Authors response to two reviewers and to the comments of L.A. Smith

In the following we respond to the comments given by two reviewers and L.A. Smith. We first give their comments in italic, followed by our response. Where relevant we will point to the lines in the *revised* manuscript where changes have taken place.

Answers to comments of reviewer # 1 (Peter Thorne)

I find the hook to pre-industrial tenuous given that the authors make no attempt to estimate a true pre-industrial based value. They would be better, in my view, to state that they are making an estimate relative to the late 19th Century / early global instrumental record. This would be a fairer reflection of what is actually done and consistent with e.g. IPCC AR5 which deliberately avoided in the published version implying that 1850-1900 constituted pre-industrial as noted in Hawkins et al. Indeed, the final plenary of the WG1 involved a long discussion that I was personally involved in around the topic whereby the parties agreed that pre-industrial was earlier than 1850. It would be unwise, in my view, for the authors to reopen this issue. I note in a couple of places that there are phrases which could imply IPCC used 1850-1900 as pre-industrial, and they did not. Such implications absolutely must be avoided outright in any resubmission.

The discussion linking their work to the pre-industrial era would be far better being given exclusively in the Discussion section and, to my view, the authors should remove allusions to providing an estimate relative to pre-industrial earlier than this. Bottom line: They either should estimate relative to true-pre-industrial or be honest with respect to what they are estimating relative to for the paper to be acceptable. As I see it there is no rigorous attempt to estimate changes since pre-industrial. Rather, there is a rigorous attempt to estimate it since 1880 which in itself is useful and valuable. The authors should be honest in this regard and not oversell their work by claiming it's an estimate relative to pre-industrial when it demonstrably is not.

We agree with the reviewer and will adapt the text in the way he suggests. Our uncertainty and sensitivity analysis is relative to 1880, and not 1850, or relative to the period 1720-1800 (as in Hawkins et al. 2017), or even relative to the period 1400-1800 (as in Schurer et al., July 24, 2017 - Nature Climate Change). The reason we choose for 1880, is (i) data availability and (ii) the increasing uncertainties in GMT estimates for years earlier than 1880. For example, the Hadley Centre estimates the GMT value plus uncertainty in 1900 to be -0.20 [-0.34, -0.06] ºC (95% confidence limits). For 1850 the GMT estimate is -0.37 [-0.59, -0.16] ºC. We also remove any text suggesting that IPCC has defined pre-industrial levels (but simply refer objectively to the pragmatic reference to a fixed period as done by IPCC). E.g., see lines 295-296.

In the revised text we follow the comment to treat the role of 'pre-industrial' solely in the discussion. See lines 293-313. We added the results of Schurer et al. (2017) who analyze the role of GHGs, solar radiation and volcanic dust from 1401 onwards. They find that GHGs had a significant effect on global warming if the period 1401-1800 is compared to 1850-1900: from 0.02 to 0.20 ºC (5-95% confidence limits). If all forcings are combined (GHG, solar, volcanic) they find 0.09 [0.03 - 0.19] °C.

We explicitly note that the results in our table 1 are relative to 1880, and not 1850, 1720 or 1401. See lines 298-302.

I also find the Section at the end of the paper alluding to RCPs and end of Century to be out of scope and a distraction. It should either form an integral part of the paper integrated throughout or be dropped. Given journal scope I would lean heavily toward its removal. The year 2100 is not in the past (at least yet)!

Agreed. We have removed 'the future' in Section 5.2, including Figure 5.

Finally, given the authors apparent desire to explore uncertainty I find the omission of the JMA observational analysis and the NOAA 20CR product odd. I could see a case for omission of 20CR, but I see no logical case why the JMA analysis should be omitted here as it has the same non-peer-reviewed basis as e.g. the Berkeley global (not land, but global) estimate. JMA uses a fundamentally distinct set of SSTs and so would better span uncertainty that the authors lament in Section 2.1.

We have studied the global series of the Japan Meteorological Agency (JMA) carefully. There is a however a practical problem: the JMA series start in 1891. Thus, we miss the important period 1880-1890. In addition, the meta data is only in Japanese. Finally, studies which show the JMA series are limited. E.g., it is not named in IPCC (2013, Ch. 2). We therefore have chosen for five GMT data products as described in Section 2.1 and we did not add trend analyses for JMA to Table 1. This choice is consistent with recent studies such as Medhaug et al. (2017 - their figure 1a) or Rahmstorf et al. (2017 - their figures 1 and 2). These studies use the 5 datasets as we do. Nevertheless, the referee addresses a relevant issue.

As a test we estimated linear trends for all five data products shown in Table 1 and additionally the JMA series. It appears that the JMA incremental value for the period 1891-2016 equals the low end of the five data products we apply in our Table 1 (i.e., the incremental value of the HadCRUT4 series). Thus, the incremental value based on the JMA series, does not fall outside the range of values based on HadCRUT4, NASA, NOAA, HadCRUT4 adapted by Cowtan and Way, and BEST.

We have hesitated to include this argumentation and analysis in the manuscript. However, the revised article is already loaded with results and sensitivity analyses. It would influence the readability of the text in a negative way, we feel.

As for the NOAA 20CR series we have two arguments for not adding it to our study. First, the 20CR series covers the period 1851-2011. Thus, data for the important period 2012-2016 are missing. Second, the series is a combination of modeling (weather prediction models) and data. For our study we prefer to make a distinction between GMT series directly derived from temperature registrations and models, be it GCMs or weather prediction models.

We note that we give a number of details on data products in the new lines 117-133. These details are certainly not exhaustive. However, how data products are made, including complex interpolation schemes, etc etc, is not the topic of this article. To compensate for this, we cite all relevant literature.

I have a number of further comments, suggestions and requests which I refer to in the order they arise chronologically below:

1. Line 19 per above remove 'and what is 'pre-industrial'?' as you make no attempt to robustly address that question.

Removed

2. Line 47 GMTs have …. So following the 21st

Okay, changed.

3. Lines 53-56 do not reflect the IPCC approach. This was not an attempt to inform on post-pre-industrial changes and it did not involve expert judgement. Rather the stated range is the range of available estimates and their uncertainties after correcting for AR(1) and using OLS. The text here significantly overcomplicates both what was done and why. As the IPCC author who undertook the lead on this analysis I can assure the authors it was not as complicated as they imply here. This should be revised to reflect the actual process.

We changed the text in a way that IPCC did not pretend to give GMT trend progression since pre-industrial. See new lines 53-58. However, we decided to keep the words 'and expert judgement'. This might surprise both reviewers #1 and # 2. Two of the authors of this article were also at the IPCC discussions on this point (Bram Bregman and Arthur Petersen). The addition of 'expert judgment' was proposed by Petersen and agreed upon. The role of judgments here is shown in Box 2.2 of IPCC (2013 - pages 179 and 180).

4. If retained (and note earlier major suggestion to move this to discussion) line 55 forwards should constitute the beginning of the paragraph currently starting line 57.

Agreed and changed

5. Line 73 or similar do not

Agreed and changed

6. Line 73. Reader will ask so what? You need to be explicit that the approach limitations matter in a period of rapid change.

We now explain this point in lines 75-77.

7. Line 76 progression to specific (remove allusion to pre-industrial per major comment)

Removed

8. Line 88 the main one being

Done.

9. Lines 108 to 121 omit the by far largest overlap of all in that the NOAA and NASA products are based on identical underlying land and ocean datasets differing solely in the applied post-processing. This needs to be acknowledged for this discussion to be acceptable. More generally this discussion is incomplete. It needs to be expanded and may be better if supported by a table.

The referee addresses an important point, but, as explained above the exact construction of data products is not the topic of this article. We apply the data sets in the same way as for GCM simulation data sets. To describe the details of all applied datasets (from observations and model results) would be a huge complicated effort and beyond the scope of this work. For example, the differences between NOAA and NASA are quite complicated given the corrections of Karl et al. (2015). However, to address this useful point of the referee, we have carefully checked the completeness of the references and emphasized our approach in the text.

10. Feels odd not to discuss and cite Cowtan et al at lines 125-127

Agreed. We added the reference, see line 140.

11. Lines 155-157. First please clarify whether the AR1 factors are calculated on the annual series. This is important information that is being omitted. Secondly, even at annual scales the AR(1) is primarily an artefact of variability and not forcing so the assertion here is wrong as you note in lines 175-177. Your two cheek-to-jowl statements here cannot both be right. The AR arising from variability is the correct one here. Year-to-year autocorrelation does not arise mainly due to forcing.

Agreed, we added 'annual series' in line 171. Furthermore, we removed 'forcing' and replaced by persistence in natural processes: lines 172-173.

12. Line 202 you should clarify what the implications of ignoring this are or, preferably, perform the extra work necessary for its inclusion. Presumably the impact would be artificially reduced uncertainty ranges? In which case is it really safe to ignore this issue? I'm not entirely convinced and would suggest that extra work leading to its inclusion is instead warranted. Even if it ends up showing no change it would make the piece more robust. As you yourselves state the effect is statistically significant, in which case it really should be included.

Agreed. We now show the effect on correcting for this small but significant AR(1) correlation in the innovation series of our Kalman filter model. See lines 223-225. Also uncertainty bands in table 1 are adapted accordingly.

13. Lines 224-227. This is true a. for this particular period and b. this particular small (and non-independent as noted in Section 2.1) draw from the broad range of plausible means by which to estimate historical changes in GMT. Hence I believe this statement oversimplifies the issues and as a result is more confident than is, in reality, warranted. The findings do not have the universality implied here and may not even be true if we instead had a further draw from the sample of plausible *approaches to estimating GMTs from observations. Here, JMA's inclusion may fundamentally alter this finding which would imply non-robustness*

We feel that the revised version contains a number of lines which show that these results are based on this choice of GMT products, this choice of trend methods and this choice of 1880 (in stead of 1850, 1720 or 1401). We discussed the point of *not* adding the JMA series above.

Answers to comments of Anonymous Referee #2

This study considers the question of estimating by how much global temperatures have changed since 'pre-industrial' times, assessing the uncertainty in different trend models and due to different global temperature datasets. The analysis is interesting, though the results are not too surprising. However, I have some major concerns:

1) Framing: the authors emphasize repeatedly that they are estimating changes since a particular baseline and implying that this is what the Paris agreement meant by 'preindustrial'.

This is not the case - the introduction of Hawkins et al. (which the authors cite) discusses this issue at length. In addition, Schurer et al. (2017, NCC) was very recently published, highlighting again that there was likely some additional warming due to anthropogenic factors before 1850. The authors may also like to examine Otto et al. (2015) for an alternative approach to estimating the warming since the 19th century. The text in the discussion on this topic is appropriate however.

Agreed. We now treat the topic of 'pre-industrial' more clearly in the discussion section, as we pointed out in our response to Reviewer #1. We added the references to Schurer et al. (2017) and Otto et al. (2015). Consequently, we address their findings that GHGs had a significant effect on global warming if the period 1401-1800 is compared to 1850-1900: from 0.02 to 0.20 ºC (5-95% confidence limits). If all forcings are combined (GHG, solar, volcanic) they find 0.09 [0.03 - 0.19] °C. See lines 293-313. Otto et al. is named in line 83.

*2) Terminology: some of the phrasing is very confusing when referring to and/or distinguishing between natural *forced* variability (volcanic, solar) and internal *unforced* variability. These terms are sometimes mixed and it's not always clear what the authors mean. For example, in the abstract (and L86) the authors claim the models are corrected for natural variability, when they mean the forced component, but the introduction uses natural variability to mean both forced and unforced variations. On L133,* *the authors refer to the 'historicalNat' runs 'for natural unforced variability', which is not true - those runs include both natural forced and internal unforced variations as the next sentence correctly states. Variability is also used for the spread or range between different estimates, adding further confusion. The authors should carefully check each use of this type of phrasing and make it far more precise.*

Agreed. We checked the phrasing of 'natural variability' carefully, this in combination with the terms 'forced' or 'unforced' or both, 'internal variability' and 'spread'. See also the reply to reviewer #1 who commented on two sentences with three times the word 'variability'.

