Multiple regression analysis of anthropogenic and heliogenic climate drivers, and some cautious forecasts

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**ABSTRACT**

The two main drivers of climate change on sub-Milankovic time scales are re-assessed by means of a multiple regression analysis. Evaluating linear combinations of the logarithm of carbon dioxide concentration and the geomagnetic aa-index as a proxy for solar activity, we reproduce the sea surface temperature (HadSST) since the middle of the 19th century with an adjusted $R^2$ value of around 87 per cent for a climate sensitivity (of TCR type) in the range of 0.6 K until 1.6 K per doubling of CO$_2$. The solution of the regression is quite sensitive: when including data from the last decade, the simultaneous occurrence of a strong El Niño on one side and low aa-values on the other side lead to a preponderance of solutions with relatively high climate sensitivities around 1.6 K. If those later data are excluded, the regression leads to a significantly higher weight of the aa-index and a correspondingly lower climate sensitivity going down to 0.6 K. The plausibility of such low values is discussed in view of recent experimental and satellite-borne measurements. We argue that a further decade of data collection will be needed to allow for a reliable distinction between low and high sensitivity values. Based on recent ideas about a quasi-deterministic planetary synchronization of the solar dynamo, we make a first attempt to predict the aa-index and the resulting temperature anomaly for various typical CO$_2$ scenarios. Even for the highest climate sensitivities, and an unabated linear CO$_2$ increase, we predict only a mild additional temperature rise of around 1 K until the end of the century, while for the lower values an imminent temperature drop in the near future, followed by a rather flat temperature curve, is prognosticated.

**1. Introduction**

As heir of its great pioneers Arrhenius (1906) and Calendar (1938), modern climate science (Knutti et al., 2017) has been surprisingly unsuccessful in narrowing down its most prominent parameter - equilibrium climate sensitivity (ECS) - from the ample range 1.5 K-4.5 K (per 2xCO$_2$) as already given in the report by Charney (1979). This sobering scientific yield is often discussed in terms of various interfering socio-scientific and political factors (Hart, 2015; Lindzen, 2020; Vahrenholt and Lüning, 2020). Yet, in addition to those more “subjective” reasons for climate science to be that unsettled, there are at least two “objective” ones: the lack of precise and reliable experimental measurements of the climate sensitivity until very recently, and the unsatisfying state of understanding the complementary solar influence on the climate. Certainly, a couple of mechanisms have been proposed (Hoyt and Schatten, 1993; Gray et al., 2010; Lean, 2010) that could significantly surmount the meager 0.1 per cent variation of the total solar irradiance (TSI) which is routinely used as an argument against any discernible solar impact on the climate. Among those mechanisms, the following ones figure most prominently: the comparable large variation of the UV component with its influence on the ozone layer and the resulting stratospheric-tropospheric coupling (Labitzke and van Loon, 1988; Haigh, 1994; Soon, Posmentier and Baliunas, 2000; Georgieva et al., 2012; Silverman et al., 2018; Veretenenko and Ogurtsov, 2020); the effects of solar magnetic field modulated cosmic rays on aerosols and clouds (Svensmark and Friis-Christensen, 1997; Soon et al., 2000; Shaviv and Veizer, 2003; Svensmark et al., 2017); downward winds following geomagnetic storms in the polar caps of the thermosphere, penetrating stratosphere and troposphere (Bucha and Bucha, 1998); solar wind’s impact on the global electric current (Tinsley, 2000, 2008); and the (UV) radiation effects on the growth of oceanic phytoplankton (Vos et al., 2004) which, in turn, produces dimethylsulphide, a major source of cloud-condensation nuclei (Charlson et al., 1987). But even the very TSI was claimed (Hoyt and Schatten, 1993; Scafetta and Willson, 2014; Egorova et al., 2018; Connolly et al., 2021) to have risen much more steeply since the Little Ice Age than assumed in the conservative estimations by Wang, Lean and Sheeley (2005); Steinilhber, Beer and Fröhlich (2009); Krivova, Vieira and Solanki (2010). While neither of those mechanisms can presently be considered as conclusively proven (Solanki et al., 2002; Courtillot et al., 2007; Gray et al., 2010), they all together entail significantly more potential for solar influence on the terrestrial climate than was discussed on the corresponding one and a half pages of Bindoff et al. (2013).

In view of illusionary claims (Cook et al., 2016) of an overwhelming scientific consensus on this complex and vividly debated research topic, and the severe political consequences drawn from it, we reiterate here Eugene Parker’s prophetic warning (Parker, 1999) that “…it is essential to check to what extent the facts support these conclusions before embarking on drastic, perilous and perhaps misguided plans for global action”. We also agree with his “…inescapable conclusion (…) that we will have to know a lot more about the sun and the terrestrial atmosphere before we can understand the na-
titure of contemporary changes in climate”.

Thus motivated, and also provoked by recent experimental (Laubereau and Iglev, 2013) and satellite-borne measurements (Feldman et al., 2015; Rentsch, 2019) which pointed consistently to a rather low climate sensitivity, we make here another attempt to quantify the respective shares of anthropogenic and heliogenic climate drivers. Specifically, we resume the long tradition of correlating terrestrial temperature data with some proxies of solar activity, as pioneered by Reid (1987) for the sunspot numbers, by Friis-Christensen and Lassen (1991); Solheim, Stordahl and Humlum (2015) for the solar cycle length, and by Cliver, Boraiakoff and Feynman (1998); Mutti and Shah (2011) for the geomagnetic aa-index (Mayaud, 1972). Our work builds strongly on the two latter papers, which - based on data ending in 1990 and 2007, respectively - had found empirical correlation coefficients between the aa-index and temperature variations of up to 0.95. Notwithstanding some doubts regarding their statistical validity (Love et al., 2011), such remarkably high correlations might rise the provocative question of whether any sort of greenhouse effect is still needed at all to explain the (undisputed) global warming over the last one and a half centuries. More recently, however, any prospects for such a reversed simplification were dimmed by the fact that the latest decline of the aa-index was not accompanied by a corresponding drop of temperature. By contrast, the latter remained rather constant during the first one and a half decades of the 21st century (the “hiatus”), and even increased with the recent strong El Niño events.

