool responses are not correlated with each other (|r|<0.1, not shown), suggesting that the LWcool component is another independent source of spread that demands better understanding. The LWcool response is only correlated with the LP response for all-sky (Extended Data Fig. 2), implying that clouds may play an important role in the intermodel relationship. This is different from the case of the SWabs response in which clear-sky absorption by water vapor (WV) was shown to be critical.

**Model variability in the vertical and horizontal pattern of moisture increase**

We applied the Gregory method (Methods) to global-mean annual anomalies of specific humidity (q) at the standard atmospheric levels and to column integrated WV to compute temperature-mediated responses of these variables (Extended Data Fig. 4a). We then correlated
these responses with the temperature-mediated SW$_{\text{clr abs}}$ response across models (Extended Data Fig. 4b). The correlations are weak ($r<0.4$) for all quantities and atmospheric levels and are not statistically significant (Extended Data Fig. 4b). The temperature-mediated WV responses and their intermodel spread (in fractional sense) are largest in the upper troposphere, where WV changes have little effect on total-column SW$_{\text{clr abs}}$ (Extended Data Fig. 4a, kernel values). This likely explains the lack of a relationship between kernel-derived and model-produced temperature-mediated SW$_{\text{abs}}$ responses (Fig. 2a). We also examined intermodel variability in the horizontal pattern of the temperature-mediated response of WV but found only weak correlations between local WV responses and the global-mean temperature-mediated SW$_{\text{clr abs}}$ response (not shown).

Discussion of SW$_{\text{clr abs}}$ Sensitivity and SW Parameterizations

In the Main Text (Fig. 3c) we demonstrate that the sensitivity of SW$_{\text{clr abs}}$ to varying TPW for each model has a strong relationship with basic characteristics of the SW parameterization scheme for clear-sky WV absorption. In this section, we give a more thorough model intercomparison of SW parameterization scheme and how it relates to SW$_{\text{clr abs}}$ sensitivity. The discussion is supplemented with a figure showing the SW$_{\text{clr abs}}$ versus TPW curves for all models (Extended Data Fig. 5) and a graphical summary of the main references documenting the methodology used for parameterization development (Extended Data Fig. 6, see also Extended Data Table 1). We also comment on factors other than parameterizations of WV absorption that may affect our SW$_{\text{clr abs}}$ sensitivity metric, and discuss the radiative transfer scheme that generates surface fluxes in the CERES-EBAF observational product.
One thing that stands out in Fig. 3c is the severe underestimation of $SW_{clr_{abs}}$ sensitivity by the GISS models. In these models, solar absorption by WV is parameterized with a pseudo-k-distribution approach consisting of 15 mathematical terms\(^{55}\) (Extended Data Table 1). Some of the other CMIP5 models in our analysis, including those with the largest $SW_{clr_{abs}}$ sensitivities, use as many terms in their parameterizations (Fig. 3c). Thus the poor performance of the GISS parameterization is not simply the result of the number of computations employed to approximate SW transmission. Rather, the finer details of how the parameters of the analytical expressions (e.g., pseudo absorption coefficients and weights for terms) are developed and the quality of the reference calculations from which the parameterizations were originally based on, are probably important, among other characteristics. The GISS parameterization is developed from a combination of old and relatively new methods (Extended Data Fig. 7, Extended Data Table 1). The resulting analytical expressions, which combine pressure-temperature-spectral absorption dependency, are known to underestimate solar absorption in moist atmospheres based on comparison with modern line-by-line (LBL) calculations\(^{23}\).

Aside from the GISS models, the number of mathematical terms employed in SW parameterizations appear to exert a general influence on parameterization performance (Fig. 3c). A specific example is with models developed at IPSL and CNRM. In these models, WV absorption is parameterized with an algorithm originally developed in 1980 and later modified for use in the operational European Center for Medium Range Weather Forecasts (ECMWF) model\(^{50}\). It consists of a few SW bands, within which Padé Approximants represent gaseous absorption by WV\(^{49}\). In the IPSL models, 4 total SW bands are used. These models clearly underestimate mean $SW_{clr_{abs}}$ relative to CERES-EBAF and the sensitivity of $SW_{clr_{abs}}$ to varying TPW is smaller than that of all models except GISS (Extended Data Fig. 5). The CNRM models
employ 6 total SW bands instead of 4 [48]. Mean SWclr$_{\text{abs}}$ is considerably larger and more realistic in these models compared to IPSL and the sensitivity of SWclr$_{\text{abs}}$ to varying TPW is marginally improved as well (Extended Data Fig. 5). Thus a small increase in the number of computations can have a large impact on the realism of solar absorption, particularly for radiation schemes that incorporate coarse spectral resolution to begin with.

