Reply to Reviewer #1

We thank Reviewer 1 for their thorough review. In our response, the reviewer's comments are bolded, our answers are normal weight, and anything that we change in the paper is italicized.

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Major Comment 1: There is a misconception in transferring your results from the trended to the detrended regression analysis. The problem here is, that you use the regression coefficients β directly in some places to analyse your results (e.g. in Table 2, 3, 4 and in Fig. 3 and 5 and accompanying text) and not either the explained variance (i.e. VAR($\beta \Delta T \Delta T$)) or the regression coefficient multiplied by the standard deviation of the explanatory variable (i.e. $\beta \Delta T$

- 10 STD(ΔT)). At some places (Page 4, line 5–6) you look at these quantities, but unfortunately at Page 4, line 14–15, you draw the conclusion "This confirms the stratospheric water vapor feedback [...]" from the similarity of the regression coefficients in the trended and the detrended analysis. Unfortunately, this is an invalid conclusion. Even if the regression coefficients would stay exactly identical, the percentage of explained variance that an explanatory time series explains of the total explained variance \mathbb{R}^2 can change dramatically between the trended and detrended regression analysis. An
- 15 obvious example is an explanatory time series with a large trend and a small interannual variability. An explanatory time series like this will likely contribute a large explained variance to the trended regression analysis, but a small explained variance (in percent) to a detrended regression analysis, while its regression coefficient may be very similar in the trended and detrended analysis. Unfortunately, your example time series for ΔT in Fig. 2 looks a little like this (compared to the variance and trend of the BDC time series). Since we agree that you can't really use the trended analy-
- sis to confirm your main conclusion (Page 3, line 26–27), you have to base your conclusion that changes in tropospheric temperature cause changes in stratospheric water vapor on the detrended regression analysis. That means you have to confirm that a large part of the interannual variability of stratospheric water vapor in the detrended regression analysis comes from interannual variability in the ΔT term. That still will not be a proof of causality, but will put much more confidence in your main conclusions
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The reviewer makes an excellent point here. In response, we have added new columns to Tables 2, 3, and 4 that show the correlation coefficient scaled by the standard deviation of the predictor time series. This is described on page 5, lines 1-3 of the manuscript, and we have modified our discussion to incorporate these values (page 5, lines 3-10 for the century regressions, and page 6, lines 32-35 for the decadal regressions). Additionally, we added a sentence to the conclusions, page 7, lines 29-30, the predictor time series is the predictor time series is the predictor.

30 to summarize the results.

Additional remark 1: Since it is known that variability in stratospheric water vapor comes from variations in the tropopause temperature (more exactly: Langrarian dry points, see e.g. Fueglistaler, 2013), it would put much more confidence in your main conclusions if you show that tropospheric temperature and tropopause temperatures correlate in your models.

We have modified the text to discuss this (page 2, lines 7-10).

Additional remark 2: Giving values as explained variances makes it easier to compare values between different time 40 series as ΔT and BDC. In the moment, it is easy to compare between models in the rows of your tables, but impossible to do that between the columns of your tables.

We have added new columns to Tables 2, 3, and 4 that show the correlation coefficient scaled by the standard deviation of the predictor time series. This is described on page 5, lines 1-3 of the manuscript, and we have modified our discussion to incorporate these values (page 5, lines 3-10 for the century regressions, and page 6, lines 32-35 for the decadal regressions).

Additionally, we added a sentence to the conclusions, page 7, lines 29-30, to summarize the results.

Additional remark 3: I have to emphasize that I am pretty sure that the trend in ΔT and in stratospheric water vapor are causally connected, I just think that a trended regression analysis is not the tool to show that. You have to avoid the

impression that your trended regression analysis is a proof of that. My suggestion is the following: Add values for the explained variance of the explanatory time series (e.g. in ppm^2) to the tables 2, 3 and 4 (you can keep the regression coefficients or replace them by these values). Alternatively, you can add values for the regression coefficients multiplied by the standard deviations of the explanatory time series to the tables. Both explained variance and standard deviation

5 have advantages and disadvantages: The explained variances of the explanatory timeseries add up to the overall explained variance (under the assumption that the explanatory time series are uncorrelated), but values in ppm^2 are not very intuitive. Standard deviations are more intuitive, but don't add up. Thus, I will not give a recommendation what is better here. Next, change Figure 3 to show explained variances or standard deviations, or add an additional figure doing this. Then, base your discussion on the explained variances, where it does matter for your conclusions (e.g. in

section 3.2). 10

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We have added new columns to Tables 2, 3, and 4 that show the correlation coefficient scaled by the standard deviation of the predictor time series. This is described on page 5, lines 1-3 of the manuscript, and we have modified our discussion to incorporate these values (page 5, lines 3-10 for the century regressions, and page 6, lines 32-35 for the decadal regressions). Additionally, we added a sentence to the conclusions, page 7, lines 29-30, to summarize the results.

Major Comment 2: It is not straightforward that more stratospheric water vapor means more warming of the troposphere, and there is not enough discussion in your paper in the moment to support your main conclusion "A stratospheric water vapor feedback exists, where a warming climate increases stratospheric water vapor, leading to further

- tropospheric warming". Please at least discuss the literature on that shortly (e.g. Oinas et al., 2001; Solomon et al., 20 2010). That would give much more confidence that this statement is actually correct. Is the feedback by an increase in downward longwave radiation from the stratosphere? That does not seem to be straightforward to me. One the one hand, you have more water vapor to emit radiation. On the other hand, the stratosphere gets cooler, which reduces radiation. In a simple picture, where water vapor only emits longwave radiation and the stratosphere is heated by
- shortwave radiation by ozone, wouldn't the outgoing longwave radiation from a layer where you add more water vapor 25 just stay constant to maintain radiative equilibrium, by a lowered radiative equilibrium temperature?

We replaced the first sentence of the paper, with a sentence referring to the literature describing this process (page 1, lines 11-12), and removed the sentence in question. That said, we have not added any discussion of this to the paper because this is a well-documented phenomenon.

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Major Comment 3: It seems to me that you take the positive correlation between tropospheric temperature and stratospheric water vapor as very obvious. However, this is not simple and obvious at all. Again, discuss the literature on that shortly, and try to avoid the impression that this is an obvious fact.

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We have added a short discussion of this to the manuscript (page 2, lines 10-13) and have hopefully changed the tone, per the reviewer's comment.

Major Comment 4: Since multiple regression can only show correlation but not causality, some more discussion on 40 the supposed reasons for the correlations would be very helpful, in particular for the ΔT term. In my opinion, it should also be discussed that the reasons for a correlation can be very different in a model and in reality (i.e. based on observations). Just to give a simple example: The correlation between tropospheric temperatures and stratospheric water vapor can possibly be caused by excessive transport or diffusion of water vapor over the tropopause in the models (see Hardiman et al., 2015): Higher tropospheric temperatures means more moisture, which then could be transported

45 by spurious vertical numerical diffusion into the stratosphere. A way to test for things like this could be e.g. to look at the tropical tropopause temperatures and their correlation to tropospheric temperatures and stratospheric water vapor.

We have added a caveat to this point on page 2, line 10.

Major Comment 5: Relating to this: There is a lack of information on the model performance and parameterizations of the used models. At least some information of the following list would be very helpful to assess your results. I acknowledge that it would be a lot of work to answer all of these questions for all of the models. But I think that there should be at least some discussion about how the processes in the model can affect the results. Of course, I don't want

- 5 you to discuss all of these issues in detail, but to discuss things that are important for your results, i.e. take the list below as a list of suggestions.
 - What is the tropopause temperature in the models, and how does it compare to measurements in terms of bias, annual cycle and trends? Can it explain the water vapor in the model or are there additional processes at work?
 - How well is the Brewer-Dobson circulation represented?
 - How is convection parametrized? How well does it compare to observations? Is there overshooting?
 - How is radiation parametrized? What is the effect of clouds on radiation?
 - What is the spatial pattern of Local dry points (LDPs) in the models and compared to reality? Can a shift in their distribution cause the correlation?
 - Effect of (spurious) diffusion and transport?
- Our paper is narrowly focused on quantifying the contributions of various processes to $[H_2O]_{entry}$ variability. There are many branches we could take in our discussion and we feel that we've covered the essential information required to achieve our objective. If the reviewer has a specific topic they would like to see discussed, we're happy to consider that suggestion. We also note that most of the suggestions listed above by the reviewer is already available in the literature (Gettelman et al. (e.g. 2010) compares TTL temperatures in the models; individual model papers discuss their parameterizations have been added to
- 20 table 1 (also listed in Morgenstern et al. (2010, 2017)).

Specific Comment 1: Page 1, line 1 and page 2, line 14: Please give a citation here, e.g. Gettelman et al. (2010) (e.g. Fig 17) or Kim et al. (2013)

ACP does not prefer that citations be in the abstract, so for page 1, line 1, we will leave this to the discretion of the editor. The sentence on page 2 line 14 of the original manuscript has been removed from the current version of this manuscript.

Specific Comment 2: Page 1, line 4: You probably mean stratospheric humidity. Please Clarify.