This paper aims at supplementing the previous work of Cliver, Boraiakoff and Feynman (1998); Pulkkinen et al. (2001); Mutti and Shah (2011); Zherebtsov et al. (2019) by taking seriously into account both observations: the nearly perfect correlation of solar activity with temperature over about 150 years, and the notable divergence between those quantities during the last two decades. Using a multiple regression analysis, quite similar to that of Soon, Posmentier and Baliunas (1996), but with the time series of the aa-index as the second independent variable (in addition to the logarithm of CO$_2$ concentration), we will show that the temperature variation since the middle of the 19th century can be reproduced with an (adjusted) $R^2$ value around 87 per cent. Such a goodness-of-fit is achieved for specific combinations of the weights of the aa-index and of CO$_2$ that form a nearly linear function in their two-dimensional parameter space. Best results are obtained for a climate sensitivity in the range between 0.6 K-1.6 K (per 2x CO$_2$), with a delicate dependence on whether the latest data are included or not. Derived from empirical variations on the (multi-)decadal time scale, this climate sensitivity should be interpreted as a transient climate response (TCR), rather than an ECS. Our range corresponds well with that of Lewis and Curry (2018), 0.8 K-1.3 K, but is appreciably lower than the “official” 1.0 K-2.5 K range (Knutti et al., 2017). The lower edge of our estimation will be plausibilized by recent experimental (Laubereau and Iglev, 2013) and satellite-borne measurements (Feldman et al., 2015; Rentsch, 2019). It is also quite close, although still higher, than the particularly low estimate of less than 0.44 K, as advocated by Soon, Conolly and Conolly (2015) after comparing exclusively rural temperature data in the Northern hemisphere with the TSI. The upper edge, in turn, is not far from the spectroscopy-based estimation by Wijngaarden and Happer (2020).

With the complementary share of the Sun for global warming thus reaching values between 30 and 70 per cent, any climate forecast will require a descent prediction of solar activity. This leads us into yet another controversial playing field, viz., the predictability of the solar dynamo. While the existence of the short-term Schwabe/Hale cycles is a truism in the solar physics community, the existence and/or stability of the mid-term Gleissberg and Suess-de Vries cycles are already controversially discussed, and there is even more uncertainty about long-term variations such as the Eddy and Hallstatt “cycles”, which are closely related to the sequence of Bond events (Bond et al., 2001).

In a series of recent papers (Stefani et al., 2016, 2017, 2018; Stefani, Giesecke and Weier, 2019; Stefani et al., 2020a,b; Stefani, Stepanov and Weier, 2020), we have tried to develop a self-consistent explanation of those short-, medium- and long-term solar cycles in terms of synchronyization by planetary motions. According to our present understanding, the surprisingly phase-stable 22.14-year Hale cycle (Vos et al., 2004; Stefani et al., 2020b) results from parametric resonance of a conventional $\alpha - \Omega$ dynamo with an oscillatory part of the helical turbulence parameter $\alpha$ that is thought to be synchronized by the 11.07-year spring-tide periodicity of the three tidally dominant planets Venus, Earth, and Jupiter (Stefani et al., 2016, 2017, 2018; Stefani, Giesecke and Weier, 2019). The medium-term Suess-de Vries cycle (specified to 193 years in our model) emerges then as a beat period between the basic 22.14-year Hale cycle and some (yet not well understood) spin-orbit coupling connected with the motion of the Sun around the barycenter of the solar system that is governed by the 19.86-year synodes of Jupiter and Saturn (Stefani et al., 2020a; Stefani, Stepanov and Weier, 2020). Closely related to this, some Gleissberg-type cycles appear as nonlinear beat effects and/or from perturbations of Sun’s orbital motion from other synodes of the Jovian planets. Finally, the long-term variations on the millennial time-scale (Bond events) arise as chaotic transitions between regular and irregular episodes of the solar dynamo (Stefani, Stepanov and Weier, 2020), in close analogy with the super-modulation concept introduced by Weiss and Tobias (2016).

Being well aware of the conjectural nature of this synchronized solar dynamo model, we nevertheless dare to make a cautious prediction of the aa-index for the next 130 years, based on some simple 3-frequency fits to the aa-index data over the last 170 years. While our choice for three frequencies is motivated by the dominance of one Suess-de Vries and two Gleissberg-type cycles, we employ different versions of fixing or relaxing their frequencies, which leads to a certain variety of forecasts. A common feature of all of them is, however, a noticeable decline of solar activity until 2100, and a recovery in the 22nd century. Those predictions for
the aa-index are then combined with three different scenarios of CO$_2$ increase, including an unfettered annual increase by 2.5 ppm and two further scenarios based on hypothetical decarbonization schemes. The 3 × 3 models thus obtained are then blended with the different combinations of weights for the aa-index and CO$_2$ as derived before in the regression analysis. For the “hottest” scenario we predict an additional temperature increase until 2100 of less than 1 K, while all other combinations lead to less warming, partly even to some imminent cooling, followed by a rather flat behaviour in which decreasing solar activity and a mildly increasing trend from CO$_2$ compensate each other to a large extend.

2. Multiple regression analysis

In this section, we perform a multiple (or better: double) regression analysis of the temperature data (dependent data) on the geomagnetic aa-index and the logarithm of the CO$_2$ (independent data). We do this in an intuitive and easily reproducible way by showing the fraction of variance unexplained (FVU), i.e. the ratio of the residual sum of squares to the total sum of squares, whose minimum is then identified. From those FVU’s we will derive the corresponding $R^2$ value, both in its usual and in its adjusted variant. Let us start, however, with a description of our data base.

2.1. Data

While reliable CO$_2$ data are available for quite a long time, we decided to restrict our data base to the time from the middle of the 19th century, for which both temperature data and the aa-index are readily available.

2.1.1. Temperature data

There are quite a number of different temperature series which might be considered as basis for regression analysis. In order to make contact with the work of Mufti and Shah (2011), we decided to use the Hadley Centre Sea Surface Temperature (HadSST) data set in its updated version HadSST.4.0.0.0, available from www.metoffice.gov.uk, which provides us the sea surface temperature anomaly from 1850 until 2018, relative to the 1961-1990 average (Kennedy et al., 2019). Actually, these data are not gravely different from the combined sea/land surface temperature (HadCRUT), apart from some slight but systematic divergence during the last two decades. At this point, our preference for HadSST is also supported by their better agreement with the UAH satellite data (starting only in 1978) with their significantly broader spatial coverage.