A comparison of the models that implement a 7-band SW parameterization originally developed by ref. [63] (BCC-CSM1.1, BCC-CSM1.1(m), CCSM4, INM-CM4, MRI-CGCM3, NorESM1-M) sheds light on specific characteristics of parameterizations of gaseous absorption, other than number of mathematical terms, that appear important for SWclr$_{\text{abs}}$. The original parameterization for WV by ref. [36] consists of a 7-term pseudo-k-distribution summation with absorption coefficients and weights determined by fits to empirical and LBL calculations, respectively$^{57,63}$. It is employed by the INM-CM4 and MRI-CGCM3 models (Extended Data Fig. 6). The parameterization was later modified to account for additional near-infrared WV absorption based on updated spectroscopic data and continuum absorption in the SW, which resulted in refitting the 7 parameterized absorption coefficients$^{43}$. The updated parameterization is employed in the BCC-CSM1.1, BCC-CSM1.1(m), CCSM4, and NorESM1-M models. The models using the updated parameterization exhibit improved SWclr$_{\text{abs}}$ sensitivity by a small but non-negligible amount (Extended Data Fig. 6). Consideration of weak WV absorption lines and continuum absorption are therefore important for accurate simulation of changes in solar absorption in a warming climate, albeit in a minor way. This is consistent with the findings presented in refs. [43] and [78]. Note that most parameterizations with larger and more realistic SWclr$_{\text{abs}}$ sensitivities tend to account for continuum absorption (Extended Data Fig. 6).
Our analysis does not isolate the effect of aerosols, including scattering, on SWclr_{abs} and its sensitivity to varying TPW. CMIP5 models differ in their simulation of aerosol concentrations (whether prescribed or computed from emissions with a chemistry model), optical properties of aerosols, and the quantitative treatment of aerosol scattering. To the extent that these factors are correlated with TPW in space and time (e.g., more absorbing aerosols with higher WV concentration, or larger absorption in moist atmospheres due to a more sensitive aerosol scattering treatment), they too may play a role in the difference in the SWclr_{abs} versus TPW curves shown in Extended Data Fig. 5. Thus the SWclr_{abs} sensitivities may not completely reflect the physics of WV absorption. One particular instance where differences in aerosols may affect the SWclr_{abs} sensitivity to varying TPW is with the GFDL models. All three GFDL models (GFDL-CM3, GFDL-ESM2G, GFDL-ESM2M) use the same parameterization for WV absorption and scattering by aerosols\textsuperscript{53,54}; yet the CM3 absorbs more solar radiation in moist conditions, leading to a larger and more realistic SWclr_{abs} sensitivity (Extended Data Fig. 5). The CM3 implements an interactive aerosol scheme with different aerosol optical properties than the ESM models (which prescribe aerosols), resulting in enhanced and more realistic downward clear-sky surface SW flux due to reduced aerosol direct effects\textsuperscript{51}. We speculate that the reduced aerosol direct effects may lead to more solar radiation available for absorption by lower tropospheric WV, and thus larger SWclr_{abs} in moist conditions in the CM3. The extent that differences in aerosol concentrations/properties affect the variability in SWclr_{abs} sensitivity to TPW among other models is unknown without a more rigorous and controlled investigation. However, we suspect these effects are generally small, as SWclr_{abs} sensitivities computed using different forcing scenarios (e.g., historical and RCP8.5, which potentially exhibit large variability in aerosols) are very similar to those computed with the piControl (not shown).
Stratospheric ozone is another strong absorber of solar radiation. As with aerosols, ozone may influence the SWclr$_{\text{abs}}$ versus TPW relationship (Extended Data Fig. 5) if its concentration varies systematically with atmospheric moisture. Although column-integrated ozone tends to decrease with increasing TPW in 16 models that have available ozone output, there is no cross-model correlation between the sensitivity of ozone decrease and sensitivity of SWclr$_{\text{abs}}$ increase to varying TPW (not shown). Furthermore, SWclr$_{\text{abs}}$ sensitivities are similar to those in Extended Data Fig. 5 when they are computed from a smaller sample of locations and months exhibiting little variability in column-integrated ozone (not shown). These findings suggest ozone is not significantly affecting model variability in the SWclr$_{\text{abs}}$ versus TPW relationship. However, the parameterization of ozone absorption likely influences the mean position of the SWclr$_{\text{abs}}$ versus TPW curve for each model (i.e., average SWclr$_{\text{abs}}$ over the range of TPW analyzed). One possible example of this is with the INM-CM4 and MRI-CGCM3 models. Both models use the same parameterization for WV absorption$^{63}$, but have different treatments of solar absorption by ozone$^{64,76}$. We speculate that this partly explains the similar slopes but different vertical placement of the SWclr$_{\text{abs}}$ versus TPW curves for these models (Extended Data Fig. 5).

Small spatial and monthly variations in surface albedo and/or solar zenith angle within the tropical oceans could potentially influence the computed SWclr$_{\text{abs}}$ sensitivities if they are correlated with TPW. However, SWclr$_{\text{abs}}$ sensitivities computed with just locations and months having very similar surface albedo or zenith angle (variations of no more than 0.01 or 1°, respectively) are highly correlated across models with the original sensitivities computed from all locations and months (not shown). This suggests that the influence of these factors is negligible. Finally, other details of the CMIP5 SW parameterizations, including the treatment of scattering by aerosols and molecules and of overlapping absorption by multiple gaseous
species, have not been thoroughly investigated here. They too may influence the intermodel spread in SWclrabs sensitivity to varying TPW. If these details are indeed influencing our metric of SWclrabs sensitivity, however, it would not change the conclusion that SW parameterizations \textit{in general} are important for the spread in simulated hydrologic cycle intensification.

Regardless of the complete physical interpretation of the intermodel spread in our SWclrabs sensitivity metric, the CERES-EBAF estimate provides a suitable observational constraint. As described in Methods, the CERES-EBAF fluxes are based on satellite measurements at the top-of-atmosphere (TOA) and radiative transfer computations at the surface, with the latter being constrained by TOA fluxes\cite{Knorr2014}. The radiation code used to compute surface fluxes employs the formal correlated-k-distribution framework with absorption coefficients (k-values) being determined directly from detailed LBL-generated k-distributions\cite{Johnson2013, Johnson2014}. This approach is arguably superior to that in most CMIP5 models, in which k-values are in many cases determined with non-physical mathematical optimization procedures (e.g., refs. [53] and [69]). In addition, the treatment of pressure-temperature-concentration dependence of k-values in the CERES-EBAF scheme is more physical and higher in resolution than most CMIP5 models\cite{Johnson2013}. The final parameterization describing WV absorption in CERES-EBAF also has many (>50) mathematical terms approximating SW transmission\cite{Johnson2013, Johnson2014}.

**Supplementary References**