30 Yes, "humidity" has been changed to "stratospheric humidity" in this line.

Specific Comment 3: Page 1, line 4: In case you base that statement on your trended regression analysis, is it really correct? Correlation does not imply causality, especially in a trended regression analysis. The statement that you give on page 3, line 26-27 is a direct contradiction of what you state here. In fact, I think you cannot support that statement with the information you currently give in the paper. I would try to phrase that more carefully, e.g. by speaking of correlations, or make clear that this conclusion comes not from your trended analysis, but from some other source.

We acknowledge that correlation does not imply causality, and we believe that we clearly base our conclusions on the detrended analysis.

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Specific Comment 4: Page 1, line 3-5: Since there is the contradicting trend from increasing cooling by the BDC (as you note here and is seen in your figure 2), can you really make the statement that the net trend in humidity is primarily driven by tropospheric warming (that would imply to me that, say, something like 80% or 90% of the net trend comes from the Δ T term)? It seems to me that the trend by the BDC is in the same order of magnitude (but that the net effect

of both trends is normally positive). Please add a figure showing the trends by the BDC term and the ΔT term for every model to quantify the trends and to underpin your statement. I think such a figure is probably easy to add.

We added a paragraph, beginning on page 4, line 30, discussing this.

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Specific Comment 5: Page 1, line 6-7: I don't quite understand why you split your time series into 10 year chunks? Would it not be ok to compare the 100 year time series to the 10 years of observations directly?

There are obviously many ways to compare to the MLS-based results. Our opinion is that the best way is the way we've done it in the paper. If one wants to compare the MLS results to the entire 100-year CCM run, the reader can do that by comparing the MLS coefficients (Table 4) to those from the detrended 100-year regressions (Table 3). We have added text on page 5, lines 13-14 to clarify our comparison.

Specific Comment 6: Page 1, line 8: It is not clear to me what exactly you are referring to. Is it really that new to apply a linear regression model to these data (one of your own papers did that already: Dessler et al. (2013)? I suggest to delete that last sentence of the abstract or be more specific here: What is superior to what?

We do consider this new in that we show the utility of comparison between models as a way to evaluate them. This is clearly superior to previous comparisons, Gettelman et al. (e.g. 2010).

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Specific Comment 7: Page 1, line 11 to Page 2, Line 2: Instead of speaking of the TTL temperatures as the determining factor, one can get more specific here. It is the temperature of the coldest point along each air mass trajectory (i.e. the Lagrangian dry point) which determines the stratospheric water vapor (except for direct injection by overshooting). In many cases this temperature will be reached at or near the tropical tropopause.

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In order to be more specific, we have modified the text on page 1, lines 16-19.

Specific Comment 8: Page 1, line 18-19: Would be nice to add a citation here, e.g. one of the Fueglistaler papers

30 We modified the text, and added several citations to support our claim regarding the Brewer-Dobson Circulation and QBO on page 2, lines 3-6.

Specific Comment 9: Page 2, line 1-2: No, it doesn't imply that. See general comment 2. In addition: the local effect of more water vapor is more cooling in the stratosphere, so it is better to be more specific and to write "further tropospheric warming".

We have made that change.

Specific Comment 10: Page 3, line 14: Probably, it is better to speak of "autocorrelation in the residuals" than of "autocorrelation of the time series", since it is only the remaining autocorrelation in the residuals that affects the uncertainty.

We have changed "autocorrelation of the time series" to "autocorrelation in the residuals".

Specific Comment 11: Page 3, line 18-19: You are aware that subtracting a constant does only change β_0 , but does not change anything else in the regression analysis

We know that. We believe our method is clear, as written.

Specific Comment 12: Page 4, line 14-15: No, it doesn't confirm that, see major point 1.

We have removed the sentence.

Specific Comment 13: Page 4, line 18-19: This doesn't really tell you anything, see Page 4, line 14-15.

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While we agree with the reviewer's point that this should not be over-interpreted, we also feel that this is a statement worth making here. We do not believe what is written is incorrect.

Specific Comment 14: Section 4: I don't really get the additional benefit of splitting the time series into 10 year chunks.
Wouldn't a direct comparison of the observational 10 year time series and the model 100 year time series give all the information important?

There are obviously many ways to compare to the MLS-based results. Our opinion is that the best way is the way we've done it in the paper. If one wants to compare the MLS results to the entire 100-year CCM run, the reader can do that by comparing the MLS coefficients (Table 4) to those from the detrended 100-year regressions (Table 3). We have added text on page 5, lines 13-14 to clarify our comparison.

Specific Comment 15: Page 7, line 8-9: I find the statement that you can assess the realism of the model trend by a linear regression somewhat problematic. If there is a trend in stratospheric water vapor in the models and there is a trend in one of the explanatory variables, the explanatory variable will try to fit this trend, whatever the magnitude is and whatever the underlying physical reason of the trend is. If it turns out then, that the fit of the interannual variability is also good, that may give you confidence. But in general, you always have the problem that a linear regression analysis does not tell you anything about causal relationships.

25 We have changed the sentence to read: "We demonstrated in this paper a new way to evaluate the physical processes underlying these model trends."

Specific Comment 16: Page 7 line 13: See second specific comment for page 1, line 4. I would phrase that more carefully.

30 We don't know what the reviewer is referring to, more clarification would be appreciated.

Specific Comment 17: Page 7, 13-16: I think it would make sense to cite some studies here and to discuss your results in comparison to other studies (briefly), e.g. studies that deal with the absence of the QBO in many models that show the influence of the BDC on tropopause temperatures and its increasing trend etc.

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We have added citations to page 7,lines 26-30; page 8 lines 1-3, that investigate influences of both the BDC and QBO on the TTL.

Specific Comment 18: Page 7, line 21: I would agree, but I would base that statement mainly on the detrended regression analysis. If there is a good overall fit of the detrended model, you can have some confidence that the explanatory time series actually are relevant processes for the regression variable, and that the magnitude of their fit does tell you something. Since, regression analysis does not tell you anything about causal relationships however, you need to put some a priori knowledge into that. For that reason, I would be very careful to interpret the trended analysis, since there is the danger that there is no causal relationship between the trends (and the trends lead to a correlation between

45 explanatory variables, which can make the magnitude of the fit for these variables a little bit arbitrary in the worst case.

We agree but don't believe this is a problem, as written.

Specific Comment 19: Page 7, line 22: That is a conclusion I would mainly draw from comparison with observations or

testing the model's processes. A regression model can only help you in confirming this. E.g. What would happen if all models would overestimate variability of water vapor in the future? Your fit coefficients would get larger to try to fit this variability better. Do you learn from that that the model does a good job?

5 We have modified the text on page 8, lines 8-9 to account for this.

Specific Comment 20: Page 7, line 22-23: This might however also be a deficiency of the regression approach, e.g. an explanatory variable that is no perfect proxy for the BDC, or that the trends dominate the fit (which gives rise to correlation between the explanatory variables leading to uncertainties in the magnitude of the fit for the BDC.

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It's always possible that our analysis might be wrong (for a large number of reasons), but we feel our work is adequately caveatted. If the author has a specific uncertainty/caveat that they'd like us to add, we're happy to consider it.

Technical Revision 1: In the title you write "lower-stratospheric", later you write "lower stratospheric" would be nice to have consistency.

"Lower stratospheric" has been changed to "lower-stratospheric" throughout the paper.

Technical Revision 2: Page 2, line 27: Change "ozone-depleting substance" to "ozone-depleting substances"

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Done

Technical Revision 3: Page 2, line 31: Change "described described" to "described".

25 Done

Technical Revision 4: Page 5, line 12: A period is missing ("...regression. However").

Done

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Technical Revision 5: Page 7, line 22: Change "appear do" to "appear to do"

Done

Reply to Reviewer #2

Smalley et al. analyse CCM model predictions of stratospheric water changes over the 21st century. A multivariate linear regression is applied to the models' stratospheric water entry mixing ratios (" $[H_2O]_{entry}$ "), with the explana-

5 tory variables being a "tropospheric temperature index", a "Brewer Dobson strength" index, and a QBO index; this analysis follows the method of Dessler et al. (2013). Overall, the analysis is straight- forward, and the results are clearly described. I do not comment on the aspects of the statistical analysis brought up by the other reviewer.

However, this reviewer cannot quite see that "Our approach provides more insight into model processes than sim-10 ply comparing $[H_2O]_{entry}$ or TTL temperatures." (Page 7/Line 19).

We strongly disagree with this comment. Comparing water vapor and TTL temperatures tells you nothing about the contribution of individual processes that are responsible for $[H_2O]_{entry}$ variability. Or analysis breaks down variability in $[H_2O]_{entry}$ by process. That being said, we modified the text on page 8, lines 8-10 to try to make this clearer.

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Rather, the paper is somewhat superficial (it certainly does not help that (Page 2/Line 13): "Finally, a warmer troposphere tends to increase $[H_2O]entry$, although whether this is through influence on TTL temperatures or some other mechanism such as convective ice lofting, is not clear."), and results are few. It would be great if the authors would work out the connection between tropopause temperatures and $[H_2O]_{entry}$ in the models, and the connection between "tropospheric temperature" and tropopause temperature.