The HadSST data are shown as open circles in Fig. 1a, together with two exemplary centered moving averages with windows 11 years (full line) and 23 years (dashed line), which we will frequently refer to in this paper. These curves show the typical temporal structure comprising a slow decay between 1850 and 1905, a rather steep rise between 1905 until 1940, again a mild decay until 1970, followed by a steep increase until 1998. As for the last two decades, we first see the “hiatus” between 1999 and 2014, being then overwhelmed by the recent strong El Niño events. We will come back to those latest years further below.

2.1.2. aa-index data

The aa-index measures the amplitude of global geomagnetic activity during 3-hour intervals at two antipodal magnetic observatories, normalized to geomagnetic latitude ±50° (Mayaud, 1972). Inspired by the work of Cliver, Boriskoff and Feynman (1998) and Mufti and Shah (2011) who pointed out the remarkable correlation of up to 0.95 between (time averaged) temperature anomalies and the geomagnetic aa-index, we will use the latter data as a proxy for solar activity. A viable alternative would have been to use sunspot data, or various versions of the TSI, as exemplified by Soon, Conolly and Conolly (2015). Given, on one side, their generally high correlation with sunspots numbers (Cliver, Boriskoff and Bounar, 1998), and, on the other side, their high reliability based on precise measurement down to 1844 (which avoids some ambiguities concerning the correct variability of the TSI (Soon, Conolly and Conolly, 2015; Connolly et al., 2021)), we focus here exclusively on the aa-index, leaving...
multiple regressions analyses with other solar data to future work.

The bulk of the aa-index data, between 1868-2010, was obtained from ftp.ngdc.noaa.gov. As in Mufti and Shah (2011), the early segment between 1844 and 1867 was taken from Nevanlinna and Kataja (1993). The latest segment, between 2011 and 2018, was obtained from www.geomag.bgs.ac.uk. All these aa-index data were annually averaged. Together with their 11-year and 23-year moving averages, the annual aa data are shown in Fig 1b. Already by visual inspection, between 1850 and 1990 we observe a remarkable similarity of their shape with that of temperature, while after 1995 the aa-index steeply declines, whereas the temperature continues to increase. We will have more to say on that divergence further below.

2.1.3. CO₂ data

The CO₂ concentration data until 2014 were obtained from iac.ethz.ch/CMIP6/. The four additional data points from 2015 and 2018 were taken from the website www.co2.earth. Together with their 11-year and 23-year moving averages the annual data is shown on Fig. 1c.

2.2. Are we dealing with the most relevant data?

After having presented the data that actually will be used in the remainder of this paper, we make a short break to consider whether these are indeed the most relevant data. Our reliance on the aa-index might indeed be questioned, as other studies (Vahrenholt and Lüning, 2020) have claimed a strong temperature dependence on ocean-atmosphere variations, such as the Pacific Decadal Oscillation (PDO) (Man-tua and Hare, 2002) and the Atlantic Multidecadal Oscillation (AMO) (Wyatt, Kravtsov and Tsonis, 2012), with their similar time structures governed by a sort of 60-70-year “cyclicity”. On the other hand, there is also evidence for direct correlations of the aa-index with regional features, such as the Northern Annular Mode (NAM) (Roy et al., 2016). In order to make contact with these possible links, in Fig. 2 we show exemplarily the 23-year averages of the AMO and the PDO data, together with the previously shown aa-index (appropriately shifted and scaled) and ΔT. It is clearly seen that the aa-index and ΔT have a particularly parallel behaviour until 1990, say. There is also some similarity with AMO, while PDO has a different time dependence.

In Table 1 we quantify those relationships in terms of the empirical correlation coefficients r for different data combinations. We do so for different end points of the time interval, namely 2008, 2003 and 1998 (note that these are the centered points of the last moving average interval, into which the annual data from up to 11 years later are included). Our first observation is that both the correlations of CO₂ and of the aa-index with ΔT have similar r-values in the order of 0.9, which is a first indication for their comparable influences. However, there are some subtleties to discern: the correlation for CO₂ acquires its highest value (r = 0.916) for the full time interval, and decreases slightly to 0.869 when the time interval is shortened by 10 years. By contrast, the correlation of aa-index with ΔT has only a value r = 0.8 for the full interval, but grows to 0.95 for the restricted interval. This latter result confirms that of Mufti and Shah (2011) obtained for a similar period, and by Cliver, Borriakoff and Feynman (1998) for a still shorter interval. Given the visual similarity of AMO and ΔT in Fig. 2, their correlation is surprisingly small, but would increase if the overall upward trend of ΔT were subtracted. The PDO seems to show no relevant correlation with ΔT.

In Fig. 3 we show some further correlation dependencies, this time on the time shift δt between the two respective data, which possibly could give a clue about intrinsic delay effects. One curve shows the correlation between the aa-index and the AMO index, whereby the aa-index at earlier times is correlated with AMO at later times. While the correlation is not large, we see at least a clear maximum at δt = 11 years, as if the AMO-index lagged behind the aa-index by this delay time. The second curve shows the corresponding relationship between ΔT and AMO, with the correlation reaching a maximum of 0.3 at δt = 6 years. While this looks like a sort of inverted causality (AMO lags behind ΔT) it could simply mean that ΔT is indeed governed by the aa-index, which also determines the AMO-index at later times.

