## Supplementary Material to

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

In our study we have selected trend models which not only estimate a trend over time but also yield uncertainties for trend increments. However, this requirement appears to limit our model choices considerately. First, many methods are not statistical in nature, such as moving averages (Hansen et al., 2010; Smith et al., 2015; Fyfe et al., 2016), binomial filters (Morice et al., 2012), wavelets with scale dependencies (Lin and Franzke, 2015), EEMD decomposition (Wei et al., 2015; Yao et al., 2015) or linear trends based on stair-step averages with variable lengths (De Saedeleer, 2016). A historic example is given in figure SM.1, based on the work of Callender (1938).

Next to that, a number of methods do not generate estimates at the beginning and ending of the GMT series due to the dependence on 'windows'. Examples are moving averages, OLS linear trends with moving windows (Risbey et al., 2015; Marotzke and Forster, 2015) and the staircase approach by De Saedeleer (2016).

Trend models applied to GMT datasets can be categorized methods into three groups:

- Empirical models. These are trend models which are in principle data-based and may be steered by qualitative physical insights, such as the choice of a fixed window in combination with moving averages (Easterling and Wehner 2009; Hansen et al., 2010; Cowtan and Way, 2014; Roberts et al., 2015). Other trend models are OLS linear trends with varying sample periods (IPCC 2013 - Box 2.2, figure 1a; Karl et al., 2015; Rajaratnam et al., 2015), linear trends with change points (Cahill et al., 2015), binomial filters (Morice et al., 2012), splines (IPCC, 2013 - Box2.2, figure b), EEMD decomposition (Wei et al., 2015; Yao et al., 2015), structural time series models (Visser and Molenaar, 1995; Mills, 2006, 2010) and long-memory trend models (Lennartz and Bunde, 2009; Rea et al., 2011).
- Semi-empirical methods with stationary regressors. These methods are also data-based but physics may enter trend estimates by adding stationary climate indices in the context of regression models. An example is given by Forster and Rahmstorf (2011) who apply a linear regression model with three regressors (MEI, AOD and TSI). Other references are Visser and Molenaar (1995), Yao et al. (2015) and Trenberth (2015).
- Semi-empirical methods with non-stationary regressors. These models differ from semi-empirical models in that non-stationary regressors are used as well, such as global $CO_2$ emissions. Typical examples are given by Imbers et al. (2013) and Hawkins et al. (2017). An example where GMT data are treated *as regressor* to model global sea levels, has been given by Rahmstorf (2007).

A detailed description of methods is given in table SM.1. For background information please see Chandler and Scott (2011), Mudelsee (2014) and Visser et al. (2015).

From the range of available trend methods we selected trend methods from the group of empirical models, that is models (8) and (16), based on cubic spline functions and Structural Time series Models (STMs) and the Kalman filter, resp. As mentioned in the Introduction, the rationale for choosing these particular models from table 1 is twofold: (i) the models are flexible, this in contrast to methods based on linear trends, and (ii) the models contain full uncertainty information for trend estimates and trend increments. Based on these choices, models (3) - (6), (18) and (19) are less appropriate since they all assume linearity; models (1), (7), (9) - (15) and (17) are less appropriate since these methods are not statistical in nature. Next to that, models (1), (2) and (5) are not very well suited for tracking GMT signals since they assume fixed windows which implies that no trend estimates are available at the beginning and ending of the GMT series.

Furthermore, we decided not to use models from the semi-empirical approaches since relations in in the climate system are (highly) non-linear. Therefore, we preferred GMT curves derived from GCM simulations where these non-linearities and feedbacks are accounted for (see main text).

*Linear trend*

The first trend we select is a linear fit by ordinary least squares (OLS), 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 (IPCC 2013 - Ch. 2 Sup. Mat.). This correction is important since residuals are not white noise. Estimates are shown in figure SM.1

*The Integrated Random Walk*

The Integrated Random Walk (IRW) trend model is part of the wider class of Structural Time series Models (STMs) and reads as:

$$y_t = \mu_t + \varepsilon_t \quad \text{and} \quad \mu_t - 2\mu_{t-1} + \mu_{t-2} = \eta_t \tag{1}$$

where $y_t$ denotes a measurement at time t and $\mu_t$ the trend component. The terms $\eta_t$ and $\varepsilon_t$ are independent, normally distributed, white noise processes with zero mean. The variables $x_{1,t}$ and $x_{2,t}$ stand for the inclusion of explanatory variables (regressors). The OLS linear trend, as applied in models (3) - (6), is a *special case* of the IRW trend approach (arising if the noise process $\eta_t$ is set to zero). The IRW trend can therefore be seen as a natural extension of the straight line, in which the full uncertainty information is retained (Visser 2004; Visser et al., 2012; Visser et al., 2014). The noise variance $\eta_t$ can be seen as the flexibility parameter of the trend model and this noise variance can be optimized by Maximum Likelihood (ML) optimization.