We disagree that the paper is superficial. We view this as an important new technique to diagnose processes in CCMs, which can reveal problems in the CCMs not apparent by just looking at $[H_2O]entry$ and TTL temperatures. That said, we have added more text (lines 7-13 on page 2) that discusses the connection between tropospheric temperature, TTL temperature, and $[H_2O]_{entry}$.

The QBO results would also deserve some further analysis - for the 21st century analysis, annual mean data is analysed. This evidently removes much of the variance associated with the QBO, and it appears that the lack of influence of the QBO (as e.g. shown in Figure 2) is due to a lack of a trend in the QBO index. This evidently begs the question why the model does not have a QBO trend when it has been argued that the tropospheric expansion associated with global

- 30 the model does not have a QBO trend when it has been argued that the tropospheric expansion associated with global warming would have an impact on the lower stratospheric QBO - and as such would be reflected in the QBO index. While this may not have an impact on $[H_2O]entry$ (because the QBO influence at the rising tropopause level main remain constant over time), it would be useful to have some more information why the QBO index (as e.g. shown in Figure 2) does not show a trend.
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We first note that this comment shows the usefulness of our analysis (contradicting the reviewer's earlier comment): just comparing $[H_2O]entry$ and TTL temperatures would not reveal this problem with the QBO. That said, we disagree with the overall comment. Our paper is designed to understand how these processes (BDC, QBO, ΔT) affect $[H_2O]entry$, not why the processes evolve as they do. Understanding why the BDC, QBO, etc. evolve as they do over the 21st century is far beyond the scope of this paper. Our paper is nonetheless an extremely useful result — by identifying this issue, our paper will spur

40 the scope of this paper. Our paper is nonetheless an extremely useful result — by identifying this issue, our p additional research into why the QBO is not impact water vapor in the way suggested by the models.

Two additional minor comments:

45 Please provide a reference for the statement that "Virtually all climate models ..." (page 2/Line 14)

This sentence has been removed from the current manuscript

and some more information about the differences in results for models that participated in CCMI-I and CCMVal-2

would be useful.

After lengthy consideration, we've decided that there's no easy way to summarize the differences in the models in these two groups because there are no systematic differences. Trying to summarize the differences in the text therefore was unwieldy and created difficult-to-read, boring text. If people are interested in this, they can determine it using the Tables in our paper.

Testing chemistry-climate models' regulation of tropical lower-stratospheric water vapor

Kevin M. Smalley¹, Andrew E. Dessler¹, Slimane Bekki², Makoto Deushi³, Marion Marchand², Olaf Morgenstern⁴, David A. Plummer⁵, Kiyotaka Shibata⁶, Yousuke Yamashita^{7,8}, and Guang Zeng⁴ ¹Department of Atmospheric Science, Texas A&M, College Station, Texas, USA. ²LATMOS, Institut Pierre Simon Laplace (IPSL), Paris, France ³Meteorological Research Institute, 1-1 Nagamine, Tsukuba, Ibaraki 305-0052, Japan ⁴National Institute of Water and Atmospheric Research (NIWA), Wellington, New Zealand ⁵Canadian Centre for Climate Modelling and Analysis, Environment and Climate Change Canada ⁶School of Environmental Science and Engineering, Kochi University of Technology ⁷National institute for Environmental Studies (NIES) ⁸Now at Japan Agency for Marine-Earth Science and Technology (JAMSTEC), Yokohama, Japan *Correspondence to:* Andrew Dessler (adessler@tamu.edu)

Abstract. Climate models predict that tropical lower stratospheric lower-stratospheric humidity will increase as the climate warms, with important implications for the chemistry and climate of the atmosphere. We analyze the trend in 21st-century simulations from 12 state-of-the-art chemistry-climate models (CCMs) using a linear regression model to determine the factors driving the trends. Within CCMs, the warming of the troposphere primarily drives the long-term trend in humidity is primarily

- 5 driven by warming of the tropospherestratospheric humidity. This is partially offset in most CCMs by an increase in the strength of the Brewer-Dobson circulation, which tends to cool the tropical tropopause layer (TTL). We also apply the regression model to individual decades from the 21st century CCM runs and compare them to observations. Many of the CCMs, but not all, compare well with observations, lending credibility to their predictions. One notable deficiency in most CCMs is that they underestimate the impact of the quasi-biennial oscillation on lower stratospheric-lower-stratospheric humidity. Our analysis
- 10 provides a new and potentially superior way to evaluate model trends in lower stratospheric lower-stratospheric humidity.

1 Introduction

Variations of stratospheric water vapor can impact both the climate and chemistry of the atmosphereStratospheric water vapor is well-known to be a greenhouse gas (e.g. Manabe and Wetherald, 1967; de F. Forster and Shine, 1999; Solomon et al., 2010; Maycock et al so increasing it will lead to additional warming of the climate system. Because of this, understanding the processes that control

15 the humidity of air entering the tropical lower stratosphere (hereafter $[H_2O]_{entry}$) has been a high priority of the scientific community since Brewer (1949) first described the stratospheric circulation.

It is now well established that the fundamental control over $[H_2O]_{entry}$ comes from the <u>coldest</u> temperatures found in the tropical tropopause layer (TTL) (Fueglistaler et al., 2009b), frequently referred to as the Lagrangian dry point, and that variability in these temperatures translates into variability in $[H_2O]_{entry}$. The most well-known example of this is the so-called "tape recorder," in which the seasonal cycle in TTL temperatures is imprinted on tropical stratospheric water vapor (Mote et al., 1996).

On interannual time scales, variability in $[H_2O]_{entry}$ originates from processes such as the Brewer-Dobson Circlation (BDC) (Randel et al., 2006; Castanheira et al., 2012; Fueglistaler et al., 2014; Gilford et al., 2016) and the quasi-biennial os-

- 5 cillation (QBO) (O'Sullivan and Dunkerton, 1997; Randel et al., 1998; Dunkerton, 2001; Fueglistaler and Haynes, 2005; Choiu et al., 200 More recently, Dessler et al. (2013, 2014) has suggested that the temperature of the troposphere also exerts an influence on $[H_2O]_{entry}$. This implies the existence of a stratospheric water vapor feedback, whereby a warming elimate would increase stratospheric water vapor, leading to further warmingwas based on the well-established observation that models predict a warming TTL during global warming [e.g., Gettelman et al. 2010]; in the models analyzed here (described in the next section)
- 10 the tropospheric temperature is highly correlated with TTL temperatures, with a mean correlation of 0.91. There are good physical reasons for this connection [Lin et al., 2017]. In addition, Dessler et al. [2016] demonstrated in two CCMs that a warming climate also caused increased amounts of water to be directly injected into the stratosphere via deep convection, providing another mechanism for tropospheric temperature to affect $[H_2O]_{entry}$.

Putting these factors together, Dessler et al. (2013, 2014) demonstrated that observed $[H_2O]_{entry}$ anomalies could be accu-15 rately reproduced with a simple linear model:

$$[H_2O]_{entry} = \beta_0 + \beta_{\Delta T} \Delta T + \beta_{BDC} BDC + \beta_{QBO} QBO + \epsilon \tag{1}$$

Where ΔT is the temperature of the troposphere, BDC is the strength of the Brewer-Dobson circulation, QBO represents the phase of the QBO, and epsilon is the residual. As expected, they found that a stronger BDC, which tends to cool the TTL, reduces $[H_2O]_{entry}$; this is consistent with previous analyses (Brewer, 1949; Randel et al., 2006; Castanheira et al., 2012; Fueglistaler et al.

20 They also found that the QBO introduces significant variability with a time scale of a few years, also consistent with previous work (O'Sullivan and Dunkerton, 1997; Randel et al., 1998; Dunkerton, 2001; Fueglistaler and Haynes, 2005; Choiu et al., 2006; Liang et Finally, a warmer troposphere tends to increase [H₂O]_{entry}, although whether this is through influence on TTL temperatures or some other mechanism, such as convective ice lofting, is not clear.

Virtually all climate models predict that $[H_2O]_{entry}$ will increase as the climate warms. Dessler et al. (2013) analyzed

- 25 Dessler et al. (2013) analyzed the 21^{st} century trend in one chemistry-climate model (CCM) to better understand this trend (CCMs hereafter, CCM; they are similar to general circulation models, but with a more realistic stratosphere and higher vertical resolution in the TTL) and found that the regression model worked well in reproducing the CCM's $[H_2O]_{entry}$ trend over the 21^{st} century. They further found concluded that the increase in $[H_2O]_{entry}$ was driven by the increase in tropospheric temperatures, which was partially offset by a strengthening BDC.
- 30 Dessler et al. (2013)'s analysis provided regression method provides a novel way to examine the regulation of $[H_2O]_{entry}$ in CCMs and compare it to observations. The purpose of this paper is to use this technique to examine a set of CCMs, with the goal of providing insight into the realism of the models.

2 Models

We analyze model output from 7 CCMs participating in Phase 2 of the Chemistry-Climate Model Validation Project (CCMVal-2) (Morgenstern et al. (2010); SPARC (2010)) and output from 5 CCMs participating in Phase 1 of the Chemistry-Climate Model Initiative (CCMI-1) (Morgenstern et al. (2017)). Table 1 lists the models model specifics and documentation.