Additionally, we now treat the role of natural unforced variability and natural forced variability (i.e., the role of changes in irradiance of the sun and changes in volcanic activity) separately in a third item in the discussion section: lines 315-336.

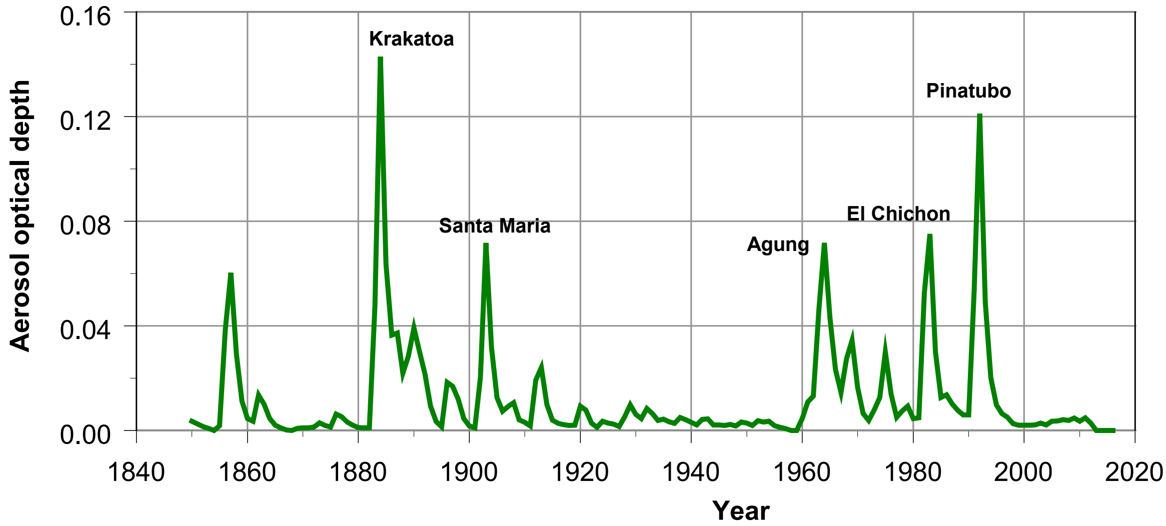
The trend analyses as given in our Table 1 are based on the IPCC definition of climate change (Glossary AR5): anthropogenic forcing combined with decadal to centennial natural variability. However, UNFCCC defines climate change as originating from GHG forcing only. In their philosophy we could argue that the Paris limits of 1.5 and 2.0 C should originate solely from anthropogenic forcing. We now quantify this second view on the Paris limits.

To do so we make use of the recent study of Schurer et al. (2017, their figures S2 and S3), and the lower panel of figure 4 in our original manuscript. Next to that we estimated the role of volcanos in a time-series setting by extending the Integrated Random Walk (IRW) model. For details we refer to Visser and Molenaar (1995) and Visser et al. (2015).

See lines 315-322 and the **new** table SM.2, in the Supplementary Material section.

It shows that the incremental values shown in Table 1 for the IRW trend are 0.04 ºC degree lower. If estimated in combination with the OLS straight line, i.e. a regression model with one explanatory variable, estimates are 0.02 °C lower than those shown in table 1. This effect, although small, will be due to the Krakatoa eruption in the period 1880-1890.

The indicator for volcanic dust is taken from NASA: aerosol optical depth (AOD). See graph below:



This graph is the new figure 5 in the revised text.

3) GCM analysis: the 106 members used cannot be 'one per model' as there were not that many models in CMIP5. It's not clear what the authors have used here - there must be more than one historical part of the runs for some of the models.

The reviewer addresses a good point. What we meant here is that we used one member per model, **given the use of a specific RCP scenario**. Thus, we have used 42 members for emission scenario RCP4.5, 25 members for emission scenario RCP6.0 and 39 members for emission scenario 8.5, making up a total of 106 members. We clarify this in the text: lines 143-146.
There are also 43 piControls on Climate Explorer, and very few are less than 200 years, not only the 20 that the authors have used - why have they not used the others?

Agreed. We have calculated all AR(1) coefficients for all 41 piControl runs, available in the KNMI Climate Explorer (note: there are 41, not 43). Three of those runs showed a jump or a strong linear trend over the simulation period (varying from 200 to 1000 years). We omitted these. For the remaining 38 runs we have omitted the lowest two AR(1) coefficient estimates (lying around 0.0) and the two highest estimates (lying around 0.75). The remaining range equals the range given in our manuscript: [0.28 - 0.60]. We have adapted the text for this finding. See lines 192-194.

Also, in section 3.2, the authors could use the AR(1) value from each model's own control run to fit a spline to the historical run of that same model, rather than assume the same across every model.

In our revision we give values for smoothing by splines with $\varphi=0.28$ and $\varphi=0.60$, similar to shown in our figure 3. Period: 1861-2016. This gives a small change in the upper panel of our old figure 4. The spread is for both smoothing options identical ± 0.50 ºC (2σ). The mean value of all 106 increments is 1.15 for the smoothing option with $\varphi=0.28$ and 1.00 for $\varphi=0.60$. See lines 261-266.

Also, how has the correction for natural forcings been applied (L250)? Has the mean across the historicalNat runs been subtracted from each historical run? If so, this is inconsistent as the response to volcanic eruptions varies significantly across models.

In the revised text we do not correct GCM simulations anymore. The reason is that inferences in sections 3.1 and 3.2 would become inconsistent: estimates in §3.1 are not corrected for solar and volcanic forcings either.

Smaller points:

L47 - 21th -> 21st

Done.

L56 - this uncertainty does not include expert judgement

We discussed this point in our answer to reviewer #1.

L87 - this sentence could be read to imply that GCMs should have 'priority' over the observations for answering the question of how much the surface has warmed, but I don't think the authors mean that?

We removed this wording.

L146 - I’m not sure the UNFCCC would suggest that pre-industrial should be defined when a particular dataset happens to begin?

In the revised version we name UNFCCC in the context of warming definitions, in contrast to the definition of IPCC: lines 78-84. What we meant in the line L146 is that 'pre-industrial' is often denoted as a *period*. However, in the context of trend modeling one does not define any period. The outcome of the analysis solely depends on the sample period chosen, thus 1880-2016, 1850-2016 or 1401-2016, or similar. We did not change the text here.

L163-4 - do you need all five of those references to the lead author’s previous papers?

We removed two references here. See line 178.

L191 - this not appropriate for a scientific analysis

Okay, removed.

L216 - delete ’is’?

Done.

L220 & L307 - three ’variability’ in the same sentence, all referring to slightly different things?! The first is a ’range’? The sentences following this are also not clear.

Agreed. We have replaced 'variability' by 'range' on both places. See lines 243-246.

L279 - not sure this is quite true - there is a signal of these eruptions in the observations but it is probably weaker than the GCMs suggest. But I agree this is probably partly a coverage issue.

We did not change the text here.

L288 - most of the time, the models are not tuned to the trend, but are tuned on the mean present-day climate state.

Agreed.

L303 - is ’best guess’ the appropriate term?

We replace 'best guess' to 'trend' .

L315 - it would be useful to use other historical ensemble members to check this statement (where they exist), as they provide another estimate of the change in temperature for the same model.

Agreed, but we confined our analysis to these 106 simulations from CMIP5 (and discuss the role of 'tas' versus 'blended'). Indeed, new simulations will give new insights, that is how science works. Our main point for choosing data products and not GCM output is given in the new lines 348-354. Hopefully, the wide spread in incremental values as shown in our new figure 4 will become less wide. But we cannot know this at this moment.

Answers to major points of L.A. Smith

Visser et al (2017) provide an interesting and insightful discussion of signal detection in global mean temperature (GMT), focusing on the 1.5 degree target of the Paris Agreement of 2015. This paper could be made more informative by further consideration of three topics: (1) clarifying what is meant by “signal” and by “noise”, and more specifically how (whether) natural variability can be “corrected for” in an evolving nonlinear system, (2) implications of using CMIP5 models, given that those models display a wide range of values for today’s GMT, and (c) a cleaner definition of how one would detect failure to stay “well below” a temperature target, or to exceed it. These points are expanded upon below.

Specific Comments

“Natural variability” is said to be a dominant source of uncertainty which has been “corrected for” (24). Although discussions of a climate signal coming “out of the noise” are common, the notions underlying the distinction between signal and noise in the climate context is unclear; it is not the traditional distinction of observational noise superimposed on a imprecisely measured but well-defined signal. Superposition can only be assumed in nonlinear systems given purely observational noise that has no impact on the system: natural variability, internal variability and the like alter the dynamics, and thus the “signal” itself, if such a separation exists (Smith (2001,2002)). A more appropriate conceptualization in nonlinear systems is found in consideration of an ensemble of systems each subject to a common driving and independent realizations of the relevant noise. In this case, the ensemble median would provide a well-defined signal while the distribution about it would capture the effects of noise processes. This view is of limited utility in climate science, where there is only one realization (the Earth): particular realizations need not reflect the (unobservable, non-

empirical) "signal"; indeed they can diverge arbitrarily far from it. So in no sense can one expect "the" signal to emerge from the noise, given observations of a single realization. While vague appeals to something somewhat reminiscent of an adiabatic change in thermodynamics may be voiced, clear clarification of the meaning of signal and noise in the climate context would be of value.

In short: it would be useful to clarify how "natural variability" and "internal variability" might be isolated in the case of a complicated, nonlinear, evolving planetary system. How are we to make sense of the traditional notions of "signal" and "noise" given that the "noise" is not mere observational noise but actually a component of the system dynamics, and given that in nonlinear systems we cannot appeal to a principle of superposition of solutions (Smith, 2002).

The modeling of climate data by stochastic climate models have been described in Mudelsee (2014, sections 2.5.1 and 2.6). He describes the suitability of climate modeling with AR(1) processes (and the more general ARIMA models as well) to describe the persistence in data.

The reviewer is right that correlated noise is not the same as climate variability arising from nonlinear systems. However, statistical modeling has proven fruitful in a wide field of ecological modeling. To stick to the modeling of global mean temperatures, we refer to our review of (statistical) trend analyses in the peer-reviewed literature in the Supplementary Material section of our manuscript (table S.1). Furthermore, Visser et al. (2015) show in their table 1 that researchers in the field of sea level rise apply 30 trend methods for quantifying "the signal" in sea level data, all with different mathematical formulations.

Note: we do not use trend models for **prediction**. Next to that, projections up to the year 2100 are removed in the revised text.

It is also worth noting that the statistics community and the physical science community often hold very different notions of what a trend is: for the first, it is a statistically consistent combination of two well-defined models (the trend model and the noise model), while for the second it is merely a systematic, often obvious drift. Statisticians require, and quantify, consistency between these two components, and reject identification of a trend if that consistency is lacking. Physical scientists often require the observations to look trendy, and the ability to reject simple statistical models given the data, when those models are known by construction not to admit a trend. The second bar is much lower.

The claim that modelling groups "have not been very successful in tuning to the observed trend" (299) suggests some knowledge as to how large the spread would be in *the absence of each group knowing the observed trend (aiming for the same target). It has been argued elsewhere that knowledge of such spread would be very useful to have if, perhaps, impractical to obtain.*

Visser et al (2017) state that "mean progression derived from GCM-based GMTs appear to lie within the range of the trend-dataset combinations" (311). It would be interesting to see the variations among individual CMIP5 simulations (not the mean over them, but their distribution). The IPCC AR5 reports that variations in the global mean temperature of today's CMIP5 GCMs have a range exceeding 2.5 degrees (see right side axis labels of Figure 9-08 of Flato et al (2013)); what are the implications of our best models showing a range of GMT almost twice the 1.5 degree target? Physical and biological processes are driven by actual temperature, not anomalies. Given the current (limited) level of realism in these models, and the fact there is a great deal more in them than their basis in physical understanding, the authors might wish to reconsider calling today's GCMs "fully physics-based" (86).