We also show the corresponding curves for aa-index and

| Correlated data | 1867-2008 | 1867-2003 | 1867-1998 |
|-----------------|-----------|-----------|-----------|
| CO₂ with ΔT     | 0.916     | 0.894     | 0.869     |
| aa with ΔT      | 0.806     | 0.900     | 0.950     |
| AMO with ΔT     | 0.260     | 0.164     | 0.106     |
| aa with AMO     | -0.015    | -0.013    | -0.028    |
| PDO with ΔT     | -0.131    | -0.001    | 0.126     |
| aa with PDO     | 0.050     | 0.049     | 0.074     |
\[ \Delta T, \text{ in the two versions for the full time interval and the} \]
\[ 10\text{-year shortened one. For the full interval, } r \text{ starts at the} \]
\[ 0.8 \text{ for } \Delta t = 0, \text{ and reaches a maximum of 0.915 for } \]
\[ \Delta t = 10 \text{ years. While on face value this seems to indicate a} \]
\[ 10\text{-years lag between the aa-index and } \Delta T, \text{ it is more likely} \]
\[ connected with the implied cancellation of the last 10 years} \]
\[ during which the aa-index was decreasing. In order to test} \]
\[ this, in the second curve we have omitted the last 10 years of} \]
\[ both data completely. Here we find an } r = 0.95 \text{ at } \Delta t = 0, \]
\[ which still increases to a maximum of } r = 0.962 \text{ at } \Delta t = 3 \text{ yr.} \]
\[ This sounds indeed like a reasonable time delay between} \]
\[ cause (aa-index) and effect } (\Delta T).} \]

2.3. Regression

After those preliminaries, we start now with the multiple regression analysis. For that purpose, we model the temperature data using the ansatz

\[ \Delta T_{\text{model}} = w_{\text{aa}} \cdot \text{aa} + w_{\text{CO}_2} \cdot \log_2(\text{CO}_2/280 \text{ ppm}) \]

with the respective weights} \[ w_{\text{aa}} \text{ and } w_{\text{CO}_2} \text{ for solar and CO}_2 \]
\[ forcing, and compare them with the measured data } \Delta T_{\text{meas}} \text{.} \]
\[ This procedure is very similar to that of Soon, Posmentier and Baliunas (1996) who had used though, instead of aa, the} \]
\[ length of the sunspot cycle, the averaged sunspot number,} \]
\[ and a more complicated composite as proxies of solar irradiance.} \]
\[ While Soon, Posmentier and Baliunas (1996) translate} \[ all these proxies into some percentage of TSI variation (fixing their “stretching factor” by the best fit of modeled and} \]
\[ observed temperature history), we stick here to the somewhat} \[ weird unit K/\text{mT for } w_{\text{aa}} \text{ without specifying in detail the} \]
\[ physical mechanism(s) underlying the solar-climate connection.} \]
\[ In case of a dominant Svensmark effect, say, this unit} \[ would indeed have an intuitive physical meaning, whereas} \]
\[ in case of a dominant UV radiation impact on the ozone layer} \[ (plus subsequent coupling of stratosphere and troposphere),} \]
\[ it would just represent a very indirect, co-responding proxy.} \]
\[ One of the non-trivial questions to address beforehand is which} \[ time average should be used. Evidently, the structures of} \]
\[ temporal fluctuation of the three data are quite different.} \]
\[ As for the independent data, the CO}_2 \text{ curve is the smoothest} \]
\[ one, so the results of any regression will be widely independent} \]
\[ on the widths of the averaging window. Much more} \]
\[ fluctuating is the aa-index, with its dominant 11-year periodicity} \[ which had been taken into account, though in different ways,} \]
\[ by Cliver, Boriakoff and Feynman (1998) and Mufti and Shah (2011).} \]
\[ Cliver, Boriakoff and Feynman (1998) have been working both} \]
\[ with a decadal average and the so-called aa-baseline } (aa_{\text{min}}), \text{i.e.} \]
\[ the minimum value which generally occurs within one year following the sunspot minima. The empirical correlation coefficient of } r = 0.95 \text{ between } aa_{\text{min}} \text{ and the 11-year average temperature turned out to be even better than that between two decadal averages} (r = 0.9).} \]
\[ Mufti and Shah (2011), in turn, worked with 11-year and 23-year averages, which will also serve as a first guidance for our study, though later we will consider the dependence on the widths of the averaging windows in a more quantitative manner.} \]
\[ The dependent variable, i.e. } \Delta T, \text{ is also characterized by} \]
\[ significant fluctuations, although not with the dominant 11-year periodicity of the aa-index whose climatic impact is} \]
\[ thought to be smoothed out by the large thermal inertia of the} \]
\[ oceans. By contrast, } \Delta T \text{ is strongly influenced by short-term} \]
\[ variations due to the El Niño-Southern Oscillation (ENSO} \[ and volcanism, which had been considered in the multiple} \]
\[ regression analysis of Lean and Rind (2008). Our deliberate} \]
\[ neglect of those short-term variations, and the focus on} \]
\[ (multi-)decadal variations, thus requires some averaging on the} \]
\[ decadal time scale.} \]
\[ In addition to that distinction between different averaging} \]
\[ windows, we will also consider three cases with different} \]
\[ end-years of the utilized data. In the first case, we take into} \]
\[ account all data until 2018. As evident from Fig. 1, it is in} \]
\[ particular the last decade which shows the strongest discrepancy} \]
\[ between the decreasing aa-index and the partly stagnant} \]
\[ (“hiatus”), partly increasing temperature (in particular during} \]
\[ the last El Niño dominated years). Hence, in order to} \]
\[ assess the specifics of this divergence between the two data,} \]
\[ and to compare them with the high correlations found by} \]
\[ Cliver, Boriakoff and Feynman (1998) and Mufti and Shah} \[ (2011), we will also consider two shortened periods with end} \]
\[ years 2013 and 2008, respectively.} \]
\[ Let us start, however, with the full data ending in 2018.} \]
\[ For the two moving average windows (abbreviated henceforth as} \]
\[ “MAW”) of 11 years and 23 years, Figs. 4a and} \]
\[ 4b show the fraction of variance unexplained } (\text{FVU}), \text{i.e.} \]
\[ the ratio of the residual sum of squares to the total sum of} \]
\[ squares, in dependence on the respective weights of the aa-
index ($w_{aa}$, on the abscissa) and the logarithm of CO$_2$ ($w_{CO_2}$, on the ordinate axis). The latter value provides us immediately with a sort of instantaneous climate sensitivity of the TCR type. The minimum $F_{VU_{min}} = 0.107$ is obtained for the weights’ combination $w_{aa} = 0.011$ K/nT and $w_{CO_2} = 1.72$ K in case of $MAW = 11$ years, and $F_{VU_{min}} = 0.102$ is obtained for $w_{aa} = 0.0162$ K/nT and $w_{CO_2} = 1.54$ K in case of $MAW = 23$ years. From the ellipse-shaped contour plots of $FVU$ we see that those minima reflect a dominating influence of CO$_2$ over the aa-index. The two red curves in Fig. 6c show now the corresponding temperature reconstructions based on those optimized values of $w_{aa}$ and $w_{CO_2}$, for $MAW = 11$ years (full line) and for $MAW = 23$ years (dashed line). For both lines we obtain a reasonable fit of the general upward trend of $\Delta T$, but a poor reconstruction of its oscillatory features. This clearly corresponds to the comparable high value of $w_{CO_2}$ compared to that of $w_{aa}$. Any putative higher share of $w_{aa}$ would lead to a drastic decrease of the reconstructed $\Delta T$ for the last two decades, resulting in forbiddingly large $FVU$ values when compared with the relatively high observed $\Delta T$ in this late period.