- We use simulations from the REF-B2 scenario of CCMVal-2. In this scenario, greenhouse gas concentrations during the 21st century come from the A1B scenario, which lies in the middle of the SRES scenarios (IPCC, 2001). Ozone-depleting substance substances come from the halogen emission scenario A1 described by (WMO, 2007). CCMVal-2 specifics can be found in SPARC (2010) and Morgenstern et al. (2010). We use the refC2 scenario of the CCMI-1. In this scenario, greenhouse gas concentrations come from the RCP 6.0 scenario (Meinshausen et al., 2011) and ozone-depleting substances come from the
- 10 halogen emission scenario A1 described described by (WMO, 2014) by WMO (2014). CCMI-1 model specifics can be found in Morgenstern et al. (2017). In order to maintain a consistent reference period between models, our analysis covers 2000-2097, which we will hereafter refer to as "the 21st century".

For each model, we fit CCM $[H_2O]_{entry}$ using the multivariate linear regression (MLR) model described above. We use tropical average 80-hPa water vapor volume mixing ratio anomaly as a proxy for $[H_2O]_{entry}$ (all tropical averages in this

- 15 paper are averages over 30°N-30°S; anomalies are calculated by subtracting off the mean annual cycle from the time series). For our BDC index, we use 80-hPa diabatic heating rate anomalies (see Fueglistaler et al. (2009a) for details). The tropospheric temperature index is the 500-hPa tropical average temperatureanomaly, and for the few CCMI-1 simulations that only produce variables on hybrid pressure levels (CMAM, CCSRNIES-MIROC3.2, and MRI-ESM1r1), we choose a hybrid pressure level close to the 500-hPa pressure surface (See Table 1). All of these choices are similar to those used by Dessler et al. (2013, 2014).
- For the QBO index, we take the standardized anomaly of equatorial 50-hPa zonal winds (anomalies in this paper are calculated by subtracting the mean seasonal cycle). By examining 21^{st} century 50 hPa zonal winds (shown in supplement figures), we find that only 5 of the 12 models simulate a QBO (table 1). As a result, we do not expect the QBO to significantly impact $[H_2O]_{entry}$ in all-many of the models.

The MLR returns the coefficients for each regression coefficient regressor in Equation 1, along with an uncertainty for each coefficient. Unless otherwise noted, we use 95%-confidence intervals in this paper. Autocorrelation of the time series in the residuals is accounted for in the uncertainties following Santer et al. (2000).

3 Century Analysis

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We first analyze the long-term trend in $[H_2O]_{entry}$ over the 21^{st} century. To do this, we calculate annual average values of $[H_2O]_{entry}$ and perform a MLR against annual averages of the indices for BDC, QBO and ΔT . All annual averages For consistency, all annual average time series have had the 2000-2010 average mean subtracted out.

Figure 1 shows that the fits to most of the models generate adjusted R^2 values greater than 0.8. The NIWA-UKCA century MLR has the lowest adjusted R^2 , with a value of approximately 0.6. Overall, this result confirms the result of Dessler et al.

(2013) that the regression model does an excellent job reproducing the models' $[H_2O]_{entry}$. Because we have left long-term trends in the time series, we will refer to this as the "trended analysis".

3.1 Detrended 21st Century

One concern with the trended analysis is that the $[H_2O]_{entru}$ time series, the BDC, and ΔT indices time series are all dominated by long-term trends. In such a case, an MLR may produce a high adjusted R^2 even if there is no actual relation between the 5 variables. To eliminate the influence of long-term trends on adjusted R^2 , we detrend each variable using a Fourier Transform filter (Donnelly, 2006) to remove long-term variability (> 10 years). We then use the MLR on the detrended $[H_2O]_{entry}$ and the detrended indices. Detrending by removing the long-term linear trend yields similar results.

Figure 1 shows the adjusted R^2 for the detrended calculation. For most of the models, the adjusted R^2 for the detrended MLR is only slightly smaller than that for the trended one. This confirms that the long-term trends in the data tend to inflate 10 the adjusted R², at least a bit, and also that the models' interannual variability and long-term trends are detrended variability are also well represented by the same linear model (Equation 1). Large differences do exist for some CCMs. For instance, the CCSRNIES trended century MLR captures approximately 90% of the variance in $[H_2O]_{entry}$, while the detrended century MLR only explains about 40% of interannual detrended variance; the CNRM-CM5-3, NIWA-UKCA, and WACCM show something similar.

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3.2 **Physical Process Effects**

The coefficients from the trended and detrended calculations are listed in Tables 2 and 3 respectively. The product of the regression coefficient and its index quantifies that process' impact on $[H_2O]_{entry}$. As an example, MRI $[H_2O]_{entry}$ increases by about 1.2 ppmv during the 21st century (Figure 2). The regression shows that this is the result of a large increase in $[H_2O]_{entru}$

due to ΔT increases (1.5 ppmv) that is offset by a strengthening BDC, which reduces $[H_2O]_{entry}$ by approximately 0.3 ppmv; 20 this is consistent with the results of Dessler et al. (2013). The regression finds virtually no change in $[H_2O]_{entry}$ in response to the QBO, which does not comport with analyses of observations, which suggests that the QBO causes short-term variations in $[H_2O]_{entry}$ of 0.3 ppmv (Dessler et al., 2014).

Figure 3 shows that $[H_2O]_{entry}$ increases as ΔT increases in all models and that the ΔT regression coefficients are similar

for both trended and detrended MLRs. On average, $[H_2O]_{entry}$ increases by about 0.3 ± 0.1 ppmv K⁻¹, with individual models</sup> 25 yielding values ranging from about The coefficient for individual models ranges from 0.1 to 0.6 ppmv K⁻¹. This confirms that the stratospheric water vapor feedback identified by Dessler et al. (2013) occurs in all CCMs, although the exact magnitude varies, with an average of 0.32 ppmv K^{-1} and a standard deviation of 0.15 ppmv K^{-1} .

This figure also shows that the BDC coefficient is generally negative, meaning that a strengthening BDC reduces $[H_2O]_{entru}$.

This is consistent with previous research, which showed that a stronger BDC reduces TTL temperatures and lower stratospheric 30 lower-stratospheric water vapor (Randel et al., 2006; Gilford et al., 2016). The trended and detrended BDC coefficients are similar in sign and magnitude coefficient for individual models ranges from -12. to 4.3 ppmv (K/Day)⁻¹, with an average of -3.55 ppmv (K/Day)⁻¹ and a standard deviation of 4.45 ppmv (K/Day)⁻¹. Two models (CNRM-CM5-3 and NIWA-UKCA) yield positive BDC coefficients, indicating potential problems with these models. And the MRI-ESMr1 produces, relative to other similar models, much larger BDC coefficients than MRI. This could explain why the detrended adjusted R^2 value for MRI-ESMr1 is so much smaller than that of MRI.

Figure 3 shows that all QBO regression coefficients are small, generally within \pm 0.04 ppmv, with even the sign of the 5 effect in doubt. Interestingly, one of the CCMs not simulating a QBO, CMAM-CCMI, produces the largest QBO regression coefficients of 0.082 \pm 0.04 and 0.077 \pm 0.04 ppmv for the trended and detrended calculations, respectively. Among CCMs that do simulate a QBO, the ensemble average QBO regression coefficient does not differ much from the same quantity (approximately 0 ppmv) for the other models. We will discuss this further in the next section.

We have also calculated the long-term linear trend of $[H_2O]_{entry}$ for each model, as well as the trend in each component of

10 $[H_2O]_{entry}$, as determined by the multivariate fit (e.g., the trend in the components plotted in Fig. 2). We find that ΔT makes the largest contribution to the trend in $[H_2O]_{entry}$, with a smaller negative effect from the a strengthening BDC on $[H_2O]_{entry}$, and a trend of close to zero for the QBO (Figure 4).

To provide additional information about the relative contribution from the individual terms in eq. 1, we have also calculated standardized regression coefficients. To do this, we take each regression coefficient and multiply it by the standard deviation of

15 the associated regressor index. The values are listed in tables 2 and 3 and they confirm that, in the trended calculations, ΔT is the dominant cause of the trend in $[H_2O]_{entry}$. The BDC acts to reduce the trend, but its overall impact is much smaller than ΔT .

In the detrended calculations, the standardized ΔT regression coefficients are smaller than those from the trended calculations, while the magnitude of the BDC coefficients remains relatively constant. For variability associated with short-term variability.

20 this suggests that the BDC is more important than ΔT . In all of our calculations, we find that the QBO has little impact on $[H_2O]_{entry}$. Again, we will discuss this further in the next section.

4 Decadal Analysis

Ideally, we would compare the results of the last section to observations. Unfortunately, we don't have 100 years of observations to test the models against. Instead, we will compare regressions of 10-year segments from the CCMs to regressions of 10-years

25 of observations. This will help us evaluate how good the models are and provide us with an indication of how representative a single decade is.