The upper panel of the old figure 4 shows in part what the reviewer asks for. We discuss the implication of the wide range of incremental values in the new discussion section 4.2. Here, we argue that GCM simulations are less suited for tracking the signal in GMTs due to their wide range. Another argument will be that GCM simulations in CMIP5 are up to date up to the year 2005. Estimates for the period 2006-2016 are less reliable.

We added the important comment of the reviewer that GCMs give a wide range of estimates for the global temperature over the period 1961-1990. Not as anomalies but in **absolute temperatures**. Indeed, figure 9.8 of the AR5 WGI report (2013, page 768) shows a range from 12.6 ºC to 15.3 ºC, based on 36 models. This range is almost the double of the 1.5 ºC limit.. Also see figure 1 upper panel in Hawkins and Sutton 2016 BAMS 963-980. See lines 351-352.

Finally, we removed the expression that GCMs are 'fully physics based'. That is, indeed, not true.

Lastly: what precisely does it mean to hold GMT "well below" (14) some temperature threshold? How would we know if we had missed this target? Can this be phased with sufficient precision to allow, say, an insurance contract or legal wager to hinge onits occurrence? Issues include the duration for which the threshold is exceeded (An instant? A month? A year? A decade?) and how to deal with the imprecision in measuring the global mean temperature, even today. In practice, simply setting the target as an absolute value of GMT, inspired by the agreed 1.5 change, would prove more *straightforward both scientifically and legally, even if not politically or diplomatically.*

Good point. However, we propose to remove Section 5.2 where we extend the historical analysis to the year 2100. Therefore, this important comment is not directly applicable anymore to our revised text.

Additional changes to the revised manuscript

A new aspect in the revised text is the role of warming definitions. We did not address this point in the original manuscript. This aspect is now addressed throughout the revised text (the Abstract, introduction, ...).

Furthermore, we have removed section 5.2. All text on future projections has been removed, including figure 5.

Changes made to the Supplementary Material

There are three changes made to the Supplementary Material. First, we have added table SM.2. Here, the role of adding volcanic activity as a regression variable is shown. Second, we have added figure SM.2, which we moved from the main text of the original manuscript. Finally, we have added two regression variables in equation (1) to show how the IRW model is extended from 'trends only' to 'trends plus the influence of explanatory variables'.

Signal detection in global mean temperatures after "Paris": an uncertainty and sensitivity analysis

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Abstract. In December 2015, 195 countries agreed in Paris to 'hold the increase in global mean surface temperature (GMT) well below 2.0 °C above pre-industrial levels and to pursue efforts to limit the temperature increase to 1.5 °C'. Since large financial flows will be needed to keep GMTs below these targets, it is important to know how GMT has progressed since pre-industrial times~~, taking short-term and long-term (decadal) natural variability into account.~~. However, the Paris Agreement is not conclusive as for methods to calculate it. Should trend progression be deduced from GCM simulations or from instrumental records by (statistical) trend methods? Which ~~trend model~~simulations or GMT datasets should be chosen, and ~~what~~which trend models? What is 'pre-industrial'~~? Does trend progression depend on~~, and finally, are the ~~specific GMT dataset chosen~~Paris targets formulated for total warming, originating from both natural and anthropogenic forcing, or do they refer to anthropogenic warming only? To find answers to these questions we performed an uncertainty and sensitivity analysis where datasets and model choices have been varied. For all cases we evaluated trend progression ~~since pre-industrial,~~ along with uncertainty information. To do so, we analysed four trend approaches and applied these to the five leading GMT products. ~~As a parallel path, we calculated GMT progression from an ensemble of 106 GCM simulations, corrected for natural variability.~~ We find GMT progression to be largely independent of various trend model approaches. However, GMT progression is significantly influenced by the choice of GMT datasets. Both sources of uncertainty are dominated by natural variability. As a parallel path, we calculated GMT progression from an ensemble of 106 GCM simulations. Mean progression derived from GCM-based GMTs appears to lie ~~within~~in the range of~~ the~~ trend-dataset combinations. A difference between both approaches lies in the width of uncertainty bands: ~~bands for GCMs are much wider. Results appear to be robust as for specific~~

~~choices for 'pre-industrial'. Our "Paris" policy recommendation would be to choose a spline or IRW trend model and estimate it on the average of the five leading GMT datasets, where 1880 is taken as base year. Given this choice trend progression for 2016 accounts for 1.01 ± 0.13 ºC (2-σ).~~GCM simulations show a much wider spread. Finally, we discuss various choices for pre-industrial baselines and the role of warming definitions. Based on these findings we propose an estimate for signal progression in GMTs since pre-industrial.

1. Introduction

Global mean surface temperature (GMT) is undoubtedly one of the key indicators of climate change. Tollefson (2015) denotes the GMT indicator as 'the global thermostat'. Over the years many articles have been published in relation to GMT series and the patterns therein. These patterns combine an anthropogenic signal – induced by growing concentration of greenhouses and processes such as aerosol cooling – as well as natural variability. Natural variability can be regarded as a correlated noise process consisting of ~~-~~(i) internal random unforced (chaotic) variability and (ii) external radiatively forced changes. Here, internal variability is steered by short-term processes such as weather in the high latitudes or El Niño and La Niña, as well as by decadal processes such as the Interdecadal Pacific Oscillation (~~IPO), and will result in correlated noise in GMTs (~~e.g., Trenberth, 2015; Fyfe et al. 2016; Xie, 2016; Meehl et al., 2016), and will result in correlated noise in GMTs (Mudelsee, 2014; Roberts et al., 2015). Externally forced variability is mainly due to volcanic eruptions and variations in solar irradiance ~~(IPCC, 2013~~. It influences global temperatures on annual to centennial scales (IPCC, 2013 - Ch. 10; Forster et al., 2013; Mann et al., 2016). A recent realization of internal variability led to a fierce debate in the popular media: GMTs were showing a claimed "slowdown", "pause" or "hiatus" from the year 1998 onwards (e.g., Lewandowski et al., 2015; Hedemann et al., 2017; Medhaug et al., 2017 - their figure 1).

GMTs has ~~become~~been a crucial indicator in climate negotiations for a long time and it has even become more so at the the ~~21th~~21st Conference of Parties (COP21) in Paris, December 2015. The final accord, approved by 195 countries, agreed on GMT targets which aim to avoid ~~an increase~~increases of 1.5 and 2.0 °C compared to pre-industrial temperatures (UN, 2015). IPCC (2014a) showed that meeting such GMT targets will require deep reductions of GHG emissions at the cost of high investments in mitigation measures worldwide. Given the fact that all goals are formulated on the basis of this single GMT indicator, the question arises: what is the current GMT level since pre-industrial?

So far, little attention has been paid to this topic. IPCC (2013), in its attempt to clarify the meaning of GMT measurements, applied linear trends to three different GMT datasets. They ~~report~~reported a trend progression -Δμ of

0.85 [0.65, 1.06] °C ~~over~~for the period 1880-2012. The uncertainty range stands for 90% confidence limits, originating from differences in datasets, natural variability of the climate system (forced and unforced), and expert judgment~~.~~ (IPCC 2013 - Box 2.2). Hawkins et al. (2017) ~~recently~~and Schurer et al. (2017) addressed the topic of trend progression *since pre-industrial* ~~by quantifying~~and quantified the role of various choices for ~~'~~pre-~~industrial'~~industrial baselines.

~~They~~Hawkins et al. found that the period 1720-1800 would be the most suitable in physical terms, despite incomplete information about radiative forcings and very few direct observations during this time. Additionally, they concluded that the 1850-1900 period would be a reasonable surrogate for pre-industrial GMTs~~ by~~, being only 0~~,~~.05 °C warmer than the 1720-1800 period. Subsequently, Hawkins et al. ~~analysed~~analyzed GMT progression since pre-industrial by calculating the GMT mean over the 20-year period 1986-2005 for various GMT products and other instrumental data (their figure 4). Trend progression itself was approximated in the study by multiple regression models with non-stationary explanatory variables such as historic GHG forcing curves or local temperature series (the Central England Temperature series or the De Bilt series). Schurer et al. found that GHGs had a significant warming effect on global temperatures if the period 1401-1800 is compared to 1850-1900: from 0.02 to 0.20 ºC (90% confidence limits). If all forcings are combined (GHG, solar, volcanic), they found a similar warming effect of 0.09 [0.03 - 0.19] °C.

In this article, we build on the work of Hawkins et al. but we do not base our GMT progression estimates on linear regression models with non-stationary regressors. The drawback of this approach is simply the linearity assumed, while the climate system is (highly) non-linear with a number of feedback processes. Therefore, we follow two other trend estimation approaches: (i) statistical trend models and (ii) global temperature trends derived from Global Climate Models (GCMs). Furthermore, we avoid methods or presentations based on subjectively selected time-windows (such as Moving Averages). The drawback of time windows is that averages over ~~20~~21-year periods or ~~alike~~similar do not give estimates for the beginning and ending of the sample period chosen~~.~~ (thus, we would have no trend estimates for the period 2007-2016).

A final topic we address is that of warming definitions. Should the Paris targets be interpreted as warming due to both anthropogenic and natural forcings, or as warming due to anthropogenic warming only? The terms 'global warming' or 'total warming' are interpreted in most literature as the sum of anthropogenic warming plus long-term (decadal to centennial) natural warming, consistent with the IPCC definition of climate change (IPCC Annex II, 2014). However, some researchers interpret 'global warming' as anthropogenic warming only, consistent with the definition proposed by UNFCCC in their article 1 (Otto et al., 2015; Millar et al. 2017). In both definitions, short-term natural variability – such as seen in "the hiatus period" – is smoothed from warming trends.

Our approach is that of an uncertainty and sensitivity analysis as promoted by Saltelli et al. (2004), Saisana et al. (2005) and Visser et al. (2015). We ask the following ~~two~~three major questions:

- How robust are estimates for GMT progression~~ since pre-industrial~~ as for specific choices of trend modelling, use of GCMs and specific choices of GMT datasets?
- How do these choices influence uncertainties in GMT progression in relation to uncertainties due to forced and unforced natural variability?

- Does the choice for a specific pre-industrial baseline or period play a role? And are our estimates sensitive to forced natural variability on decadal to centennial scales? In other words, does it matter if we interpret the Paris targets as total warming, or as anthropogenic warming only?

Since there is no ‘true’ or ‘best’ trend approach (Visser et al., 2015), we explore four trend methods and apply these to five leading GMT products (similar to Hawkins et al.). This leads to a 4-by-5 matrix of GMT trend progressions since ~~pre-industrial.~~1880. As a parallel path, we compare these trend progressions to those deduced from GCMs. We analyse an ensemble of 106 GCM experiments from the Coupled Model Intercomparison Project phase 5 (CMIP5), corrected for natural variability. ~~Clearly,~~ GCMs are ~~fully~~for a large part physics-based, in contrast to trend methods~~, and it seems logical to give them priority in relation to the questions raised here.~~. However, there are also drawbacks, the main one being that GCMs are only approximations to the real climate system and have considerable biases. Although GCMs are tuned to meet the main characteristics of instrumental data (Voosen, 2016), GMTs derived from GCMs still show a wide range of trend-progression estimates, as we ~~will~~ show.

In the discussion section, we address the role of various assumptions as for pre-industrial baselines, and differences in trend progression if Paris targets are interpreted as 'total warming' versus 'anthropogenic warming'.