Under the assumption of normality, the Kalman filter provides optimal estimates. In mathematical jargon, the filter yields the minimum mean square estimator (MMSE) of trend estimates. If the noise processes are not normally distributed, the filter generates the minimum mean square linear estimator (MMSLE). We refer to Harvey (1989), Durbin and Koopman (2001), and Chandler and Scott (2011 – Section 5.5) for details. Estimation results for the HadCRUT4 dataset are shown in figure 2.

*Cubic splines*

Smoothing splines have frequently been applied in environmental research. For a theoretical background we refer to Hastie et al. (2001) and Chandler and Scott (2011 - Section 4.1.3). An application of splines to GMT series has been given in IPCC (2013 - Box 2.2, figure 1). Smoothing splines are not statistical in nature and, thus, do not generate uncertainty estimates. However, uncertainty bands can be reconstructed by Monte Carlo (MC) simulation. A detailed procedure is given by Mudelsee (2014 - Section 3.3). We followed the approach of generating so-called surrogate series. The procedure is illustrated in figure 1.

The flexibility of the trend shown in the upper panel of figure 1, is chosen by expert judgment and closely resembles the smoothing spline shown in IPCC (2013 - Box 2.2, figure 1). However, this flexibility can also be steered by characterizing the correlation structure of residuals, that is the difference between the GMT series and the spline. This correlation structure can be found by quantifying the noise structure in natural variability of GCM simulations. Such simulations are available as ‘PiControl runs’ in the CMIP5 suit of simulations.

The correlation structure of natural variability can be quantified by estimating AutoRegressive Moving Average (ARMA) models to the individual control runs (Hunt 2011, Roberts et al. 2015). From the analysis of 20 PiControl runs we 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. We note that in some cases MA(1) or ARMA(1,1) models performed somewhat better as checked by comparing AIC values. Thus, the AR(1) is a compromise to ease the analysis. Next to that AR(1) models are widely applied in climate research (e.g., Mudelsee, 2014). Results are shown in figure SM.4 where we have chosen the endpoints of the φ range: 0.28 and 0.60.

**Table SM.1.** Summary of three groups of modeling approaches to global mean temperatures: (i) empirical, (ii) semi-empirical with stationary regressors, and (iii) semi-empirical with non-stationary regressors. In the fourth column the presence of uncertainties for rates of change is given ($[\mu_t - \mu_s] \pm ?$). The term 'not explicitly' means that uncertainties could be calculated in principle but not shown by the author(s).

| **Empirical approaches** | | | **$[\mu_t - \mu_s]$ ± ?** |
|---|---|---|---|
| 1 | Decadal aggregation, no trend | Callendar (1938 - figure SM.1), IPCC (2013 - figure SPM.1a & figure 2.19) | no |
| 2 | Moving averages with prescribed window length (varying from 5 to 50 years) | Callendar (1938), Easterling and Wehner (2009), Hansen et al. (2010, Figure 9), Kokic et al. (2014), Cowtan and Way (2014), Roberts et al. (2015) Smith et al. (2015), Fyfe et al. (2016) | no |
| 3 | OLS linear trends, with various corrections for correlated noise | Rajaratnam et al. (2015) | yes |
| 4 | OLS linear trends for varying sample periods, with corrections for correlated noise | IPCC (2013 - Ch.2: Box 2.2, figure 1a), Karl et al. (2015) | yes |
| 5 | OLS linear trend with moving windows | Risbey et al. (2014), Marotzke and Forster (2015) | only for $[\mu_t - \mu_{t-1}]$ |
| 6 | Linear trends with change points (CP) | Cahill et al. (2015), Rahmstorf et al. (2017) | not explicitly |
| 7 | Linear trends, based on stairstep averages with variable lengths | De Saedeleer (2016) | yes, by color graphs |
| 8 | Splines with Monte Carlo simulation | IPCC (2013 - Ch.2: Box 2.2, figure 1b), this article (with CMIP5-derived AR(1) noise) | yes |
| 9 | 21-term binomial filter | Morice et al. (2012) | no |
| 10 | Hodrick-Prescott and Butterworth low-pass filters | Mills (2006) | no |
| 11 | Smooth transition trends | Mills (2006) | no |
| 12 | Adaptive filtering with padding | Mann (2008) | no |