Specifically, we split 21^{st} century of each CCM run into 10 decades (2000-2010, 2010-2020, 2020-2030, 2040-2050, etc.) and fit each individual decade using the regression model (Equation 1). The regression calculation used on each 10-year segment is identical to the century analysis, except monthly averaged anomalies <u>of all quantities</u> are used instead of annual

30 mean anomalies. Following Dessler et al. (2014), decadal regression terms are lagged in order to maximize MLR fit: we lag ΔT by 3 months, the BDC by 1 month, and the QBO by 3 months. These lags reflect the time between changes in each index and the impact on $[H_2O]_{entry}$.

Figure 5 shows the median \pm one standard deviation of the ten decadal adjusted R² values generated by each CCM. The ensemble average is approximately 0.60.61 \pm 0.25, with some spread among the models. Also plotted are the adjusted R² from two regressions of the tropical average Aura Microwave Limb Sounder (MLS) 82-hPa water vapor mixing ratio observations from Dessler et al. (2014). One regression uses Modern-Era Retrospective Analysis for Research and Applications reanalysis

(MERRA) data (Rienecker et al., 2011) and the other uses European Centre for Medium-Range Weather Forecasts interim re-5 analysis (ERAI) (Dee et al., 2011) for the ΔT and BDC indices; the QBO index is standardized anomaly of monthly and zonally averaged equatorial 50-hPa winds obtained from the NOAA Climate Prediction Center (http://www.cpc.ncep.noaa.gov/data/indices). The MLS data covers the time period 2004-2014.

Many of the models have a range of adjusted R^2 values that overlaps overlap with the observational regression However,

- not all do: the CCSRNIES, CNRM-CM5-3, and NIWA-UKCA have median. However, of the models producing the smallest 10 decadal adjusted R² values below 0.4, well below the observational values. It's worth nothing that these models also had issues in the century regressions. The WACCM and LMDZrepro models also have median -: these are the models that produced the poorest fits to long-term detrended $[H_2O]_{entry}$. In particular, CCSRNIES CNRM-CM5-3, and NIWA-UKCA, have the smallest adjusted \mathbb{R}^2 values below the observations for both detrended and decadal $[H_2O]_{entry}$.
- 15 Figure 6 shows the median and one standard deviation of each coefficient (values are listed in table 4), along with the coefficients from the regression of the MLS data (taken from Table 1 of Dessler et al. (2014)). We find that the CCMs agree unanimously that increases in ΔT are associated with increased $[H_2O]_{entry}$. Overall, though, though the CCM ensemble tends to underestimate the observational estimate, although most fall within the observation's 95% confidence intervals. The only models that don't fall within both observational ranges are CCSRNIES, CMAM-CCMI, and CNRM-CM5-3.
- 20 In addition, the spread between the different decades for a single model tends to be small, with most CCM decadal ΔT regression coefficient distributions confined to a narrow range of ± 0.1 . The coefficient for individual models ranges from 0.01 to 0.4 ppmv K^{-1} , with an average of 0.15 ppmv K^{-1} and a standard deviation of 0.11 ppmv K^{-1} around the model's median. This gives us some confidence that the comparison between the CCMs and one decade of observations is meaningful.
- Figure 6 shows that there exists a high degree of variability significant spread in the CCMs' decadal BDC regression coefficients, with a CCM ensemble average value of about -4 ± 2 . The coefficient for individual models ranges from -8.4 to 2.9 25 ppmv $(K/Day)^{-1}$, with an average of -3.55 ppmv $(K/Day)^{-1}$, but with individual CCM values ranging between approximately -12 and +5 and a standard deviation of 3.58 ppmv (K/Day)⁻¹. On all timescales, we expect a strengthening BDC should cool the TTL and reduce $[H_2O]_{entry}$, so the coefficient should be negative. We see that the median is indeed negative for all CCMs except for the CNRM-CM5-3 and NIWA-UKCA, both of which yield a positive median BDC coefficient (these models also
- 30 generated positive BDC coefficients for the century analysis).

Comparing to observations, we find that the model ensemble does well. This nonetheless hides a significant spread among the models. The CCSRNIES, CCSRNIES-MIROC-3.2, CMAM, CMAM-CCMI, LMDZrepro, MRI-ESM1r1, and WACCM decadal BDC regression coefficients fall within 95% confidence of MERRA, and only CCSRNIES-MIROC-3.2, LMDZrepro, and WACCM fall within 95% confidence interval of ERAI. As with the ΔT coefficient, the spread between the different decades for a single model tends to be small; this again gives us some confidence in our comparisons to analysis of a single decade of observations.

As expected, figure Figure 6 shows that, for CCMs not simulating a QBOall CCMs, the ensemble average decadal QBO coefficient is approximately 0 ppmv. But even those that do simulate a QBO, as seen in the century analysis, see little impact

5 on $[H_2O]_{entry}$ from it, with an ensemble average of approximately $0.03\pm0.04\ 0.02\pm0.03$ ppmv. This is significantly smaller than the response to the QBO in the observations, and this appears to be a clear deficiency in the model ensemble.

Only CCSRNIES-MIROC3.2 and CMAM-CCMI decadal regressions produce QBO coefficients approaching those from both observational regressions. Again, CMAM-CCMI does not simulate a QBO, and it is not clear to us why the model does so well in this aspect of our analysis.

- Previous studies found that the QBO significantly influences TTL temperatures and subsequently $[H_2O]_{entry}$ (Zhou et al., 2001; Geller et al., 2002; Liang et al., 2011), so the lack of response in the model ensemble seems appears to be a problem for in the models. Previous studies have investigated this issue, finding that a higher vertical resolution within the stratosphere can help resolve the QBO's impact on the lower stratosphere (Rind et al., 2014; Anstey et al., 2016; Geller et al., 2016). Clearly, this needs to be investigated further.
- 15 Similar to both the trended and detrended regression analysis, we calculated standardized regression coefficients for the decadal regressions, and the values are listed in Table 4. Within most models, we see that the BDC, on decadal timescales, has the largest impact on $[H_2O]_{entry}$, with ΔT having a smaller impact.

5 Century and Decadal Regression Coefficient Comparison

- One interesting question is whether the regression coefficients from the decadal analyses are related to regression coefficients from century regressions. To answer this, Figure 7 shows the coefficients from the trended century regressions of each CCM plotted against the median of the decadal regressions from the same CCM. Also shown is a linear least-squares fit to the points. As in the last section, uncertainties in the observational coefficients are bound by 95% confidence intervals calculated by Dessler et al. (2014). Uncertainty in the slope, intercept, and century regression predictions are constrained by 95% confidence intervals determined using each least-squares fit.
- 25 For the ΔT coefficient, the best fit line is:

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$$\beta(\Delta T, century) = 1.21 \pm 0.44\beta(\Delta T, decade) + 0.13 \pm 0.08 \tag{2}$$

All uncertainties are 95% confidence intervals. Thus, the ΔT coefficients from the trended MLRs are slightly larger than those from the decadal MLRs. Using values of $\beta(\Delta T, decade)$ from decadal_MLS observations and this fit, we can-predict $\beta(\Delta T, century)$. From equation 2, the observed $\beta(\Delta T, decade)$ correspond to $\beta(\Delta T, century)$ of 0.50 ±0.06 and 0.55 ±0.08 ppmv K⁻¹ for MERRA and ERAI indices regressions, respectively.

For the BDC coefficient, the best fit line is:

$$\beta(BDC, century) = 1.16 \pm 0.32\beta(BDC, decade) + 0.56 \pm 1.56 \tag{3}$$

The BDC coefficients from the trended MLRs are also slightly larger also have a slightly larger magnitude than those from the decadal MLRs. By fitting the observed values of $\beta(BDC, decade)$ through equation 3, we can predict $\beta(BDC, century)$. Using equation 3, the observed values of $\beta(BDC, decade)$ correspond to values of $\beta(BDC, century)$ of -3.45 ±1.09 and -2.34 ±1.09 ppmv (K/Day)⁻¹ for MERRA and ERAI indices regressions, respectively.

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 $\beta(QBO, century) = 0.75 \pm 0.40\beta(QBO, decade) + 0.004 \pm 0.01 \tag{4}$

The QBO coefficients from the trended MLRs are slightly smaller than those from the decadal MLRs. Again, using equation 4, we can predict $\beta(QBO, century)$ using observed values of $\beta(QBO, decade)$. Using equation 4, the observed values of $\beta(QBO, decade)$ correspond to $\beta(QBO, century)$ values of 0.09 ±0.03 and 0.09 ±0.02 ppmv for MERRA and ERAI indices regressions, respectively.

6 Conclusions

Climate models predict that tropical lower stratospheric lower-stratospheric humidity ($[H_2O]_{entry}$) will increase as the climate warms, with important implications for the chemistry and climate of the atmosphere. We described demonstrated in this paper a new way to evaluate the realism of quantify the physical processes underlying these model trends. Our method is based

15 on regressing CCM $[H_2O]_{entry}$ time series against three processes (that have been shown to be important to $[H_2O]_{entry}$: tropospheric temperature (ΔT), the strength of the Brewer-Dobson circulation (BDC), and the phase of the QBO) that have been shown to be important to $[H_2O]_{entry}$. Our approach provides more insight into model processes than simply comparing $[H_2O]_{entry}$ to TTL temperatures.