Our analysis is confined to historic data only (up to and including 2016). Examples for GMT projections have been given by IPCC (2013 - Ch. 12), Forster et al. (2013~~) and~~), Mann (2014~~).~~) and Schurer et al. (2017). A short-term prediction model is given by Suckling et al. (2016). ~~Similarly, we will give an impression in section 6.2 how GMTs might evolve up to the year 2100, based on the historic trend progressions found here.~~

2 Data and methods

2.1 Data

Various research groups have published global GMT datasets. IPCC (2013 - section 2.4.3) used three datasets, namely the HadCRUT4 series (Morice et al., 2012; Hope, 2016), the NOAA dataset (Vose et al., 2012) and the NASA/GISS dataset (Hansen et al 2010). In the analysis here, we instead use a recent update of the NOAA data

(Karl et al., 2015). Karl et al. applied a number of corrections which mainly deal with sea surface temperatures, such as the change from buckets to engine intake thermometers. In addition, we added two series, i.e. the version of the HadCRUT4 data in which the missing data have been filled in as published by Cowtan and Way (2014) and the GMT series by Rohde et al. (2013). Note that these datasets are not independent. They start from roughly the same station data over land, and more importantly are based on only two SST analyses: HadSST3 and ERSST v4.

Cowtan and Way re-analysed the HadCRUT4 series by applying a statistical interpolation technique (Kriging) and satellite data for regions where data are sparse. Their series shows higher GMT values in recent decades than the non-interpolated HadCRUT4 series due to the more-than-average warming of the poles. The land part of the GMT data of Rohde et al. (2013; Berkeley Earth group of researchers) systematically addressed major concerns of global warming sceptics, mainly dealing with potential bias from data selection, data adjustment, poor station quality and the urban heat island effect. The ocean part (about 70%) is taken from HadSST3.

Next to the GMT data products we apply the stratospheric aerosol optical depth (AOD) index to explore the influence of volcanic dust. These data are from NASA and are available for the period 1850-2016 (Sato et al, 1993; Ridley et al., 2014).

Since two out of five GMT products start in the year 1880, ~~our analyses will~~we use ~~“~~the period 1880~~”~~-2016 as ~~pre-industrial for practical reasons.~~our period of analysis. We return to this point in the discussion section~~ 4~~. All data were downloaded from the institution websites with 2016 as the final year.

Next to these instrumental-data based GMTs we analyze three sets of GCM simulations all taken from CMIP5 (Taylor et al., 2012; IPCC, 2013 – Ch. 9-12). GMT is defined here as the global average of near-surface temperature~~,~~ (temperature at surface or 'tas' in short), in contrast to the observational datasets that use SST over sea for practical reasons~~.~~ (also denoted as 'blended temperature series'; Cowtan et al., 2015). The first set consists of GCM simulations where the input of greenhouse gases from 2005 onwards is taken from three Representative Concentration Pathways (RCPs): 4.5, 6.0 and 8.5 W/m^2 (Van Vuuren et al., 2011; IPCC, 2014 - section 12.4 and figure 12.5). These simulations cover the period 1861-2100. We have taken a set of 106 GCM simulations with one member per model~~. GCMs from CMIP5~~ (42 members for emission scenario RCP4.5, 25 members for RCP6.0 and 39 members for RCP8.5). GMTs from CMIP5 simulations are based on wide range of modeling differences such as climate sensitivities, cloud parametrization and aerosol forcing (e.g., IPCC 2013 - Ch. 9).

The second set that we have analyzed, consists of 37 GCM runs for natural~~ unforced~~ variability, denoted as ‘historicalNat’. These runs comprise forced and unforced natural variability ~~only~~but no GHG forcing (1860-2005). See Forster et al. (2013) for details. Finally, we analyzed ~~20~~41 Pre-industrial Control (PiControl) runs ~~of~~with lengths varying between 200~~ year length.~~ and 1000 years. These runs simulate natural internal variability only. All CMIP5 runs were downloaded from the KNMI Climate Explorer website with one member per model (Trouet and Van Oldenborgh, 2013).

2.2 Trend modeling

The tracking of signals or trends in GMT series has a long history, and a wide range of methods have been applied to isolate long-term signals or 'trends'. We have summarized these in the Supplementary Material (table SM.1). As stated in the Introduction we choose statistical trend methods that allow for the quantification of trend progression where no window is needed and where uncertainty estimates are available for any incremental trend value. Furthermore, no specific period for pre-industrial has to be chosen (such as the mean of the 1851-1900 period or ~~alike~~similar). 'Pre-industrial' is reflected in the choice of the start of the sample period only.

Based on these considerations we have selected four trend approaches for our sensitivity analysis: Ordinary Least Squares (OLS) linear trends, Integrated Random Walk (IRW) trends and two approaches with splines. The first trend - a linear fit by OLS - was chosen by IPCC (2013) as their main method. Uncertainties simply follow from the linear model:

$$\mathrm{var}(\Delta\mu_{2016}) = \mathrm{var}([a+b*2016] - [a+b*1880]) = 125^2 * \mathrm{var}(b),$$

where 'a' is the intercept and 'b' the slope. The variance of 'b' follows from the OLS equations. Next to that the variance estimate is corrected by calculating effective sample sizes, based on annual data (IPCC, 2013 - 2SM).

This correction is important since residuals are not white noise~~, mainly because the forcing is not linear but increases with time. A large part of the~~ due to persistence in natural processes. The signal is therefore considered as noise with a large decorrelation scale in this approach.

The second trend approach that fulfils our uncertainty requirements, are sub-models from the class of Structural Time Series models (STMs), in combination with the Kalman filter (Harvey, 1989). From this group of models we choose the IRW trend model. The IRW trend model extends the linear regression trend line by a *flexible trend* while retaining all uncertainty information (Visser~~ and Molenaar 1995; Visser~~, 2004; Visser et al., 2012; Visser et al.,~~ 2014; Visser et al.,~~ 2015). Furthermore, the flexibility of the trend model is optimized by Maximum Likelihood (ML) optimization. The Kalman filter is the ideal filter here since it yields the so-called Minimum Mean Squared Estimator (MMSE) for the trend component in the model. The Kalman filter has been applied in many fields of research and is gaining popularity in climate research recently (e.g., Hay et al., 2015).

A third and fourth approach applies a combination of a trend model and the statistical structure of natural internal variability as derived from PiControl runs. It can be seen as a hybrid approach. To do so we have chosen the cubic spline trend model, a trend approach also applied in the AR5 (IPCC, 2013 - Box 2.2, figure 1). Smoothing splines are not statistical in nature and, thus, do not generate uncertainty estimates for GMT increments $\Delta\mu_{2016}$. However, uncertainty bands can be reconstructed by Monte Carlo (MC) simulations under the assumption of a given mean, variance and autocorrelation structure estimated directly from the underlying dataset (figure 1 and Mudelsee 2014 - section 3.3). To steer the flexibility of the cubic spline model we studied the correlation structure of internal variability. This correlation structure can be described by an AutoRegressive Moving Average (ARMA) model as proposed by Hunt (2011) and Roberts et al. (2015). They estimated ARMA models to a range of PiControl runs. Similarly, we ~~analysed 20~~analyzed 41 PiControl runs and found that~~ natural~~ variability can reasonably be characterized by AR(1) processes where the AR(1) parameter φ varies within the range [0.28 - 0.60], depending on the GCM run chosen (cf. Mudelsee, 2014 - section 2.1).

All four trend methods are designed to smooth GMTs for annual to decadal natural variability (forced and unforced). However, if Paris targets should be interpreted as anthropogenic warming only, we should estimate the role of decadal to centennial forcings from volcanic and solar activity as well. To estimate the role of volcanic eruptions we have extended the OLS linear trend model and the IRW trend model by adding the AOD index as regressor (Visser and Molenaar, 1995; Visser et al., 2015 - figure 4).

3 Results

3.1 Sensitivity analysis trend methods and data products

Based on the 1880-2016 GMT sample period we have evaluated trend progression values $\Delta\mu_{2016}$ from 1880 up to 2016 along with uncertainties for all datasets and trend approaches. This yields the 4-by-5 matrix shown in table 1. As for linear trends we corrected uncertainty estimates by a factor $\sqrt{(1.60/0.40)} = 2.0$, analogous to the approach chosen in IPCC (2013 - Ch. 2, Sup. Mat.) since first~~-~~-order autocorrelations lie around 0.60. Table 1 shows that the trend slopes for the dataset HadCRUT4, LOTI-NASA, NOAA-Karl and Cowtan and Way are close, where the lowest slope value is for the HadCRUT4 series. This dataset has poor coverage in the Arctic, where trends are much higher than the global mean. The steepest trend is found for the Berkeley Earth series, a remarkable result since the Berkeley Earth project was set-up to meet a range of critical comments from global warming sceptics. Identical patterns are found for the other trend models: lowest trend progression for the HadCRUT4 dataset and highest values for the Berkeley Earth dataset.

As for the IRW trend estimates we find reasonable flexible patterns which closely resemble the spline trend shown in IPCC (2013 - Ch.2: Box 2.2, ~~Figure~~figure 1b). An example for the HadCRUT4 dataset is shown in figure 2. Data, trend and uncertainties are shown in the upper panel. The trend increments [$\mu_t - \mu_{t-1}$] and [$\mu_t - \mu_{1880}$] are given in the middle left and right panel, respectively, along with uncertainties. The [$\mu_{2016} - \mu_{1880}$] value with uncertainty is taken as value in table 1. The lower left panel shows the innovations or one-step-ahead predictions errors which follow from the Kalman filter formulae. The lower right panel shows the autocorrelation function (ACF). We note that a prerequisite of Kalman filtering is that the one-step-ahead prediction errors follow a white noise process. The ACF shows an AR(1) value of 0.30 which is slightly significant. ~~Since~~We applied a correction for compensating for this the violation ~~is small, we did not correct uncertainty ranges~~by applying the approach of IPCC, as we did for linear trends: uncertainty bands are corrected by a factor $\sqrt{(1.30/0.70)} = 1.3$.

As for smoothing splines we have estimated trends in GMT series such that the residual series exhibits an AR(1) process with a φ value of 0.28 and 0.60. Trend estimates based on the HadCRUT4 series are shown in figure 3. Both spline approaches show quite different trend patterns. The model shown in the upper panel of figure 3 is based on a slightly correlated noise process and - as for the IRW trend from figure 2 - closely resembles the spline trend shown in IPCC (2013 - Ch.2: Box 2.2, ~~Figure~~figure 1b). The model shown in the lower panel shows a parabolic shape. This parabolic pattern closely resembles the anthropogenic signal in GMT series as shown by IPCC (2013 - figure 10.1f), derived from ‘~~-~~historicalGHG’ simulation runs (Forster et al., 2013).

It is interesting to note that none of the four trend methods show a sign of a 'hiatus', 'slowdown' or 'pause'. That is not surprising for the linear trend and the spline estimate with φ~~=~~ = 0.60 due to their stiff character. However, the IRW trend and spline with φ~~=~~ = 0.28 are more flexible and do not show any stabilisation pattern for recent years at all. We tested the residuals of the IRW trend model and these appear to be close to white noise (cf. lower panels of figure 1). This inference is consistent with recent findings on the hiatus (~~e.g.,~~ Marotzke et al., 2015; Hedemann et al., 2017; Medhaug et al., 2017; Rahmstorf et al., 2017).

Table 1 shows ~~is~~ that differences between trend model and dataset combinations can be considerable. The lowest $\Delta\mu_{2016}$ value is found for the HadCRUT4 dataset in combination with the IRW trend model: 0.90 ± 0.18°C (± ~~2-σ~~2σ). The highest values are found for the Berkeley Earth dataset in combination with cubic spline interpolation and φ = 0.28: 1.12 ± 0.13 °C. These two extremes reveal that the range of $\Delta\mu_{2016}$ ~~variability~~values due to datasets and trend models accounts for 0.22 °C. This ~~variability~~range is somewhat lower than ~~variability~~that due to natural variability alone. Based on ~~2-σ~~2σ limits, we find a low estimate of ± 0.12 °C ~~and a high estimate of ± 0.19 °C~~, leading to a maximum ~~ranges~~range of 0.24 ºC (LOTI dataset in combination with cubic spline interpolation and φ = 0.28~~) up to~~), and a high estimate of ± 0.19 °C, leading to a maximum range of 0.38 ºC (LOTI dataset and OLS linear trend).