This brings us to the question of what happens if we exclude the latest “hot” 5 years (with their strong El Niño influence), thus restricting the date until 2013 only. The corresponding results are shown in Fig. 5. Obviously, the optimal weights’ combination now shifts away from CO$_2$ to aa, with values $w_{aa} = 0.0145$ K/nT and $w_{CO_2} = 1.56$ K for $MAW = 11$ years and $w_{aa} = 0.0232$ K/nT and $w_{CO_2} = 1.21$ K for $MAW = 23$ years. Evidently, the resulting (green) temperature reconstruction curves in Fig. 5c appear now more oscillatory.

In Fig. 6 we show the corresponding plots for the case that we use the end year 2008, which basically corresponds to the database of Mufti and Shah (2011) (2007 in their case). Evidently, the regression for this shortened segment leads to a significantly stronger weight for the aa-index. The minimum $FVU$ is than obtained at $w_{aa} = 0.0190$ K/nT and $w_{CO_2} = 1.33$ K for $MAW = 11$ years, and at $w_{aa} = 0.0305$ K/nT and $w_{CO_2} = 0.80$ K for $MAW = 23$ years. Due to the dominance of $w_{aa}$ the (blue) reconstruction curves in Fig. 6c (in particular that for $MAW = 23$ years) show now a significant oscillatory behaviour.

While those three examples provide a first illustration of how sensible the solution of the regression reacts on the choice of the end year, and the widths of the MAW, the latter dependence will now be studied in more detail. For that purpose, we analyze first the coefficient of determination $R^2$, which is related to the previously used $FVU$ according to $R^2 = 1 - FVU$. The corresponding dashed curves in Fig. 7a have a rather universal shape, starting from values of 0.78...0.84 for $MAW = 3$ years to around 0.94 for $MAW = 39$ years. The monotonic increase of $R^2$, which at first glance might suggest the use of high values of MAW, should be treated with caution. The reason is that a significant share of this increase is just due to the increasing ratio of explanatory terms $p$ (in our case two: $w_{aa}$ and $w_{CO_2}$) to the “honest” number of data points $n$. The latter is not identical to the number of considered years, $N_y$, but - due to the moving average - approximately equal to $N_y/MAW$ (better estimates, using the lag-one auto-correlation $r^1$ (Love et al., 2011), might still be worthwhile). To correct for this effect, we use the so-called adjusted $R^2$, which is, in general, $R^2_{adj} = 1 - FVU \times (n - 1)/(n - p - 1)$, hence in our special case $R^2_{adj} = 1 - FVU \times (N_y/MAW - 1)/(N_y/MAW - 3)$. This adjusted $R^2$, as a much more telling coefficient of determination than $R^2$, is shown with full lines in Fig. 7a. The monotonic increase still seen for $R^2$ gives now way to a more structured curve. For the green (data until 2013) and the blue curve (data until 2008) we observe a local (if shallow)
maximum around MAW = 25 years. The red curve (data until 2018) has a very flat plateau between MAW = 11 and MAW = 27 years, with an extremely shallow maximum at MAW = 25 years. We consider those local maxima around MAW = 25 years (MAW = 27 years for the blue curve) as a sort of best fits. Although $R^2$ still rises slightly for the highest MAW values, the corresponding number of explained variables becomes then too small to allow for a decent reconstruction of the structure of the $\Delta T$ curve.

The corresponding dependencies for $w_{aa}$ and $w_{CO_2}$ are shown in Fig. 7b and 7c, respectively. Fig. 7d depicts the same solutions in the two-dimensional parameter space. In this representation, all three curves (red, green and blue) form a sort of common, weakly bent line which appears to connect the extremal values of $w_{CO_2} \approx 1.9$ K on the ordinate axis and $w_{aa} \approx 0.04$ K/nT on the abscissa. This common line is just a reflection of the ellipsoidal shape of the FVU as shown in Figs. 3-5 which, in turn, just reflects the significant ill-posedness of the underlying inverse problem. To put it differently: due to the high correlation coefficients of $\Delta T$ both with $CO_2$ as well as with the aa-index, the separate shares of the two ingredients are very hard to determine.

However questionable our fixation on the shallow maxima at MAW $\approx 25$ years might ever be: Fig. 7 also proves that any alternative choice of a higher MAW would not change the final solution drastically. In either case, both $w_{aa}$ and
$w_{\text{CO}_2}$ converge to a close-by value. Much more decisive is the distinction between the differently colored curves: for $w_{\text{CO}_2}$, they give us results somewhere between 0.6 K and 1.6 K (in the latter case we take into account the particular flatness of the maximum, which in reality might also lay at slightly lower values of $\text{MAW}$).

Actually, this is again a frustratingly wide range of values. As said, it reflects the ill-posedness of the underlying inverse problem, whose non-uniqueness leads also to a high sensitivity on neglected factors, such as ENSO, AMO, PDO, volcanic aerosols. At any rate, the temperature development during the next decade will be key: if it continues to grow we will end up at the higher end of the $w_{\text{CO}_2}$ range. In case of some imminent drop it will point to lower values of $w_{\text{CO}_2}$.

In Fig. 8 we show all three temperature reconstructions with the optimal combinations of $w_{\text{aa}}$ and $w_{\text{CO}_2}$ taken from Fig. 7, together with the original $\Delta T$ data, averaged over 25 years. The dashed segments of the green and blue curves correspond to the later time segments which were deliberately omitted in the corresponding regression analysis. As expected, they exhibit an increasing divergence from the original $\Delta T$ data. On the other hand, from the red via the green to the blue curve we also observe an improved reconstruction of the oscillatory behaviour of $\Delta T$. This is the crux of our problem: the better the reconstruction for the years until 1995, say, the larger is the deviation for the latest two decades. We will need approximately one decade of more data to being able to identify the best solution. For the green or blue lines to be valid, a significant temperature drop in the nearest future will be unavoidable.