We do this on two separate time-scales: 1) the 21^{st} century, and 2) on decadal timescales.

- We find that long-term increase in [H₂O]_{entry} in the CCMs is primarily driven by warming of the troposphere. This is partially offset in most CCMs by an increase in the strength of the Brewer-Dobson circulation, which tends to cool the tropical tropopause layer (TTL) (Randel et al., 2006; Fueglistaler et al., 2014). However, for the detrended data, we find a strengthening Brewer-Dobson circulation is of greater importance to the variability of [H₂O]_{entry}, consistent with Geller and Zhou (2007). The models show little impact from the QBO, in disagreement with observations (O'Sullivan and Dunkerton, 1997; Randel et al., 1998; Du
 this appears to be a deficiency in the models.
 - The coefficients from regressions of individual decades in the CCMs can be compared to coefficients from regressions of observations covering a decade. Overall, the CCM ensemble seems to reproduce $[H_2O]_{entry}$ observations well, except for the fact that the CCMs simulate little response of $[H_2O]_{entry}$ to the QBO, in disagreement with the observations. In addition, the good agreement on average hides some spread among the models, particularly in the response to the BDC.
- 30 Our approach provides more insight into model processes than simply comparing $[H_2O]_{entry}$ or TTL temperatures. Our overall conclusions are encouraging — the models appear do a reasonable job simulating variability in to respond to the factors that control $[H_2O]_{entry}$ in realistic ways, providing some confidence in their simulations of $[H_2O]_{entry}$. However, some

models have clear problems, e.g., the models that predict $[H_2O]_{entry}$ will increase with a strengthening BDC. In addition, nearly the entire ensemble does not reproduce the observed variations of $[H_2O]_{entry}$ with the phase of the QBO. This analysis should help the modeling groups refine their models' simulations of the 21^{st} century.

7 Data availability

5 This data can be obtained through the British Atmospheric Data Center (BADC) archive.

Author contributions. KS and AD performed this analysis and wrote most of this manuscript. The other authors contributed information pertaining to their individual models and helped revise this paper.

Competing interests. The authors declare that they have no conflict of interest.

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Table 1. CCMs used in this analysis. The resolution is listed as (lat x lon x number of pressure levels). 31 vertical levels indicates CCM datais given on isobaric levels, while CCMs simulating data on >31 levels are given on sigma (hybrid-pressure) levels

ССМ	Resolution	Dataset	Contains QBO	Institution	Reference(s)
CCSRNIES	2.8° x 2.8° x 31	CCMVal-2	No	NIES, Tsukuba, Japan	Akiyoshi et al. (2009)
CCSRNIES-MIROC3.2	2.8° x 2.8° x 34	CCMI-1	Yes	NIES, Tsukuba, Japan	Imai et al. (2013); Akiyoshi et al. (2016)
CMAM	5.5° x 5.6° x 31	CCMVal-2	No	EC, Canada	Scinocca et al. (2008b)
CMAM-CCMI	3.7° x 3.8° x 71	CCMI-1	No	EC, Canada	Jonsson et al. (2004); Scinocca et al. (2008a)
CNRM-CM5-3	$2.8^{\circ} \ x \ 2.8^{\circ} \ x \ 31$	CCMI-1	No	Meteo-France; France	Voldire et al. (2013); Michou et al. (2011)
GEOSCCM	$2.0^{\circ} \text{ x } 2.5^{\circ} \text{ x } 31$	CCMVal-2	No	NASA/GSFC, USA	Pawson et al. (2008)
GEOSCCM-CCMI	$2.0^\circ \ x \ 2.5^\circ \ x \ 72$	CCMI-1	Yes	NASA/GSFC, USA	Molod et al. (2012, 2015); Oman et al. (2011, 2013)
LMDZrepro	2.5° x 3.8° x 31	CCMVal-2	No	IPSL, France	Jourdain et al. (2008)
MRI	2.8° x 2.8° x 31	CCMVal-2	Yes	MRI, Japan	Shibata and Deushi (2008)
MRI-ESM1r1	$2.8^{\circ} \text{ x } 2.8^{\circ} \text{ x } 80$	CCMI-1	Yes	MRI, Japan	Yukimoto et al. (2011, 2012); Deushi and Shibata (2011)
NIWA-UKCA	2.5° x 3.8° x 31	CCMI-1	Yes	NIWA, NZ	Morgenstern et al. (2009, 2013)
WACCM	1.9° x 2.5° x 31	CCMVal-2	No	NCAR, USA	Garcia et al. (2007)

Table 2. Coefficients (β s) from regressions of trended [H_2O]_{entry} time series, and the change in [H_2O]_{entry} resulting from each process (β STD()), where STD() is the standard deviation of each trended process.

Trended Regression							
ССМ	ΔT		BDC		QBO		
	$\beta_{\Delta T}$	$\beta_{\Delta T} \operatorname{STD}(\Delta T)$	β_{BDC}	β_{BDC} STD(BDC)	$\beta_{\Delta QBO}$	β_{QBO} STD(QBO)	
CCSRNIES	$0.06 {\pm} 0.01$	$0.08 {\pm} 0.02$	-0.67 ± 0.95	-0.01 ± 0.02	$1.7 \mathrm{x} 10^{-2} \pm 0.01$	$7.9 \mathrm{x} 10^{-3} \pm 0.006$	
CCSRNIES-MIROC3.2	$0.40 {\pm} 0.06$	$0.39 {\pm} 0.06$	$-3.4{\pm}1.9$	-0.11 ± 0.06	$3.5 \mathrm{x} 10^{-2} \pm 0.04$	$2.2 \mathrm{x} 10^{-2} \pm 0.02$	
CMAM	$0.26{\pm}0.02$	$0.39{\pm}0.03$	-5.7±1.1	-0.07 ± 0.01	$8.0 \mathrm{x} 10^{-4} \pm 0.03$	$4.7 \mathrm{x} 10^{-4} \pm 0.02$	
CMAM-CCMI	$0.22{\pm}0.05$	$0.21 {\pm} 0.05$	$-3.8{\pm}2.6$	-0.06 ± 0.04	$8.2 \mathrm{x} 10^{-2} \pm 0.04$	$3.8 \mathrm{x} 10^{-2} \pm 0.02$	
CNRM-CM5-3	$0.27 {\pm} 0.13$	$0.26 {\pm} 0.13$	$3.7{\pm}5.4$	$0.09 {\pm} 0.13$	$1.9 \mathrm{x} 10^{-2} \pm 0.07$	$4.9 \mathrm{x} 10^{-3} \pm 0.02$	
GEOSCCM	$0.38{\pm}0.03$	$0.37 {\pm} 0.03$	-6.7 ± 0.82	-0.21 ± 0.03	$-1.3 \mathrm{x} 10^{-2} \pm 0.01$	$-3.2 \mathrm{x} 10^{-3} \pm 0.003$	
GEOSCCM-CCMI	$0.27{\pm}0.03$	$0.27 {\pm} 0.02$	$-6.6 {\pm} 0.96$	-0.17 ± 0.03	$5.2 \mathrm{x} 10^{-3} \pm 0.02$	$2.8 \mathrm{x} 10^{-3} \pm 0.01$	
LMDZrepro	$0.55{\pm}0.04$	$0.72 {\pm} 0.05$	-8.3 ± 2.1	-0.10 ± 0.04	$1.4 \mathrm{x} 10^{-2} \pm 0.04$	$6.8 \mathrm{x} 10^{-3} \pm 0.02$	
MRI	$0.57{\pm}0.03$	$0.58{\pm}0.03$	-12.±1.3	-0.34 ± 0.04	$-4.1 \mathrm{x} 10^{-3} \pm 0.03$	$-2.0 \mathrm{x} 10^{-3} \pm 0.01$	
MRI-ESM1r1	$0.36{\pm}0.05$	$0.36{\pm}0.05$	$-3.1{\pm}1.4$	-0.12 ± 0.05	$1.7 \mathrm{x} 10^{-2} \pm 0.03$	$9.5 \mathrm{x} 10^{-3} \pm 0.02$	
NIWA-UKCA	$0.20{\pm}0.07$	$0.20{\pm}0.07$	$4.3 {\pm} 4.6$	$0.06{\pm}0.07$	$-1.0 \mathrm{x} 10^{-2} \pm 0.07$	$-5.9 \mathrm{x} 10^{-3} \pm 0.04$	
WACCM	$0.24{\pm}0.04$	$0.21 {\pm} 0.03$	-3.5 ± 1.2	-0.05 ± 0.02	$1.5 \mathrm{x} 10^{-2} \pm 0.03$	$4.7 \mathrm{x} 10^{-3} \pm 0.008$	

The units of ΔT , BDC, and QBO are ppmv K⁻¹, ppmv (K/Day)⁻¹, and ppmv, while the units of $\beta_{\Delta T}$ STD(ΔT), β_{BDC} STD(BDC), and β_{QBO} STD(QBO) are all ppmv. The uncertainty is the 95% confidence interval.

Table 3. Coefficients (β s) from regressions of detrended $[H_2O]_{entry}$ time series, and the change in $[H_2O]_{entry}$ resulting from each process (β STD()), where STD() is the standard deviation of each detrended process.