To quantify the role of trend methods in more detail we have averaged trend estimates over the five GMT datasets and added it to table 1 (bottom row). It shows that ~~variability~~the range of trend progressions is small: [0.97, 1.01] ºC. At the other hand, if we average *over trend methods*, the variability due to datasets is found (right column of table 1). The variability accounts for [0.92, 1.09] ºC. Clearly, variability due to GMT datasets is dominant over specific trend approaches.

3.2 Trend progression derived from GCM simulations

Trend progression derived from GCMs have been analyzed in a range of studies, e.g. IPCC(2013 - Ch. 10), Forster et al. (2013), Marotzke and Forster (2016), Mann et al. (2016) and Meehl et al. (2016). Here, we derive trend progression since pre-industrial by taking an ensemble of 106 GCM all-forcing simulations 1861-2016. We note that underlying models have quite different characteristics. However, we did not perform an extensive sensitivity analysis as for these factors, as for example in Visser et al. (2000).

Short-term forced and unforced natural variability in individual GCM simulations is smoothed by estimating splines to each individual simulation (both for φ = 0.28 ~~or, equivalently, 7 degrees of freedom~~and φ = 0.60, as in ~~the upper panel of~~ figure 3). In this way we find 106 values for $\Delta_{i,2016} \equiv y_{i,2016} - y_{i,\cancel{1880}\,1861}$~~, which~~. Results are shown in ~~the upper panel of~~ figure 4~~.~~ (based on smoothing splines with φ = 0.28). The mean Δ_{2016} value is 1.15 ± 0.~~47~~50 ºC ~~(2-σ).~~(2σ) for smoothing all 106 curves with φ = 0.28 and 1.00 ± 0.50 ºC for smoothing with φ = 0.60. These values are consistent with those reported by Forster et al. (2013, table 3). ~~Note that the GMT is defined slightly differently~~

The GCM simulations analyzed here differ from ~~the observational estimates, with near-surface~~ data products as for their definition of temperatures ~~rather than SSTs over sea areas. There are indications that this affects the trends and in fact explains the difference (~~('tas only' versus blended temperatures). Cowtan et al~~., ~~. (2015) and Richards et al. (2016~~). Thus, strictly spoken, GMT values cannot be compared without accounting for this difference (and the difference in coverage for non-interpolated estimates such as HadCRUT4).~~ - figure 1) showed that tas temperatures differ from blended temperatures by 0.10 ºC, for the period 1860-2009. Thus, mean GCM-derived warming estimates cover the ranges [1.00 to 1.15] ºC (tas) or [0.90 to 1.05] ºC (blended). We note that these ranges reasonably correspond to the range found in table 1.

~~Since GCM simulations include externally-forced natural variability we remove forcings by volcanos and solar irradiation by analyzing an ensemble of 37 GCM simulations with natural forcing only ('historicalNat'; IPCC, 2013 - figures 10.1 and 10.7; Forster et al., 2013 - fig 2).). The mean curve with 2 standard errors (SEs) is shown in the lower panel of figure 4, along with major volcanic eruptions (eruptions with a Volcanic Explosivity Index of 5 and 6). Mean trend progression for these 37 runs accounts for 0.078 ± 0.030 ºC (2-SE), 1861-2005.~~

~~Now, if we correct GCM simulations for natural forcings we find a mean progression Δ_{2016} of 1.07 ± 0.47 ºC (2-σ).~~

4 Discussion

~~The results shown in table~~ 4.1 ~~form the central findings in this study. Here, we~~Uncertainty and sensitivity analysis

We make ~~two~~three comments concerning the robustness of ~~these~~the results given in section 3. First, as summarized in table SM.1 of the Supplementary Material section, a wide range of trend models exist in the literature, all with varying characteristics. The fact that many of these methods are not statistical in nature does not limit their application in the present context: the approach shown in figure 1 (creating surrogate GMT series by MC simulation) is also applicable to methods such as binomial filters or LOESS estimators. Therefore, we cannot rule out that the influence of trend modelling is underestimated in table 1. However, given the (i) small differences shown in the bottom row of table 1, and (ii) the wide uncertainty bands due to natural variability, we judge such an under-estimation to be relatively small.

A second comment concerns a source of uncertainty ~~not mentioned thus far, namely~~dealing with the choice for year or period that can be regarded as 'pre-industrial'. As for the analyses in section 3.1, we have chosen for the year 1880 as low end of the sample period, simply because two out of five GMT products start in 1880 (NASA and NOAA). This choice is consistent with that made by IPCC (2013) as for historic trend progression (~~although some analyses are relative to 1850-1900). Would our results and conclusions from table 1 be different if the sample period would be enlarged, starting in 1720, 1850 or 1880?~~without claiming this to be 'since pre-industrial'). In section 3.2 we have chosen the year 1861 as low end of the sample period, again since simulations are available from that year onwards.

Would our results and conclusions from table 1 or figure 4 be different if the sample period would be enlarged, starting in 1400, 1720 or 1850? Strictly spoken, we cannot answer this question since we cannot extend our analyses to these starting years due to data availability. As for instrumental dataset, we could perform some analyses from 1850 onwards but GMT estimates become inaccurate for these early decades. However, estimates based on GCM simulations are given by Hawkins et al. (2017) ~~have shown the~~and Schurer et al. (2017).

Hawkins et al. show that the GMT difference between the two periods 1720-1800 and 1850-1900 ~~to be~~is small, around 0.05 ºC, lying on the edge of statistical significance. Additionally to their analysis we compared GMT mean values over three periods: 1850-1900, 1860-1880 and 1880-1900, based on the HadCRUT4 dataset. The mean values appear to be ~~quite~~ similar: -0.~~35~~31 ± 0.03 °C, -0.~~35~~31 ± 0.06 °C and -0.~~36~~32 ± 0.05 °C, respectively (~~2 σ~~2σ limits). These differences are small if compared to the uncertainties due to natural variability, shown in table 1. ~~We conclude~~These results suggest that the choice for 1720-1800, 1850-1900, 1860-1880 or 1880-1900 as 'pre-industrial' will ~~not~~have a small influence to the findings presented here.

~~As for GCM-derived progressions we have taken~~ At the ~~year 1861 as start of 'pre-industrial'. The reason for~~other hand, Schurer et al. show from GCM simulations that ~~choice~~global warming is ~~illustrated in the lower panel of~~

~~figure 4. The period 1861-1880 is one with low volcanic activity, with only one volcanic eruption with a Volcanic Explosivity Index of 5. However, the period 1880-1900 is strongly influenced~~underestimated by ~~eruptions, notably that of the Krakatoa with a VEI of 6. This eruption led to lowering of GMTs of~~ 0.~~3~~09 [0.03, 0.19] ºC~~. Note that~~ if the period 1401-1800 is chosen as pre-industrial baseline (compared to the period 1850-1900). Their estimate for the influence of GHG only lies close to these ~~volcanic signatures are **not** resembled~~estimates, in the ~~instrumental data, probably due to poor coverage in the areas in which the signal would have been clearest, the tropics.~~range from 0.02 to 0.20 ºC. We conclude that recent simulations point to an underestimation of global warming if calculated relative to late nineteenth century estimates. The underestimation lies around 0.10 ºC.

A third comment deals with differences in warming definitions as mentioned in the Introduction. If the Paris targets should be interpreted as anthropogenic warming only, we should estimate these contributions as well. Clearly, the incremental estimates $\Delta\mu_{2016}$ shown in Table 1 do not contain corrections for decadal to centennial natural forcings from solar and volcanic activity. To estimate the role of volcanic activity on the estimates given in table 1 we have extended the OLS linear trend and the IRW trend model with a regression component where GMT series are regressed on the OAD index shown in figure 5. Results are summarized in table SM.2. The table shows that incremental estimates $\Delta\mu_{2016}$ are overestimated by 0.02 ºC for linear trends and by 0.04 ºC for IRW trends.

To estimate the role of long-term solar activity we did not choose for the time-series approach above since any explanatory variable in a regression model with some long-term trend will correlate and 'explain' the long-term trend in the dependent variable. Therefore, we refer to GCM estimates for the role of solar activity.

IPCC (2013) estimates the role of solar variability to be small and on the edge of significance. Incremental solar forcing for the period 1750-2011 accounts for 2 [0, 4] % of GHG forcing (Figure SPM.5 and Box 10.2). Schurer at al. (2017 - figure S3) estimate the incremental contribution of solar forcing on GMTs to be 0.07 [0.02, 0.12] ºC. This estimate compares the period 1850-1900 to 1990-2000. Furthermore, the long-term influence of volcanic activity is non-significant in their simulations (their figure S2).

Next to these estimates we analyzed an ensemble of 37 GCM simulations with natural forcing only ('historicalNat'; IPCC, 2013 - figures 10.1 and 10.7; Forster et al., 2013 - fig 2). ~~How do progression estimates shown in table 1 relate to GCM-derived trend progressions? In section 3.2 we estimated mean GCM progression, corrected for natural variability, to be 1.07 ± 0.47 ºC (2-σ). These estimates appear to lie within the range of trend progressions based on instrumental data. E.g., they equal trend progression as derived from the Berkeley Earth dataset, which show trend progressions around 1.06 ± 0.14 ºC (2-σ). Clearly, the uncertainty bands for instrumental trend estimates are much smaller.~~

~~We note that GMT trend estimates from instrumental data and GCMs are not independent. Modelling groups use various methods of tuning to relate their simulations to real world data (IPCC, 2013 - Ch 9; Voosen, 2016), although the very large spread indicates that they have not been very successful in tuning to the observed trend.~~

The mean curve with 2 standard errors (SEs) is shown in figure SM.2, along with major volcanic eruptions (eruptions with a Volcanic Explosivity Index of 5 and 6). Mean trend progression for these 37 runs accounts for 0.078 ± 0.030 ºC (2 SE), 1861-2005.

From these inferences we conclude that the difference between total warming and 'anthropogenic warming lies around 0.10 ºC with an uncertainty range of [0.0, 0.14].

4.2 Policy recommendation

Schurer et al. (2017) end their article with the recommendation that a consensus be reached as to what is meant by pre-industrial temperatures. In this way, the chance would be reduced of conclusions that appear contradictory being reached by different studies. Furthermore, it would allow for a more clearly defined framework for policymakers and stakeholders. We fully agree with this recommendation. However, our uncertainty and sensitivity analysis has shown that the choice of a proper pre-industrial baseline is not the only parameter that could lead to contradictory results. Decisions around data products and GCM simulations, various time series techniques, or warming assumptions should be taken into account as well.

Here, we make the following policy proposal which aims to be a reasonable compromise. First, we propose to base GMT warming estimates on data products rather than GCM simulations. Our argumentation is that Δ_{2016} values based on GCM simulations show a wide range of warming estimates (figure 4). We note that even wider ranges are found for *absolute* GMT estimates (CMIP5 estimates for the mean GMT value over the period 1961-1990 show a range of 2.5 ºC according to IPCC 2013 - figure 9-8). Another argument is that simulation estimates from CMIP5 are accurate up to the year 2005 (estimates for 2006-2016 apply approximations for GHG concentrations, and no volcanic and solar activity).

Second, since warming estimates vary as a function of the GMT data product chosen (tabel 1), we propose to estimate trends on the annual averages of all five data products.

Third, we found that the choice for specific trend methods plays a minor role, with largest differences between stiff and more flexible trend models. Therefore, we propose to apply a flexible and a stiff trend method and average the warming estimates found.