### 2.4. Some plausibility checks and comparisons

Before entering the field of predictions, we would like to check the plausibility of the obtained estimates, in particular those at the lower end of the range. For that purpose we will shortly discuss the results of three papers which are based on experimental and satellite-borne measurements.

Combining measurements at optically thick samples of CO$_2$ with a 5-layer numerical model for the greenhouse effect, Laubereau and Iglev (2013) had derived a temperature increase of 0.26 K for the 290 ppm to 385 ppm increase between 1880 and 2010, which results in a climate sensitivity of 0.636 K (per 2×CO$_2$).

Feldman et al. (2015) had published results from two clear-sky surface radiative forcing measurements with the Atmospheric Emitted Radiance Interferometer (AERI) between 2000 and 2010, when the CO$_2$ concentration increased (according to their estimate) by 22 ppm. They observed an increase of 0.2 W/m$^2$ during this decade, which amounts to 2.4 W/m$^2$ (per 2×CO$_2$). With the usual zero-feedback sensitivity parameter of 3.7 K/(W/m$^2$), this translates into 0.65 K (per 2×CO$_2$). If we were to use the modified value of 3.2 K/(W/m$^2$) (which allows for variations with latitude (Soden and Held, 2006)), we get 0.75 K.

Later on, Rentsch (2019) found a similar result by analyzing outgoing radiation under night-time, cloud-clear conditions. The CO$_2$ rise from 373 ppm to 410 ppm led to a

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**Figure 7:** Results of the regression in dependence on the width of the moving average window (MAW). (a) $R^2$ and its adjusted version $\overline{R}^2$, each for the three time intervals ending in 2018, 2013, 2008. The (shallow) local maxima of $\overline{R}$ around MAW ≈ 25 years are indicated by full symbols. (b) $w_{\text{aa}}$ in dependence on MAW. The full symbols are the values corresponding to the local maxima in (a). (c) same as (b), but for $w_{\text{CO}_2}$. (d) Regression result in the two-dimensional parameter space of $w_{\text{aa}}$ and $w_{\text{CO}_2}$. Note the universal shape of the solution given a slightly bent, but nearly linear function connecting the extremal values $w_{\text{CO}_2} \approx 1.9$ K on the ordinate axis and $w_{\text{aa}} \approx 0.04$ K/nT on the abscissa.
forcing of 0.358 W/m², corresponding to 2.63 W/m² (per 2 \(x\text{CO}_2\)), i.e. to 0.71 K (with 3.7 K/(W/m²)) or 0.82 K (with 3.2 K/(W/m²)), in nearly perfect agreement with Feldman et al. (2015).

These three papers are widely consistent among each other, giving sensitivities in the range between 0.64 K and 0.82 K, which is close to the lower edge of our estimate. We also note that this end of our regression, which corresponds to approximately 70 per cent “for the sun”, is similar to the 50-69 per cent range as once found by Scafetta and West (2007, 2008).

This said, we should also note that Wijngaarden and Happer (2020) have found the much higher value of 1.4 K value (at fixed absolute humidity) which would fit to our upper limit of 1.6 K value which is, in turn, significantly lower than their value 2.2-2.3 K, as inferred for fixed relative humidity.

The range of our estimates is slightly sharper as the range 0.4 K to 2.5 K of Soon, Conolly and Conolly (2015) (with the high value deemed unrealistic by the authors), and slightly wider than the 0.8 K-1.3 K range of Lewis and Curry (2018), but in either case quite consistent with those estimations.

3. Predictions

In the preceding section we have derived a certain plausible range of combinations of the respective weights of the aa-index and the logarithm of CO₂ by means of regression analysis of data from the past 170 years. In the following we will leave the realm of solid, data-based science and enter the somewhat “magic” realm of predictions. Given all the underlying uncertainties concerning the future time dependence of the aa-index, of CO₂, and of further climate factors such as AMO, PDO, ENSO, volcanism etc., any forecast has to be taken with more than one grain of salt. This said, we will at least do some parameter studies, by allowing the unknown time series of the aa-index and CO₂, and their respective weights, to vary in some reasonable range. Let us start with the aa-index.

3.1. Predicting the solar dynamo

This subsection is definitely the most speculative one of this paper as it is concerned with forecasts of the aa-index for the next 130 years. There is no doubt that the aa-index is strongly correlated with the sunspot number (SSN), with typical correlation coefficients of around \(r = 0.96\) when averaged over one cycle Cliver, Boriakoff and Bounar (1998). Neither is there any doubt that the SSN and the aa-index are both governed (though in a non-trivial manner) by the solar dynamo. So any prediction of the aa-index boils down to a prediction of the solar dynamo which many researchers believe to be impossible, at least beyond the horizon of the very next cycle for which reasonable (though not undisputed) “precursor methods” exist (Svalgaard, Cliver and Kamide, 2005; Petrovay, 2010).

In order to justify our audacious forecast for the aa-index, we have to make a little diversion on the solar dynamo and its short-, medium- and long-term cycles. The reader should be warned, though, that our arguments do not reflect the mainstream of solar dynamo theory. We think nevertheless that the last years have brought about sufficient empirical evidence that justifies at least a cautious try.

Let us start with some recent evidence concerning the phase stability of the Schwabe cycle, a matter that was first discussed by Dicke (1978). In Stefani et al. (2020b) we have reviewed the pertinent results derived from algae data in the early Holocene (Vos et al., 2004) and from sunspot and aurora borealis observations, combined with \(^{14}\text{C}\) and \(^{10}\text{Be}\) data, from the last centuries. Without going into the details it was shown that the Schwabe cycle is very likely phase-stable at least over some centuries, with a period between 11.04 years and 11.07 years. While certain nonlinear self-synchronization mechanisms of the solar dynamo cannot be completely ruled out as an explanation (Hoyng, 1996), the external synchronization by the 11.07-years periodic spring tides of the (tidally dominant) Venus-Earth-Jupiter system provides a suspiciously compelling alternative. Based on previous observations and ideas of Hung (2007); Wilson (2008); Scafetta (2012); Wilson (2013); Okhlopkov (2016), we have corroborated a model (Weber et al., 2015; Stefani et al., 2016, 2017, 2018; Stefani, Giesecke and Weier, 2019) in which the weak tidal forces of Venus, Earth and Jupiter serve only as an external trigger for synchronizing (via parametric resonance) the intrinsic helicity oscillations of the kink-type Tayler instability in the tachocline region. The arising 11.07-yr period of the helicity parameter \(\alpha\) ultimately leads to the 22.14 year period of the Hale cycle.