Detrended Regression							
ССМ	ΔT		BDC		QBO		
	$\beta_{\Delta T}$	$\beta_{\Delta T} \operatorname{STD}(\Delta T)$	β_{BDC}	β_{BDC} STD(BDC)	$\beta_{\Delta QBO}$	β_{QBO} STD(QBO)	
CCSRNIES	$0.05 {\pm} 0.02$	$0.02{\pm}0.006$	-0.67 ± 0.67	$-7.1 \mathrm{x} 10^{-3} \pm 0.005$	$1.7 \mathrm{x} 10^{-2} \pm 0.01$	$3.6 \mathrm{x} 10^{-3} \pm 0.003$	
CCSRNIES-MIROC3.2	$0.30{\pm}0.05$	$0.08 {\pm} 0.01$	-4.3 ± 0.83	-0.08 ± 0.02	$2.8 \mathrm{x} 10^{-2} \pm 0.01$	$1.7 \mathrm{x} 10^{-2} \pm 0.009$	
CMAM	$0.26{\pm}0.03$	$0.10 {\pm} 0.01$	-5.3 ± 0.84	-0.05 ± 0.008	$7.0 \mathrm{x} 10^{-4} \pm 0.02$	$1.9 \mathrm{x} 10^{-4} \pm 0.006$	
CMAM-CCMI	$0.26{\pm}0.05$	$0.05 {\pm} 0.01$	-3.7 ± 1.1	-0.04 ± 0.01	$7.7 \mathrm{x} 10^{-2} \pm 0.04$	$2.9 \mathrm{x} 10^{-2} \pm 0.005$	
CNRM-CM5-3	$0.19{\pm}0.05$	$0.08 {\pm} 0.01$	$0.20{\pm}1.1$	$2.5 \mathrm{x} 10^{-3} \pm 0.01$	$-3.3 \mathrm{x} 10^{-2} \pm 0.01$	$-7.1 \mathrm{x} 10^{-3} \pm 0.003$	
GEOSCCM	$0.31 {\pm} 0.04$	$0.08 {\pm} 0.009$	$-6.6 {\pm} 0.65$	-0.09 ± 0.009	$-1.0 \mathrm{x} 10^{-2} \pm 0.01$	$-1.9 \mathrm{x} 10^{-3} \pm 0.002$	
GEOSCCM-CCMI	$0.25{\pm}0.04$	$0.07 {\pm} 0.01$	-7.1 ± 0.71	-0.17 ± 0.03	$4.4 \mathrm{x} 10^{-3} \pm 0.01$	$2.3 x 10^{-3} \pm 0.007$	
LMDZrepro	$0.59{\pm}0.05$	$0.25 {\pm} 0.02$	$-5.4{\pm}1.1$	-0.05 ± 0.02	$-5.5 \mathrm{x} 10^{-3} \pm 0.03$	$-2.3 \mathrm{x} 10^{-3} \pm 0.01$	
MRI	$0.52{\pm}0.03$	$0.18 {\pm} 0.02$	-11.±1.0	-0.24 ± 0.02	$-4.6 \mathrm{x} 10^{-4} \pm 0.02$	$2.2 \mathrm{x} 10^{-4} \pm 0.01$	
MRI-ESM1r1	$0.33{\pm}0.05$	$0.09 {\pm} 0.01$	-4.3 ± 0.61	$-0.10 {\pm} 0.01$	$5.5 \mathrm{x} 10^{-3} \pm 0.01$	$3.0 \mathrm{x} 10^{-3} \pm 0.007$	
NIWA-UKCA	$0.15{\pm}0.08$	$0.04{\pm}0.02$	$2.9{\pm}1.6$	$0.04 {\pm} 0.02$	$-1.0 \mathrm{x} 10^{-2} \pm 0.02$	$-5.9 \mathrm{x} 10^{-3} \pm 0.01$	
WACCM	$0.23{\pm}0.05$	$0.06 {\pm} 0.01$	-3.5 ± 0.80	-0.04 ± 0.01	$1.5 \mathrm{x} 10^{-2} \pm 0.02$	$2.8 \mathrm{x} 10^{-3} \pm 0.004$	

The units of ΔT , BDC, and QBO are ppmv K⁻¹, ppmv (K/Day)⁻¹, and ppmv, while the units of $\beta_{\Delta T}$ STD(ΔT), β_{BDC} STD(BDC), and β_{QBO} STD(QBO) are all ppmv. The uncertainty is the 95% confidence interval.

Table 4. Median coefficients from the decadal regressions of $[H_2O]_{entry}$ monthly anomalies, and the change in $[H_2O]_{entry}$ resulting from each process (β STD()), where STD() is the standard deviation of each decadal process.

Decadal Regressions							
ССМ	ΔT			BDC	QBO		
	$\beta_{\Delta T}$	$\beta_{\Delta T} \operatorname{STD}(\Delta T)$	β_{BDC}	β_{BDC} STD(BDC)	$\beta_{\Delta QBO}$	β_{QBO} STD(QBO)	
CCSRNIES	$0.03 {\pm} 0.04$	$8.7 \mathrm{x} 10^{-3} \pm 0.01$	-1.23 ± 1.34	-0.01 ± 0.02	$5.26 \mathrm{x} 10^{-3} \pm 0.02$	$1.5 \mathrm{x} 10^{-3} \pm 0.005$	
CCSRNIES-MIROC3.2	$0.10{\pm}0.17$	$0.03 {\pm} 0.02$	$-3.29{\pm}1.44$	-0.10 ± 0.04	$6.05 \mathrm{x} 10^{-2} \pm 0.01$	$5.7 \mathrm{x} 10^{-2} \pm 0.02$	
CMAM	$0.19{\pm}0.09$	$0.05{\pm}0.03$	-6.06 ± 1.34	-0.07 ± 0.02	$2.75 \mathrm{x} 10^{-3} \pm 0.03$	$9.4 \mathrm{x} 10^{-4} \pm 0.004$	
CMAM-CCMI	$0.01 {\pm} 0.10$	$3.5 \mathrm{x} 10^{-3} \pm 0.02$	-4.70 ± 1.29	-0.07 ± 0.03	$6.13 \mathrm{x} 10^{-2} \pm 0.01$	$3.0 \mathrm{x} 10^{-2} \pm 0.02$	
CNRM-CM5-3	$0.06 {\pm} 0.14$	$0.01 {\pm} 0.03$	$2.89{\pm}1.44$	$0.05 {\pm} 0.02$	$1.84 \mathrm{x} 10^{-2} \pm 0.02$	$4.9 \mathrm{x} 10^{-3} \pm 0.01$	
GEOSCCM	$0.17 {\pm} 0.10$	$0.04 {\pm} 0.02$	-6.31±1.19	-0.13±0.03	$-1.47 \mathrm{x} 10^{-2} \pm 0.03$	$-4.9 \mathrm{x} 10^{-3} \pm 0.005$	
GEOSCCM-CCMI	$0.11 {\pm} 0.16$	$0.02 {\pm} 0.03$	$-8.00{\pm}1.89$	-0.18 ± 0.06	$2.42 \mathrm{x} 10^{-2} \pm 0.02$	$1.8 \mathrm{x} 10^{-2} \pm 0.01$	
LMDZrepro	$0.31 {\pm} 0.19$	$0.11 {\pm} 0.08$	-2.71 ± 2.71	-0.07 ± 0.05	$1.27 \mathrm{x} 10^{-2} \pm 0.01$	$-6.9 \mathrm{x} 10^{-3} \pm 0.03$	
MRI	$0.35{\pm}0.09$	$0.12 {\pm} 0.04$	-8.78 ± 2.91	-0.25 ± 0.07	$-6.56 \mathrm{x} 10^{-3} \pm 0.06$	$4.6 \mathrm{x} 10^{-3} \pm 0.03$	
MRI-ESM1r1	$0.19{\pm}0.04$	$0.05{\pm}0.01$	-4.72 ± 0.71	-0.13±0.03	$1.17 \mathrm{x} 10^{-2} \pm 0.03$	$8.9 \mathrm{x} 10^{-3} \pm 0.02$	
NIWA-UKCA	$0.05 {\pm} 0.29$	$0.01 {\pm} 0.06$	2.11 ± 3.26	$0.04 {\pm} 0.05$	$-1.88 \mathrm{x} 10^{-2} \pm 0.04$	$-1.5 \mathrm{x} 10^{-2} \pm 0.03$	
WACCM	$0.15 {\pm} 0.12$	$0.03 {\pm} 0.03$	-2.25 ± 0.85	-0.05 ± 0.02	$3.84 \mathrm{x} 10^{-2} \pm 0.03$	$9.1 \mathrm{x} 10^{-3} \pm 0.007$	
MLS/ERAI	$0.34{\pm}0.17$	$0.11 {\pm} 0.05$	-2.5 ± 0.83	-0.17±0.06	$1.1 \mathrm{x} 10^{-1} \pm 0.04$	0.11±0.05	
MLS/MERRA	$0.30 {\pm} 0.20$	$0.11 {\pm} 0.07$	-3.5 ± 1.6	-0.15±0.07	$1.2 \mathrm{x} 10^{-1} \pm 0.05$	$0.12 {\pm} 0.06$	

The units of ΔT , BDC, and QBO are ppmv K⁻¹, ppmv (K/Day)⁻¹, and ppmv, while the units of $\beta_{\Delta T}$ STD(ΔT), β_{BDC} STD(BDC), and β_{QBQ} STD(QBO) are all ppmv. The uncertainty represents the variability (one standard deviation) in the set of coefficients produced by each CCM. For observations, the error bars represent 95% confidence.

