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Interactive comment on "Agnotology: learning from mistakes" *by* R. E. Benestad et al.

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I appreciate the work that Kristoffer Rypdal has put into reading and commenting our paper. I have discussed similar questions before with him, and we have different views on the matter. That is fine. I realise that I need to explain more carefully in the paper why I'm not convinced by his arguments, and will revise the paper accordingly.

We agree on the point about the controversy about trends, and to us, this brings in the agnotological nature of this question and confusion reflecting the associated uncertainties. We also agree that in general, there may be several equally valid definition of trends.

Here, the question really is the whether the observed long-term change in the global mean temperature (let's call it a 'trend') can be explained in terms of natural/internal variations or if it requires an external cause. To be more specific, there are two papers

which look into this question (Cohn and Lins, 2005; Franzke, 2012), and they have used FARIMA type models or "phase scrambling" to represent the null-model against which the trends are assessed.

These approaches are suitable for simulating noise with memory, but we argue that they do not represent appropriate null-models because they are trained on data records which have been subject to both natural and anthropogenic forcings in the past. In fact, the proper approach would be to demonstrate that the total forcing (GHGs, solar, volcanic, etc) is devoid of similar long-term behaviour, and that the time series models are not 'fooled' by their temporal structure.

We can easily show that the total forcing data used for input to climate model simulations have this kind of behaviour (H$\sim$0.98).

We agree on the view that there are natural and internal variations, but I think we disagree on how the suitability of applying these models depends on the context. We also agree that short-memory may not be most appropriate for assessing trend, however, the null-models must not include forced response. We do have a good idea of what the current forcing is, and hence can account for these, so the missing part is the internal variability.

We also appreciate Rypdal's point about the use of the autocorrelation function (ACF) in studying long-term persistence (LTP), yet the autocorrelation is a central aspect of long-term persistence and power spectra. It is not in our interest to elaborate the exact models for the LTP here (we assume that the model development itself was thorough and state-of-the-art), as it suffices to note that the failure to account for the forced response invalidates their use in this context. If the null-models such as FARIMA and "phase scrambling" are to mimick the past data, they will be sensitive to autocorrelations. The estimation of their parameters are furthermore subject to sampling errors, and we argue that a substantial change in the ACF indicates that the null-models must account for the LPT-character in the forcing fields in order to provide reliable answers.

Our paper is not discussing Rypdal's own recent work submitted to Journal of Climate (which probably does not deserve to be in the list of cases for which we argue are flawed and lead to misguided conclusions), and we merely focus here on two published papers (Cohn and Lins, 2005; Franzke, 2012), for which we argue that the null-models do not represent the unforced variability because they were calibrated on past data which contain a response from external forcing. Hence, their use in hypothesis testing involve circular logic. This does not mean that we dismiss the presence of $\sim$60-year variations, and we certainly do not dismiss in advance Rypdal's work as "cultural production of ignorance".

I will propose the use of LTP models that takes care not to mix up the signal and noise. One strategy could be to use paeloclimatic records and data from the time before the industrial revolution. This, however, will contained forced response from natural drivers. Another approach could be to analyse time series where we do not expect a trend to be present, and yet represent the type of natural fluctuations that are expected to take place in the real world. One candidate would be data based on the barometric pressure, as we expect the atmospheric mass to be constant (e.g. AMO, ENSO or the AO).

It is furthermore not sufficient to look at one single index or series, but one needs to explain the comprehensive picture: we know that the global temperature is just one manifestation of a more general situation which involves ocean heat content, sea level, the crysosphere, and the hydrosphere.

References.

Cohn, T.A., Lins, H.F., 2005. Nature's style: Naturally trendy. Geophys. Res. Lett. 32.

Franzke, C., 2012. On the statistical significance of surface air temperature trends in the Eurasian Arctic region. Geophys. Res. Lett. 39, n/a–n/a.

———————————————————————————— Source code for addi-

tional analysis in R: ————

```
library(replicationDemos) library(longmemo) library(fracdiff)

# Examine the forcings:

an <- function(x) { # Anomalies - remove the annual cycle y <- coredata(x) m <- length(y)/12 dim(y) <- c(12,m) X <- zoo(c(y - rowMeans(y)),order.by=index(x)) invisible(X) }

data(forcings)

N <- 100 X <- as.matrix(forcings) totF <- zoo(rowSums(X[,2:11]),order.by=X[,1]) natF <- zoo(rowSums(X[,3:11]),order.by=X[,1])

f.Gn.tot <- WhittleEst(totF) confint(f.Gn.tot) f.Gn.tot # H = 0.9795453 # 2.5 % 97.5 % # H 0.8627394 1.096351

f.Gn.nat <- WhittleEst(natF) confint(f.Gn.nat) f.Gn.nat # H=0.9534198 # 2.5 % 97.5 % # H 0.8550056 1.088474

tot.fd <- fracdiff(totF,nar=10,nma=3) nat.fd <- fracdiff(natF,nar=10,nma=3)

par(bty="n") plot(totF,lwd=3) lines(natF,lwd=3,col="grey") for (i in 1:N) { ts.testF1 <- fracdiff.sim(length(totF), ar = tot.fd$ar, ma = tot.fd$ma, d = tot.fd$d) ts.testF0 <- fracdiff.sim(length(natF), ar = nat.fd$ar, ma = nat.fd$ma, d = nat.fd$d) x1 <- ts.testF1$series x0 <- ts.testF0$series x1 <- (x1 - mean(x1))/sd(x1) * sd(totF) + mean(totF) x0 <- (x0 - mean(x0))/sd(x0) * sd(natF) + mean(natF) F1 <- zoo(x1,order.by=index(totF)) lines(F1,lty=2,col="grey20") F0 <- zoo(x0,order.by=index(natF)) lines(F0,lty=2,col="grey70") } lines(totF,lwd=3) lines(natF,lwd=3,col="grey")

# Simulated global mean temperature:

data(echam5.0) f.Gn.gcm0 <- WhittleEst(an(echam5.0)) confint(f.Gn.gcm0) f.Gn.gcm0
```

```
# H = 0.9899276 # 2.5 % 97.5 #H 0.9651435 1.014712

data(echam5.1) f.Gn.gcm1 <- WhittleEst(an(echam5.1)) confint(f.Gn.gcm1) f.Gn.gcm1
# H = 0.989933 # 2.5 % 97.5 % # H 0.965149 1.014717

plot(an(echam5.1),lwd=3) lines(an(echam5.0),lwd=3,col="grey")

ghg <- fracdiff(an(echam5.1),nar=1,nma=1) ctl <- fracdiff(an(echam5.0),nar=1,nma=1)
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Interactive comment on Earth Syst. Dynam. Discuss., 4, 451, 2013.