

## ***Interactive comment on “Signal detection in global mean temperatures after “Paris”: an uncertainty and sensitivity analysis” by Hans Visser et al.***

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### General Comments

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

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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 an 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).

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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).

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 on

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its 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.

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