Fourth, two studies on the role of pre-industrial baselines have been published recently. Schurer et al. (2017) find a GHG-induced warming in the range [0.02, 0.20] ºC if the period 1401-1800 is compared to the period 1850-1900. Hawkins et al. (2017) define the period 1720-1800 as a reasonable baseline for pre-industrial and find small non-significant differences between the period 1720-1800 and 1850-1900. We choose to follow the baseline proposed by Hawkins et al. Since all five GMT data products have data from 1880 onwards and GMT mean values for 1850-1900 and 1880-1900 are of equal size (based on the HadCRUT4 data product), we propose to analyse trend progression from 1880 onwards.

Finally, we propose to interpret global warming in the context of "Paris" as the sum of natural and anthropogenic warming, consistent with the IPCC definition of climate change. One argument for this choice is that ecological systems and human society will respond to total warming and induced shifts in climate extremes *regardless of its origin*.

From these choices it follows that trend progression Δ_{2016} accounts for 1.00 ± 0.13 ºC (bottom row of table 1).

5 Conclusions ~~and outlook~~

~~5.1 Conclusions~~

We have addressed the issue of signal progression of GMT in relation to the GMT targets agreed upon in Paris~~,~~ in December 2015. Although these targets are clearly defined ~~-~~– avoiding increments of 1.5 and 2.0 °C ~~-~~– there remain a number of (scientific) questions unaswered in the agreement. We have identified ~~four~~five aspects of the accord which hamper an exact quantification of GMT progression: (i) the use of instrumental data and trend methods versus GCM-derived progression, (ii) the role of varying datasets, (iii) the role of varying trend methods ~~and~~, (iv) the role of varying choices for pre-industrial~~. These questions are also relevant as GCM outcomes and their spread are used to make assessments on~~ and (v) the ~~efforts required to reach the Paris targets with a certain "likelihood".~~role of warming definitions. Since there is no 'true' or 'best' approach (Visser et al., 2015), we have chosen to perform an uncertainty and sensitivity on GMT progression as propagated by Saltelli et al. (2004) and related articles. This allows us to test the robustness of various trend progression claims.

~~As for approaches~~*Approaches based on instrumental data*~~ we~~. We find that ~~best-guess~~trend values for GMT progression 1880-2016 vary considerately, from 0.90 ºC (HadCRUT4 dataset in combination with the IRW trend model) to 1.12 ºC (Berkeley Earth dataset in combination with cubic spline interpolation and $\varphi = 0.28$). ~~These~~The two extremes reveal that the range of $\Delta\mu_{2016}$ ~~variability~~values due to datasets and trend models accounts for 0.22 °C. This ~~variability~~range is ~~lower~~smaller than ~~variability~~that due to natural variability alone. Based on ~~2-σ~~2σ limits, we find a low estimate of 0.24 °C (LOTI dataset in combination with cubic spline interpolation and $\varphi = 0.28$) and a high estimate of 0.38 °C (LOTI dataset and OLS linear trend). Furthermore, variability due to various GMT products dominates the variability due to specific trend approaches.

~~As for approaches~~*Approaches based on GCMs*~~ we~~. We find that mean trend progressions ~~lies~~lie within the range of estimates from instrumental data. However, the uncertainty bands for 106 simulations are much wider than those derived from instrumental trend estimates. Here, GCM variability stems from a wide range of modeling assumptions such as climate sensitivities, cloud parameterization and aerosol forcing (e.g., IPCC, 2013 - Ch. 9), rather than from natural variability.

The choice of a pre-industrial period. Recent studies have shown that GHG warming prior to 1880 or 1850 cannot be neglected. Schurer et al. (2017) estimate that early warming (1401-1800 compared to 1850-1900) accounts for 0.09 [0.03, 0.19] ºC. The role of solar and volcanic activity is minimal in this comparison.

Interpretation of Paris targets as being 'total warming' or 'anthropogenic warming only'. We find that the role of solar and volcanic activity is small on centennial scale. This contribution lies around 0.10 ºC (+0.03 ºC from volcanic activity and +0.07 ºC from solar activity).

Hiatus. As a side result of our trend analyses we note that no signs of an 'hiatus', 'slowdown' or 'pause' can be discerned in GMT trend progression. This inference is consistent with recent findings~~, e.g.~~ (Marotzke et al. ~~(~~2015~~),~~, Hedemann et al. ~~(~~2017~~),~~, Medhaug et al. ~~(~~2017~~) and~~, Rahmstorf et al. ~~(~~2017).

~~5.2 Outlook~~

~~The results presented here, have relevance for upcoming climate negotiations. If countries would agree to follow the *precautionary principle* with respect to the uncertainty topics raised in this paper, the best choice for datasets is the GMT dataset published by the Berkeley Earth project: trend progression is highest for this dataset (sixth row in table 1): 1.12 ± 0.13 ºC (2-σ). If countries would agree to follow a best-guess value which is robust against the factors addressed here, we propose to choose the IRW or spline trend trend model and to apply it on the average of five leading GMT products (for psychological reasons all datasets are chosen as equally important). For this choice trend progression accounts for 1.01 ± 0.13 ºC. Although estimates based on GCMs are consistent with this estimate, as shown above, GCM simulations are not a logical choice here due to their wide spread (cf. upper panel in figure 4).~~

~~To give an impression how GMTs might evolve in the future, we have calculated two mean GCM projections: one based on the RCP2.6 scenario (32 simulations) and one based on the RCP4.5 scenario (42 simulations). All simulations are contained in the 106 GCM simulations used in section 3.2, and scaled to have a mean value of 1.01 ºC in the year 2016 (the mean value of historic trend progression as derived above). See figure 5.~~

~~We find that, if countries are able to reduce GHG emissions according to the RCP2.6 scenario, best guess GMT values will stay below the 1.5 °C target. Under unfavourable circumstances this target could be reached by the year 2040. The 2.0 °C target is never reached. Under the RCP4.5 emission scenario both temperature targets are~~

~~reached before the year 2100, even under favourable conditions.~~ *Policy recommendation.* Schurer et al. (2017) recommend that a concensus be reached as to what is meant by pre-industrial temperatures. Our analysis shows that other sources of uncertainties should be taken into account as well. If not, contradictory results will appear in different studies with direct consequences for CO_2 reductions to hold GMTs below the Paris targets. Our proposal shows a GMT progression Δ_{2016} of 1.00 ºC.

Table 1. Trend increments $\Delta\mu_{2016}$ along with ~~2-σ~~2σ confidence limits. Increments are given for five GMT series and four trend approaches.

GMT dataset	**GMT progression $\Delta\mu_{2016}$ with ~~2-σ~~2σ confidence limits (°C)**				
	OLS linear trend	**IRW trend**	**Spline with φ=0.28**	**Spline with φ=0.60**	**Mean progression**
HadCRUT4, CRU	0.90 (± 0.18)	0.93 (± 0.~~13~~17)	0.94 (± 0.12)	0.92 (± 0.14)	0.92
HadCRUT4, Cowtan and Way	0.96 (± 0.17)	1.06 (± 0.~~13~~17)	1.06 (± 0.12)	0.98 (± 0.15)	1.02
LOTI series, NASA	0.98 (± 0.19)	1.02 (± 0.~~14~~18)	1.01 (± 0.12)	0.99 (± 0.14)	1.00
Karl *et al* (2015), NOAA	0.95 (± 0.19)	0.96 (± 0.~~15~~19)	0.94 (± 0.14)	0.95 (± 0.14)	0.95
Berkeley Earth Project	1.04 (± 0.17)	1.12 (± 0.~~13~~17)	1.12 (± 0.13)	1.06 (± 0.14)	1.09

Mean progression	0.97	1.02	1.01	0.98	1.00

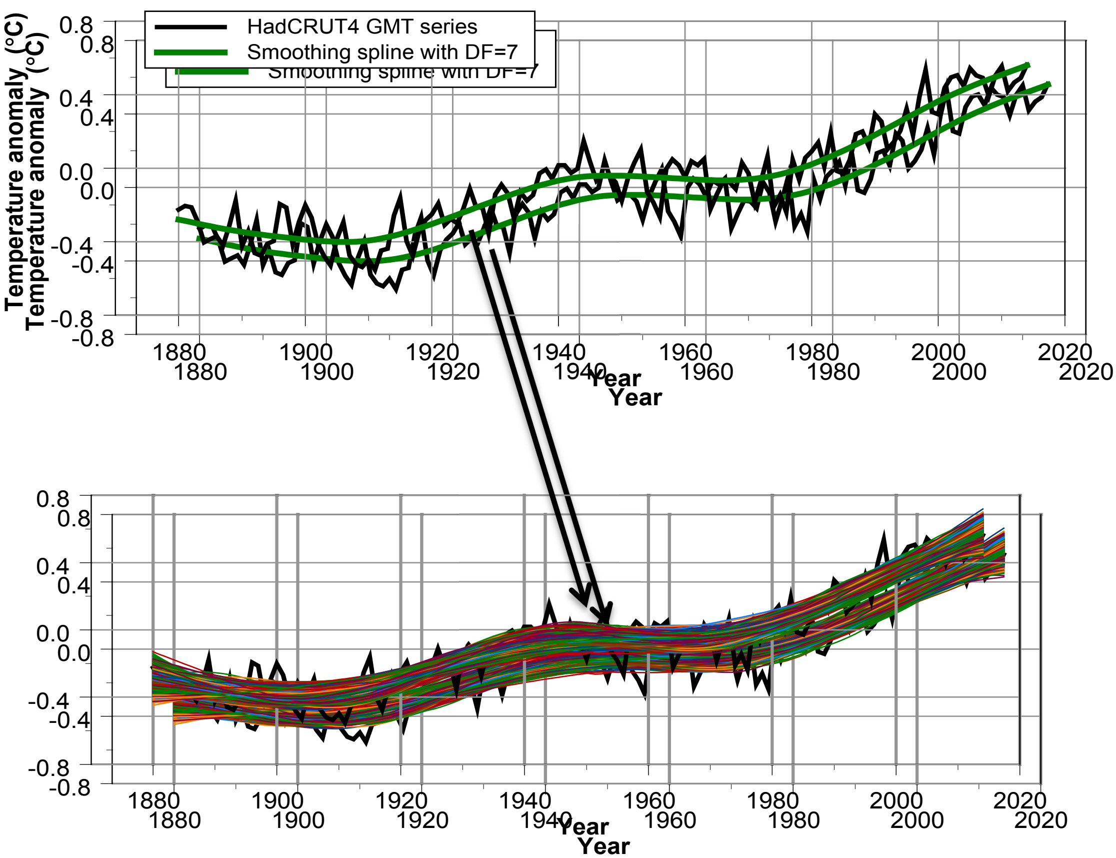
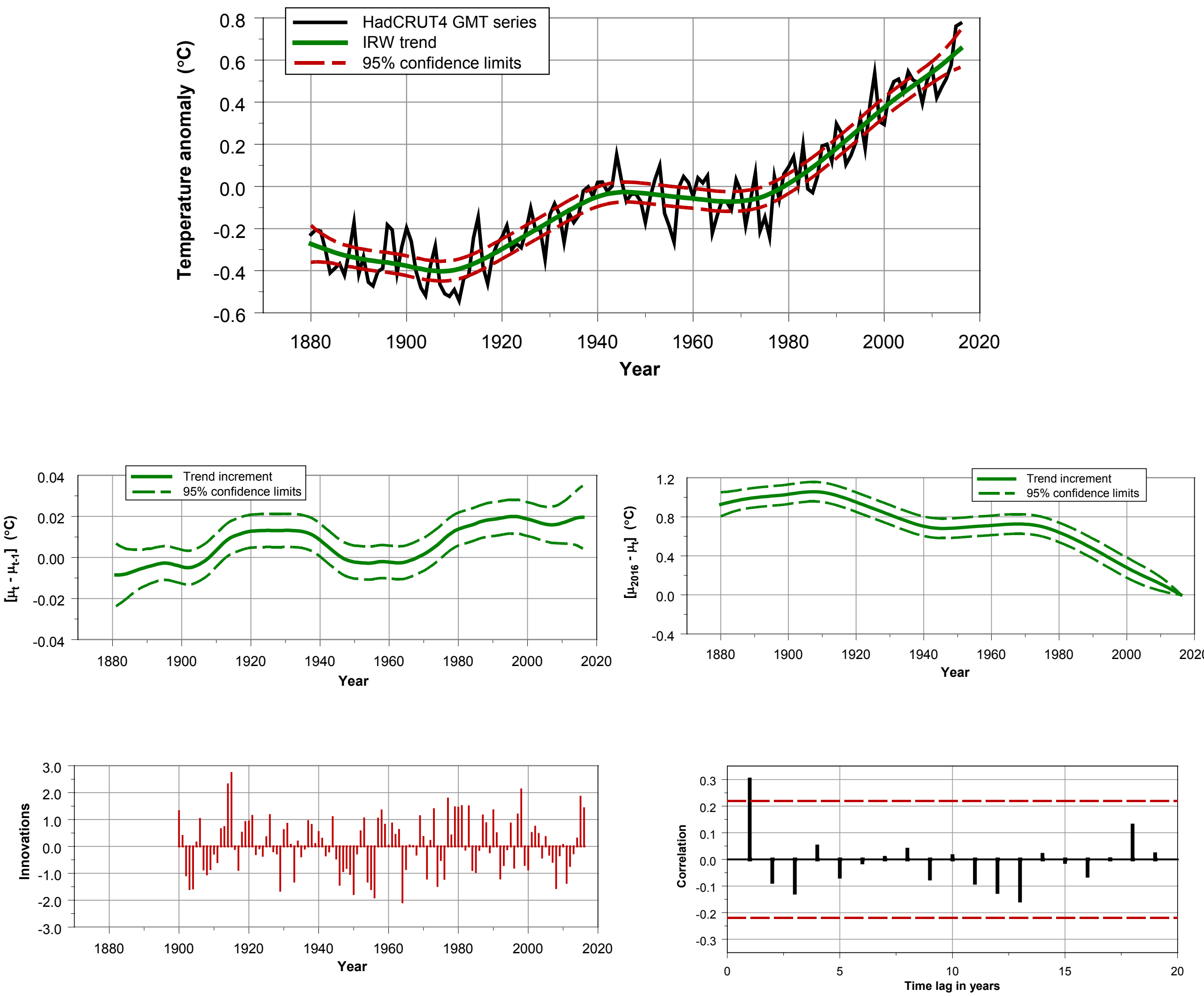