Building on this phase coherence of the Hale cycle, later (Stefani et al., 2020a; Stefani, Stepanov and Weier, 2020) we exploited ideas of Wilson (2013); Solheim (2013) to explain the mid-term Suess-de Vries cycle as a beat period between the 22.14-yr Hale cycle and the 19.86-yr synodic cy-
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Figure 9: Climate predictions until 2150. (a) 23-year moving average of the aa-index, and three 3-frequency fits to it, extrapolated until 2150. (b) Three scenarios for CO$_2$ concentration. (c) Temperature forecasts for the 1st CO$_2$ scenario (dashed curve in (b)), for the three pairs of $w_{aa}$ and $w_{CO_2}$ resulting from regression with end year 2018 (red), 2013 (green), 2008 (blue). Each of the coloured bundles comprise the three different 3-frequency fits from (a). (d) Same as (c), but for the second CO$_2$ scenario with a mild decarbonization scheme (dotted line in (b)). (e) Same as (c), but for third CO$_2$ scenario with a radical decarbonization (dash-dotted line in (b)).

In our model, the Suess-de Vries acquires a clear (beat) period of 193 years which is in the lower range of usual estimates (but see Ma and Vaquero (2020)). The situation with the Gleissberg cycle(s) was less clear: those appeared as doubled and tripled frequencies of the Suess-de Vries cycle, but also as independent frequencies resulting from beat periods of other synodes of Jovian planets with the Schwabe cycle (see Fig. 10 in Stefani, Stepanov and Weier (2020)). Further below, this vagueness of the Gleissberg cycle(s) will be factored in when fitting and extrapolating the aa-index. Lately, in Stefani, Stepanov and Weier (2020) we have tried to explain the transitions between regular and irregular intervals of the solar dynamo (the “supermodulation” as defined by Weiss and Tobias (2016)) in terms of a transient route to chaos.

With those preliminaries, we will now fit the aa-index over the last 170 years in order to extrapolate it into the future. We assume that we have safely left the irregular period of the solar dynamo, as reflected in the Little Ice Age which can be considered as the latest link in the (chaotic) chain of Bond events (Bond et al., 2001). Guided by our (double-)synchronization model, and encouraged by Ma and Vaquero (2020) who had indeed derived an 195-yr cycle in the quiet (regular) interval from 800-1340, we keep this Suess-de Vries period fixed to 193 years in all fits. Concerning the Gleissberg-type cycle(s) we will be less strict, though. In the first version, we fix the two (half and tripled) periods of 96 and 65 years, for the second one we only fix the 96 years period, and for the third one we will keep both Gleissberg cycles undetermined.

In the interval between 1850-2150, the results of those three different 3-frequency fits are presented in Fig. 9a, together with the (fitted) 23-year averaged aa-index data between 1850-2007. Evidently, all three curves approximate the original data reasonably well, and all show a similar extrapolation with a long decay until 2100, and a recovery afterwards. This behaviour is quite similar to the prediction of Bucha and Bucha (1998) (their Figure 14) as well as with the variety of predictions by Lüdecke, Weiss and Hempelmann (2015). The differences between the three fits mainly concern the high frequency part; whereas the version with three frequencies being fixed is the smoothest, the other two fits comprise some stronger wiggles. This simply reflects the fact that the Gleissberg cycle is more vague than the Suess-de Vries cycle. In the following we will always work with all three curves obtained, hoping that they constitute a representative variety for the future of the aa-index.

3.2. Some scenarios

Thus prepared, we consider now three different CO$_2$ scenarios (Fig. 9b), for each of which we further take into ac-
count the three predictions for the aa-index as just discussed, as well as the three optimal combinations of weights for the aa-index and CO$_2$ as derived in the previous section. Deliberately, we restrict our forecasts until 2150, admitting that neither the CO$_2$ trend nor the aa-index are seriously predictable beyond that horizon.

Let us start with the simple case$^1$ of an unblated linear extrapolation of the recent CO$_2$ trend to rise by 2.5 ppm annually (upper curve in Fig. 9b), which would bring us to a value 736 ppm in 2150 (still steeper trends are not completely ruled out, but perhaps not that realistic given the recent worldwide reduction commitments). For this scenario, Fig. 9c shows three red, green, and blue bundles of curves, each comprising the three different fits of the aa-index as discussed above. The red bundle (“hot”) corresponds to the red solution in Fig. 7, with a rather high CO$_2$-sensitivity of 1.5 K and an aa-sensitivity of 0.017 K/nT. The green bundle (“medium”) corresponds to the green solution of Fig. 7 based on sensitivities of 1.2 K and 0.022 K/nT. The blue bundle (“cool”) corresponds to 0.6 K and 0.032 K/nT.

We see that in 2100 the “hot” variant leads to a temperature anomaly of $\Delta T = 1.3$ K which is 0.9 K above the average $\Delta T \approx 0.4$ K from the first decade of this century. The “medium” and “cool” curves are flatter, leading to $\Delta T = 0.9$ K and $\Delta T = 0.4$ K, respectively. However, for those cases to be of any relevance, an imminent drop of the temperature would be required to reach the corresponding curves before they can continue as flat as shown.

The second scenario (dotted line in Fig. 9b) assumes a slowly decreasing upward trend of the CO$_2$ concentration towards the end of the 21st century, with a hypothetical time dependence

$$\text{CO}_2 = \frac{[382 + 2.5(t - 2007)]/[(1. + (t - 2007))/100]}{\text{ppm}}$$

reaching a final value of 529 ppm in 2150. The resulting red, green and blue curves in Fig. 9d show a rather flat behaviour.