| | | | |
|---|---|---|---|
| 13 | Wavelets with scale-dependencies | Lin and Franzke (2015) | no |
| 14 | EEMD decomposition | Wei et al. (2015), Yao et al. (2015) | no |
| 15 | ARIMA decomposition | Mills (2006) | no |
| 16 | IRW trend model, part of the STM group of models | Visser and Molenaar (1995), Mills (2006, 2010), this article | yes |
| 17 | Long memory trend models | Lennartz and Bunde (2009), Rea et al. (2011) | no |
| **Semi-empirical approaches, stationary regressors** | | | |
| 18 | Linear for selected PDO regimes | Trenberth (2015) | no |
| 19 | Multiple regression models with linear trend, aerosols and solar | Forster and Rahmstorf (2011) | yes |
| 20 | EEMD decomposition with correlations PDO and AMO | Yao et al. (2015) | no |
| 21 | STMs with regressors | Visser and Molenaar (1995) | yes |
| **Semi-empirical approaches, non-stationary regressors** | | | |
| 22 | Regression models with GHGs, SOI, TSI, volcanic, ARMA noise | Kokic et al. (2014) | not explicitly |
| 23 | Cointegration, ARIMA, trend breaks, RF, GHGs | Kaufmann et al. (2006, 2013) | not explicitly |
| 24 | Regression models with ENSO, AMO, GHG, solar, aerosols and AR(1) noise | Imbers et al. (2013), reprinted in IPCC (2013 - Ch. 10) | not explicitly |
| 25 | Regression models with forcings from GHGs, aerosols, solar activity, volcanic activity and Nino3.4 as regressors | Hawkins et al. (2017, their approach 1) | yes |
| 26 | Scaling model with local temperature series as regressors (CET, De Bilt) | Hawkins et al. (2017, their approach 3) | yes |

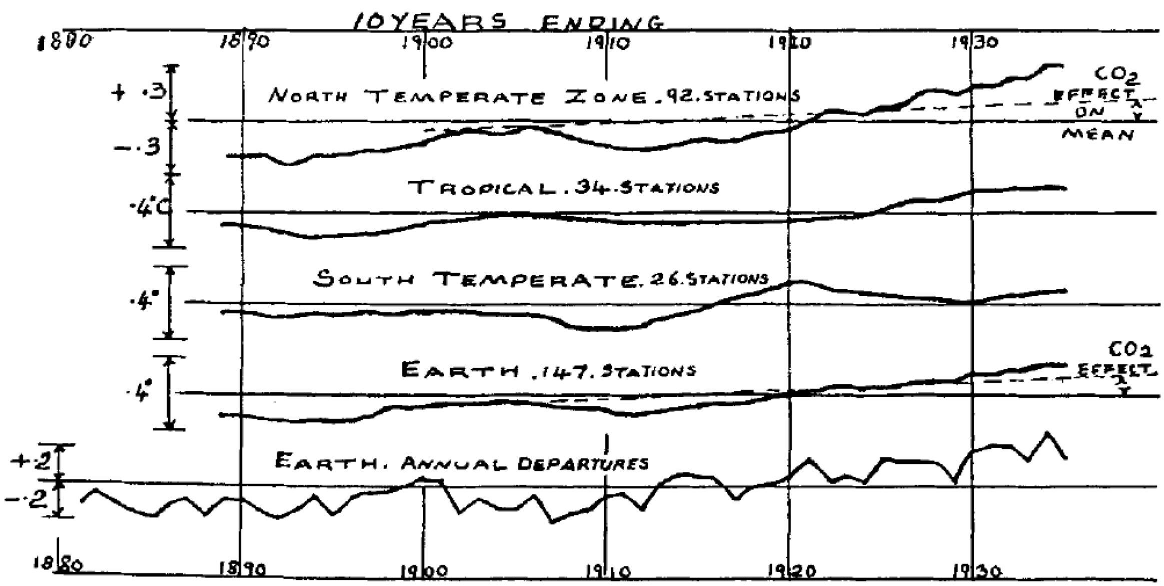


FIG. 4.—Temperature variations of the zones and of the earth. Ten-year moving departures from the mean, 1901-1930, °C.

**Figure SM.1** Graph taken from Callendar (1938). The fourth curve represents his GMT series, based on temperature data of 147 stations. To highlight smooth changes over time he used moving averages with a window of 10 years. It is interesting to note that he also addresses the specific effect of $CO_2$ emissions on global temperatures.

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