Figure 1. Construction of 1000 surrogate trend series by MC simulation, based on cubic splines. The AR(1) parameter estimated on the residuals of the spline model in the upper panel, accounts for 0.28. A surrogate GMT series $\hat{y}_{i,t}$ is formed by simulating a new residual series $r_{i,t}$ based on the AR(1) process with φ= 0.28, and adding it to the estimated spline (green line upper panel). Then, a spline trend $\mu_{i,t}$ is estimated for each surrogate $\hat{y}_{i,t}$. As an illustration we have plotted 1000 of such trends $\mu_{1,t}$, ... , $\mu_{1000,t}$ in the lower panel. Now, confidence limits can be estimated for any μ_t based on the values $\mu_{1,t}$, ... , $\mu_{1000,t}$. These confidence limits can be based on standard deviations or percentiles. Similarly, confidence limits can be calculated for the increment [μ_{2016} - μ_{1880}], based on the values [$\mu_{1,2014}$ - $\mu_{1,1880}$] ,...... , [$\mu_{1000,2014}$ - $\mu_{1000,1880}$] (Mudelsee, 2014 - Sections 3.3.3 and 3.4).


HadCRUT4 GMT series
IRW trend
95% confidence limits
Temperature anomaly (°C)
Year
Trend increment
95% confidence limits
[μt - μt-1] (°C)
Year
Trend increment
95% confidence limits
[μ2016 - μt] (°C)
Year
Innovations
Year
Correlation
Time lag in years

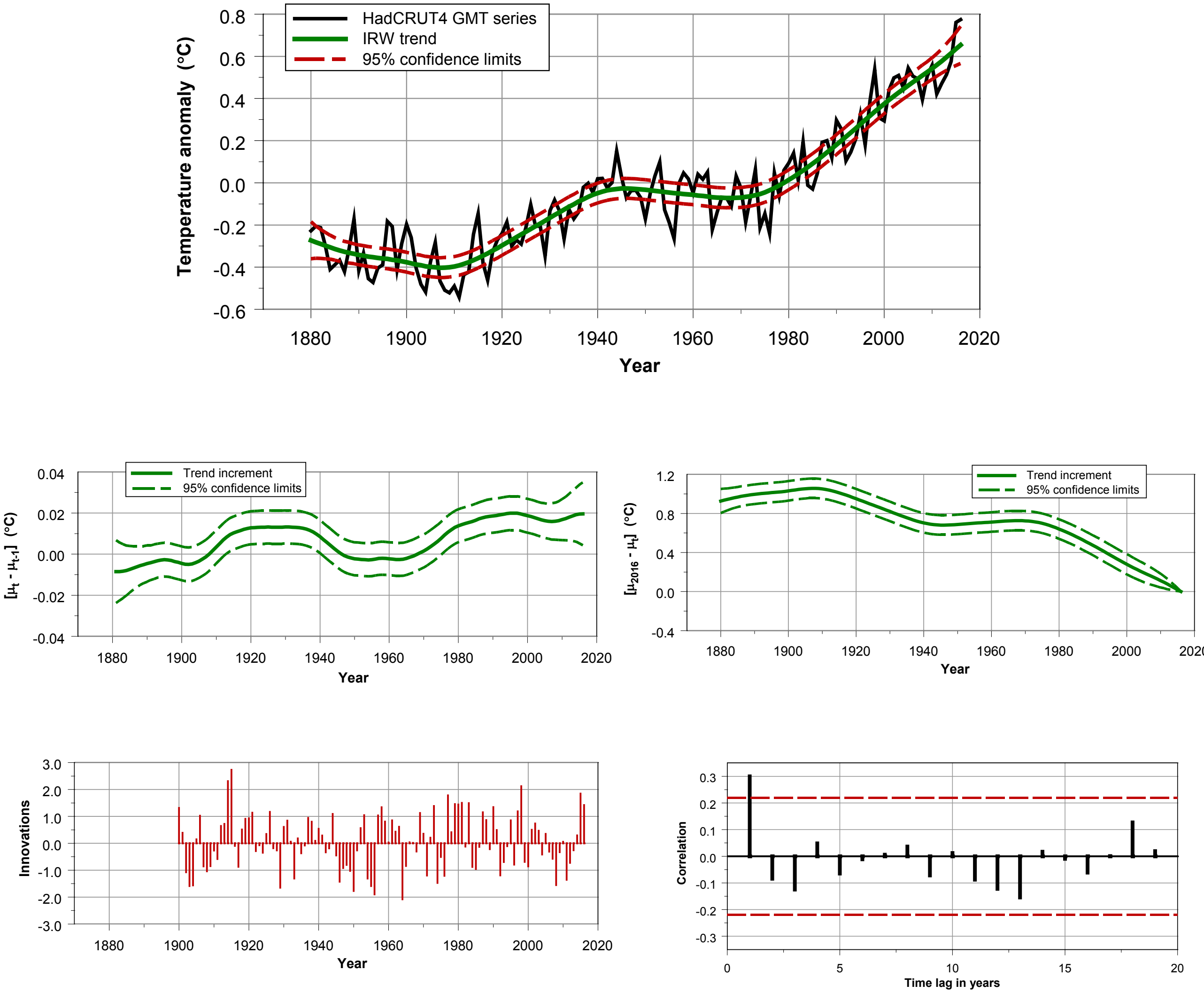


Figure 2. Results for the IRW trend model as applied to the HadCRUT4 series. Period: 1880-2016. The upper panel shows the trend (green line) along with 95% confidence limits (red dashed lines). The trend increments [μ_t - μ_{t-1}] are given in the middle left panel along with uncertainties. Idem the [μ_t - μ_{1880}] values in the middle right panel. The lower left panel shows the innovations or one-step-ahead predictions errors which follow from the Kalman filter formulae. The lower right panel shows the autocorrelation function (ACF).

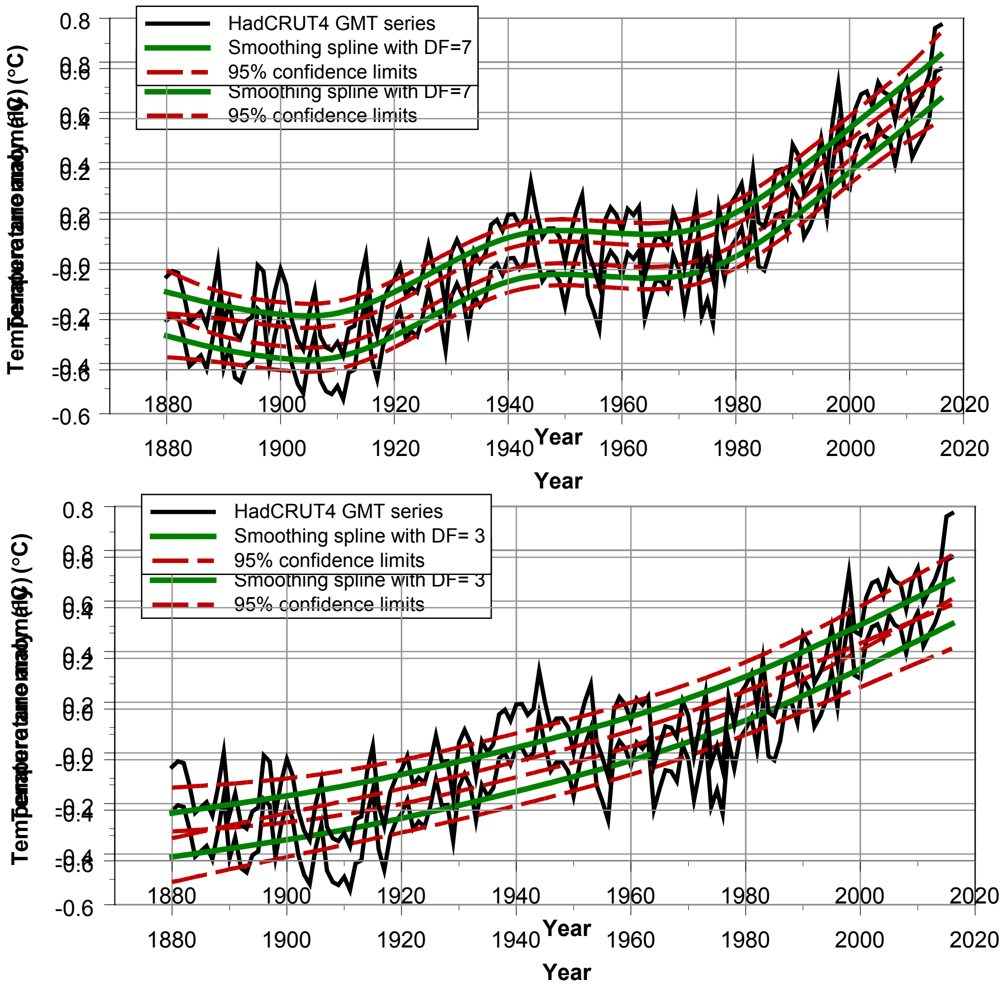
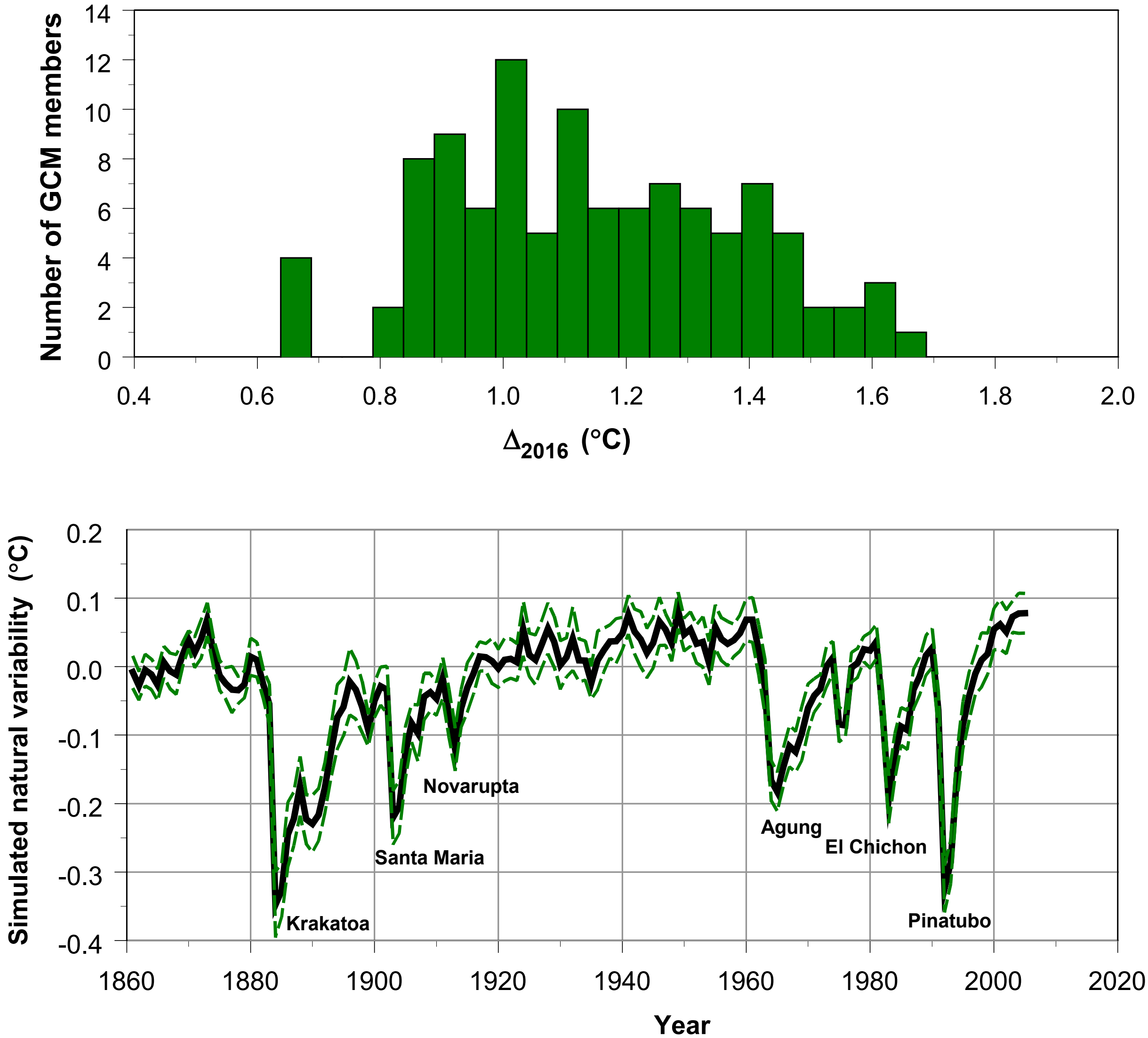