The last (and rather unrealistic) CO$_2$ scenario (dash-dotted line of Fig. 9b) assumes a radical decarbonization path with

$$\text{CO}_2 = \frac{[382 + 2.5(t - 2007)]/[(1. + (t - 2007))/50]}{\text{ppm}}.$$ 

The resulting temperature curves (Fig. 9e) are basically constant throughout the end of our forecast horizon.

4. Conclusions

This work has revived the tradition of correlating solar magnetic field data with the terrestrial climate as pioneered by Cliver, Borlaug and Feynman (1998) and Mufti and Shah (2011). Just as these authors, we have found an empirical correlation coefficient between the aa-index and $\Delta T$ with remarkably high values ranging from 0.8 until 0.96, which points to a significant influence of solar variability on the climate. Our modest innovation was to employ a multiple (double) regression analysis, with the logarithm of atmospheric CO$_2$ concentration as the second independent variable, whose pre-factor corresponds to an (instantaneous) climate sensitivity of the TCR type. For a lengths of the centered moving average window of 25 years we have identified optimal parameter combinations leading to adjusted $R^2$ values of around 87 per cent. Depending on whether to include or not include the data from the last decade, the regression gave climate sensitivity values from 0.6 K up to 1.6 K (per 2×CO$_2$), and values from 0.032 K/nT down to 0.017 K/nT for the corresponding sensitivity on the aa-index.

Ironically, if interpreted as $1.1 \pm 0.5$ K, the derived climate sensitivity range turns out to have (nearly) the same ample 50 per cent error bar as the "official" ECS value (3 ± 1.5 K), which we had criticized in the introduction. Yet, in view of the impressive 95 per cent correlation (obtained for the restricted period 1850-2008) we believe the correct climate sensitivity to be situated somewhere in the lower half of that range. This "bias" is also supported by the fact that during the last years an intervening strong El Niño, a positive PDO, and a positive AMO, have all conspired to raise the temperature to significantly higher values than what would be expected from the sole combination of aa-index and CO$_2$. With the upcoming switch to La Niña conditions, and the imminent return of the PDO and AMO into their negative phases, we expect a significant temperature drop for the coming years, which then might re-establish the strong correlation between aa-index and $\Delta T$. At any rate, the next decade will be decisive for distinguishing between climate sensitivity values in the lower versus those in the upper half of the derived range. In this sense we are more optimistic than Love et al. (2011) who believed that we “…would have to patiently wait for decades before enough data could be collected to provide meaningful tests...”. Given the high correlation for most of the past 170 years, and the good correspondence with the results of recent satellite-born measurements (Feldman et al., 2015; Rentsch, 2019), our “bets” are clearly on the lower half of that range.

Based on those estimates, we have also presented some cautious climate predictions for the next 130 years. With the derived share of the solar influence reaching values between 30 and 70 per cent, such predictions depend critically on a correct forecast of the solar dynamo (in addition to that of CO$_2$, of course). Following our recent work towards a self-consistent planetary synchronization model of short- and medium-term cycles of the solar dynamo, we have extrapolated some simple 3-frequency fits of the aa-index to the data from the last 170 years into the next 130 years. Apart from intrinsic variabilities of such forecasts (mainly connected with the vagueness of the Gleissberg-type cycle(s)), we prognosticate a general decline of the aa-index until 2100, which essentially reflects the 200-years Suess-de Vries cycle. Such a prediction presupposes that we have indeed left the irregular solar dynamo episode (corresponding to the Little Ice Age, the latest “Bond event”) and that we will further remain in a regular phase of solar activity (Weiss and Tobias, 2016; Stefani, Stepanov and Weier, 2020), similar to that between 800 and 1340 (Ma and Vaquero, 2020). Of

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$^1$While we do not refer here to IPCC’s Representative Concentration Pathways, this case has some similarity to their RCP 6.0, at least until 2100.
course, we have to ask ourselves whether our prediction of a declining aa-index could be completely wrong, with the Sun eventually becoming even “hotter” in the future, thus adding to the warming of CO₂. While such a scenario cannot be completely ruled out, we consider it as not very likely, given that the solar activity at the end of the 20th century was perhaps the highest during the last 8000 years (Solanki et al., 2004), and that it has declined ever since.

As for the CO₂ trend, we have considered three scenarios, comprising an unfettered 2.5 ppm annual increase until 2150, as well as one soft and one radical decarbonization scheme. Even in the “hottest” case considered, we find only a mild additional temperature rise of less than 1 K until the end of this century, while all other cases result in flatter curves in which the heating effect of increasing CO₂ is widely compensated by the cooling effect of a decreasing aa-index. Whatever the rationale of the advocated 2 K goal might be, it will likely be maintained even without any drastic decarbonization measures. Apart from that, we also advise that any imminent temperature drop (due to the turn of ENSO, PDO and AMO into their respective negative phases) should not be mistaken as, and extrapolated to, a long-lasting downward trend (Abdussamatov, 2015).

In this work, we have focused exclusively on a quasi-instantaneous, i.e. TCR-like climate sensitivity on CO₂. As for ECS, we agree with Knutti et al. (2017) who opined that “(k)nowing a fully equilibrated response is of limited value for near-term projections and mitigation decisions” and that “(t)he TCR is more relevant for predicting climate change over the next century”. In view of the millennial relaxation time scale underlying the concept of ECS, we fear that - perhaps much too soon - the huge Milankovic drivers will cool down mankind’s hubris of being able to significantly influence the terrestrial climate (in whatever direction).

**Data availability**

The see surface temperature data HadSST.4.0.0.0 data were obtained from ftp://www.metoffice.gov.uk/hadobs/hadsst4 on November 27, 2020 and are © of British Crown Copyright, Met Office (2020).

The aa-index data between 1868 and 2010 were obtained from NOAA under ftp://ftp.ngdc.noaa.gov/STP/GEOMAGNETIC_DATA/AASTAR/.

Monthly aa-index data between 2011 and 2019 were obtained from the website of the British Geological Survey www.geomag.bgs.ac.uk/data_service/data/magnetic_indices/aaindex.html.

CO₂ date were obtained from ftp://data.iac.ethz.ch/CMIP6/input4MIPs/UoM/GHGConc/CMIP5/yr/ atmost/UoM-CMIP-1-1-0/GHGConc/gr3-GMNHSH/v20160701.

**Declaration of competing interest**

The author declares that he has no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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