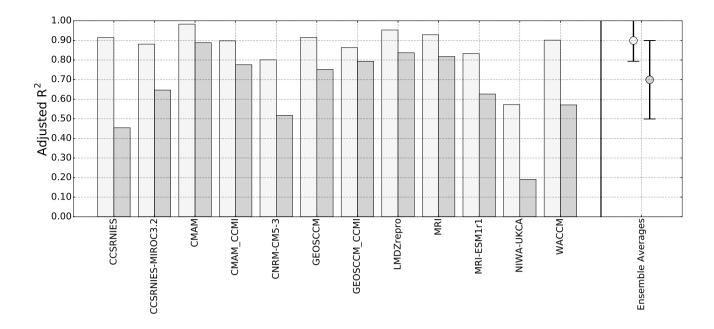


Figure 1. Bars corresponds to trended (light grey) and detrended (dark grey) adjusted R^2 values for annual-averaged data. The light grey circle represents circles represents the CCM ensemble meantrended adjusted R^2 value, while the dark grey circle represents to the CCM ensemble mean detrended adjusted R^2 value. Error with error bars on ensemble means corresponds to the indicating \pm one standard deviation of the CCM ensemble.

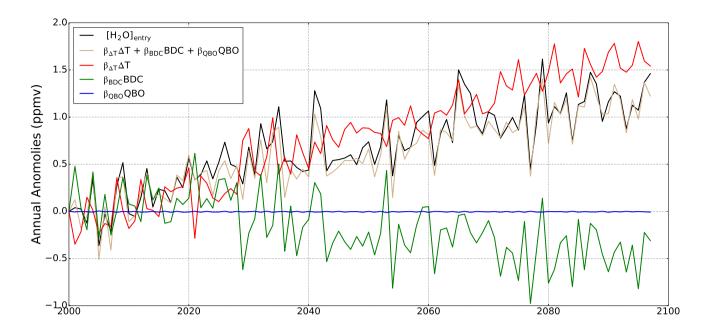


Figure 2. Time series of annual-averaged anomalies of $[H_2O]_{entry}$ from the MRI (black), and its reconstruction using a multivariate linear regression (brown). The red, green, and blue lines are the ΔT , BDC, and QBO terms from the regression, respectively.

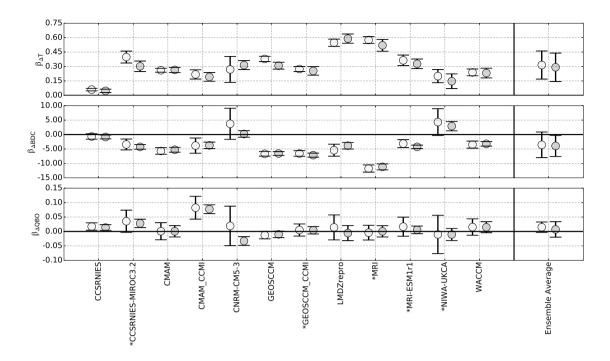


Figure 3. Circles represents the show detrended (light grey) and trended (dark grey) coefficients for each model, and; error bars correspond to 95th percentile confidence interval bounding each regression coefficient. An asterisk indicates models simulating a QBO. An asterisk on the The ensemble mean corresponds to the average QBO coefficient for only models simulating a QBO, while the ensemble mean with no asterisk corresponds to the average of all model coefficients. The ensemble mean coefficients are also represented by a circle, with associated error bars correspond to \pm one standard deviation of the ensembleset of coefficients. The units of $\beta_{\Delta t}$, β_{BDC} , and β_{QBO} are ppmv/K, ppmv/(K/Day), and ppmv, respectively.

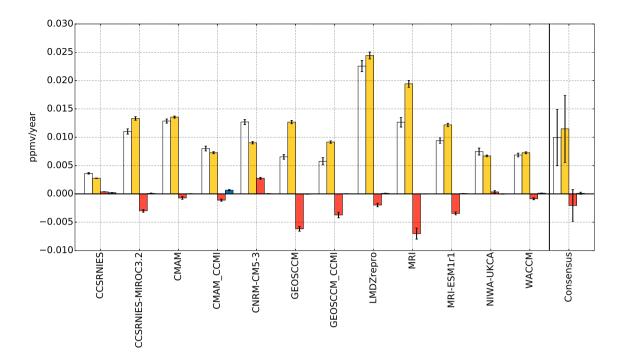


Figure 4. Trends in $[H_2O]$ entry resulting from ΔT (yellow), BDC (red), and QBO (blue) predictor time series assuming the other predictors are held constant. Each predictor trend is then compared to the trend of the full regression (white). Error bars represent 95% uncertainty. For many models, the contribution of the QBO is too small to be seen.

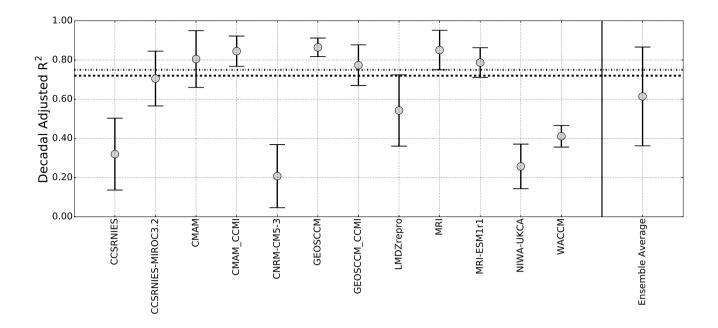


Figure 5. Circles represent the median of the adjusted R^2 value of the decadal fits. Errors correspond to the \pm one standard deviation of the adjusted R^2 values. The CCM ensemble average is also plotted, along with error bars corresponding to \pm one standard deviation of ensemble set of decadal adjusted R^2 values. The lines are adjusted R^2 values from observations combined with reanalysis (ERAI (dotted) and MERRA (dashed)) from Dessler et al. (2014).

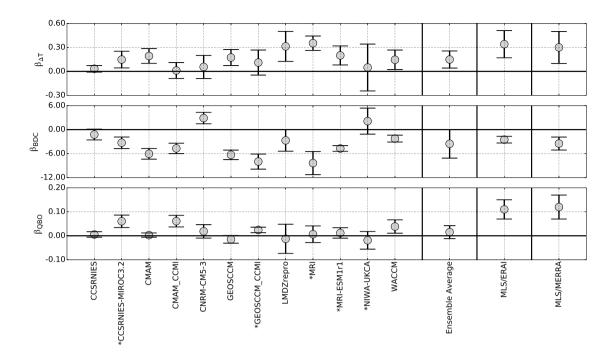


Figure 6. Circles represent the median decadal regression coefficient from each CCM, and error bars correspond to \pm one standard deviation. An asterisk indicates that the model simulates a QBO. An asterisk corresponding to the The ensemble mean corresponds to the average QBO coefficient for only models simulating a QBO, while the ensemble mean with no asterisk corresponds to an average of all model coefficients. The ensemble mean coefficients are also represented by a circle, with associated error bars correspond to \pm one standard deviation of the ensemble set of coefficients. Estimates from observations combined with reanalysis (Dessler et al., 2014) shown, along with 95th percentile confidence interval. The units of $\beta_{\Delta t}$, β_{BDC} , and β_{QBO} are ppmv/K, ppmv/(K/Day), and ppmv, respectively.

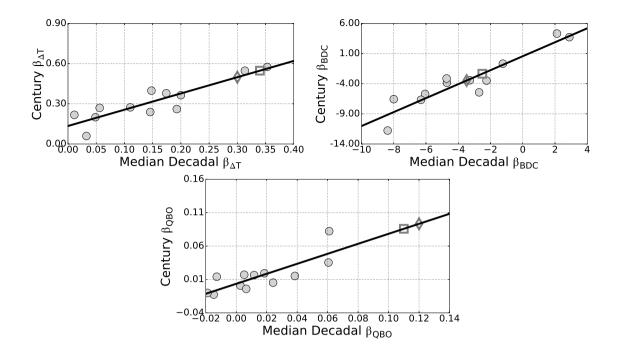


Figure 7. (Top Left) Scatter plots of trended ΔT regression coefficients (ppmv K⁻¹) vs. median decadal ΔT regression coefficients (ppmv K⁻¹) from each CCM. (Top Right) Same as top, but for BDC coefficients. (Bottom Middle) Same as top left and top right, but for QBO coefficient. Black lines in all plots correspond to a best fit line between the trended and decadal coefficients, and the observational coefficients ERAI (square) and MERRA (diamond) are fitted to each line (from Dessler et al. (2014)).