Figure 3. Two smoothing spline estimates for the HadCRUT4 GMT series, with uncertainties generated by MC simulation. All confidence limits are based on 1000 surrogate GMT series following the approach set out in Mudelsee (2014 - Section 3.3.3). Upper panel: AR(1) parameter chosen as $\varphi = 0.28$ (equivalent to 7 degrees of freedom), the low end of φ values within CMIP5 PiControl runs. Lower panel: AR(1) parameter chosen as $\varphi = 0.60$, the high end of φ values (DF=3).


Number of GCM members
14
12
10
8
6
4
2
0
0.4
0.6
0.8
1.0
1.2
1.4
1.6
1.8
2.0
Δ_{2016} (°C)
Simulated natural variability (°C)
0.2
0.1
0.0
-0.1
-0.2
-0.3
-0.4
1860
1880
1900
1920
1940
1960
1980
2000
2020
Year
Krakatoa
Santa Maria
Novarupta
Agung
El Chichon
Pinatubo

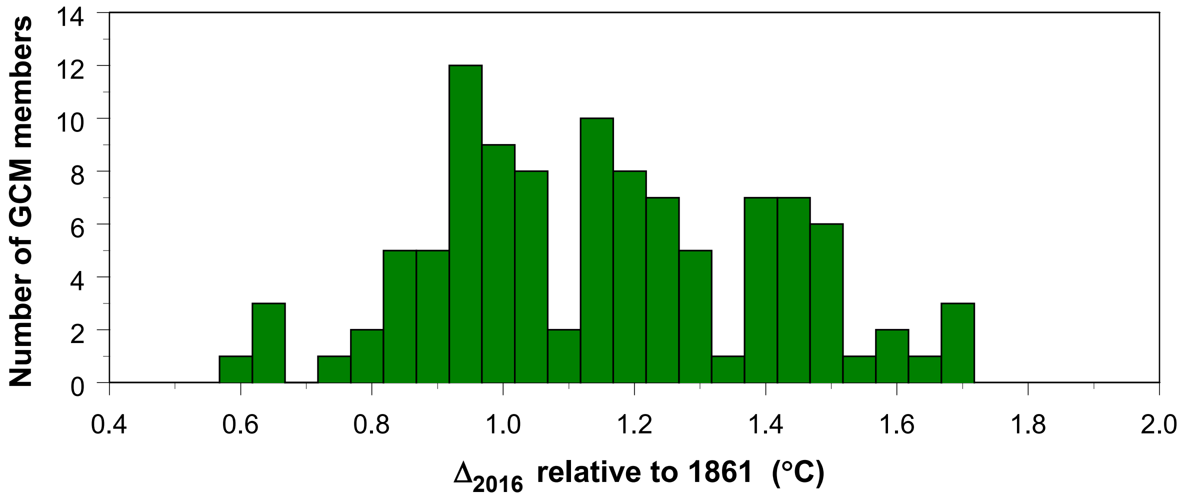
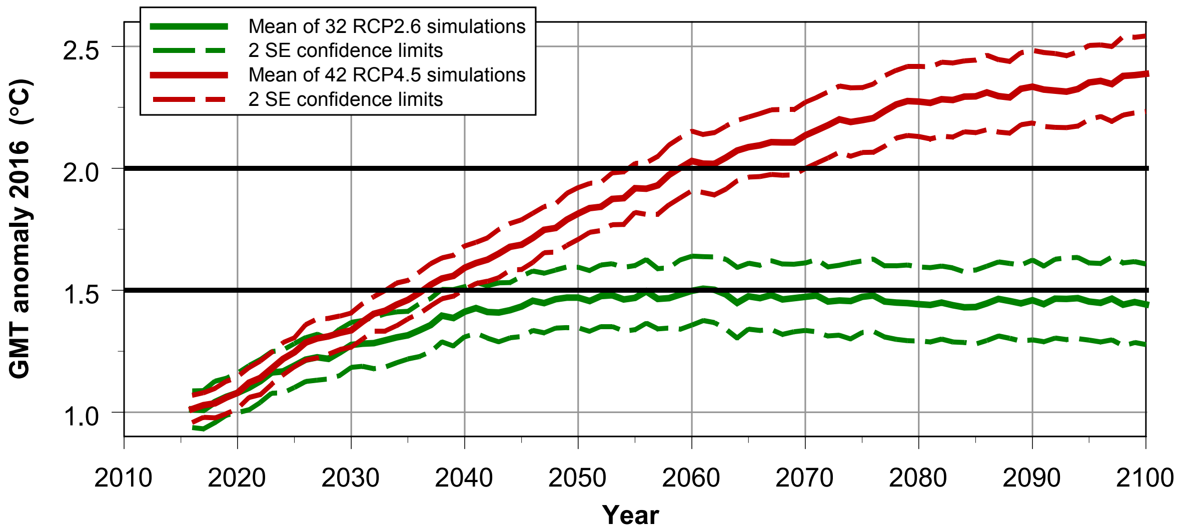


Figure 4. ~~Upper panel: histogram~~Histogram based on 106 GCM $\Delta_{i,2016}$ values~~.~~, relative to 1861. Mean value is 1.15 ± 0.~~47~~50 ºC (~~2-σ~~2σ). Individual GCM curves were smoothed by splines~~. Lower panel: natural variability based on 37 GCM simulations. Shown are mean~~ where the AR(1) parameter is chosen as φ = 0.28 (equivalent to 7 degrees of freedom), the low end of φ values ~~along with 2 standard errors. Period is 1861-2005~~within CMIP5 PiControl runs.



~~**Figure 5.** Mean GMT projections based on the RCP2.6 emission scenario (32 simulations, green lines) and based on the RCP4.5 emission scenario (42 simulations, red lines). Both mean curves are shifted such that 2016 values account for 1.01 °C. Uncertainty limits are based on 2 Standard Errors (SEs).~~

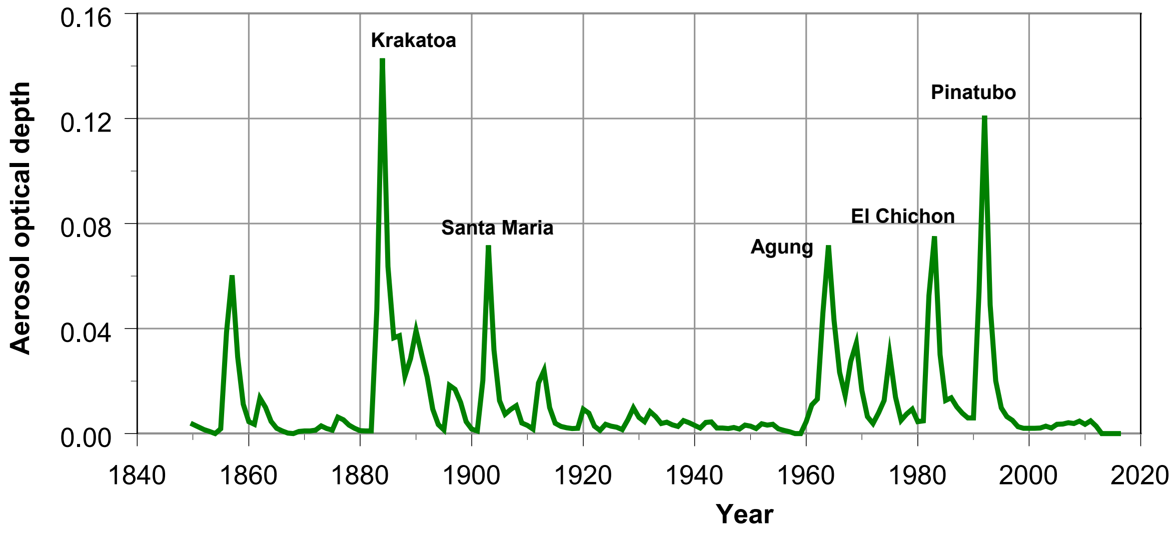


Figure 5. The AOD index series as introduced by Sato et al. (1993). Period is 1850-2016.

Code availability. IRW trends have been estimated by the TrendSpotter software. This software package is freely available from the first author. Splines have been estimated by the statistical package S-Plus, version 8.2. The scripts which are highly similar to R, are available from the first author.

Data availability. All five GMT datasets are open access and have been downloaded from the authors websites. All CMIP5 runs named in Section 2.1 were downloaded from the KNMI Climate Explorer website with one member per model (Trouet and Van Oldenborgh, 2013). The names of individual GCMs can be found there as well. Please see https://climexp.knmi.nl/cmip5_indices.cgi?id=someone@somewhere . Data used for the graphical presentations in this article can be gained from the first author.

The Supplement related to this article is available online

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

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