CIRCULAR REASONING IN CLIMATE CHANGE RESEARCH

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ABSTRACT: A literature review shows that the circular reasoning fallacy is common in climate change research. It is facilitated by confirmation bias and by activism such that the prior conviction of researchers is subsumed into the methodology. Example research papers on the impact of fossil fuel emissions on tropical cyclones, on sea level rise, and on the carbon cycle demonstrate that the conclusions drawn by researchers about their anthropogenic cause derive from circular reasoning. The validity of the anthropogenic nature of global warming and climate change and that of the effectiveness of proposed measures for climate action may therefore be questioned solely on this basis[1].

INTRODUCTION

Circular reasoning is a logical fallacy in which research design and methodology as well as the interpretation of the data subsume the finding. This fallacy can be found in published research and it is more common in research areas such as archaeology, finance, economics, and climate change where the data are mostly time series of historical field data with no possibility for experimental verification of causation. In biased research of this kind, researchers do not objectively seek the truth, whatever it may turn out to be, but rather seek to prove the truth of what they already know to be true or what needs to be true to support activism for a noble cause (Nickerson, 1998). Such confirmation bias or *yearning* (Finkelstein, 2011) is found in research areas related to religion or to activism. Confirmation bias is thought to play a role in climate change particularly since climate science provides the rationale for environmental activism and the noble cause of saving humanity or perhaps the planet from climate cataclysm (Kaptchuk, 2003) (Nicholls, 1999). This hidden hand of activism plays a role in the way climate research is carried out and in the way findings are interpreted and disseminated (Cooper, 2006) (Britt, 2001) (Bless, 2006) (Juhl, 2007) (Watkins, 2007) (VonStorch, 1995) (Enright, 1989) (Britt, 2001) (Hodges, 1992) (Curry, 2006).

A famous example of confirmation bias in research is Biblical Archaeology. William Albright, and fellow Biblical Archaeologists, convinced of the historicity of Biblical accounts, carried out extensive archaeological digs in the holy lands looking for evidence that they were sure would prove their case. In their many publications, they *proved* the historicity of Biblical stories about the patriarchs, the move to Egypt, the exodus, the wandering in the desert, the conquest of the Canaan, the period of the Judges, and finally of the grand United Monarchy of David and Solomon (Albright, 1973) (Albright2, 1973) (Dever, 2003) (Cross, 1973). Albright's findings were successfully challenged only recently by Israel Finkelstein of Tel Aviv University (Finkelstein, 2002) (Finkelstein, 1996) (Finkelstein, 1998). Finkelstein points out that Biblical chronology places the period of the patriarchs at 2100 BCE but in the quest to find archaeological evidence for the historicity of the patriarchs other dates were accepted as evidence if the material culture of the stratum could be compared with the Biblical description of the material culture of the patriarchs. The theory about the age of the patriarchs changed according to the archaeological discoveries. Any age from 1100BCE to 2100BCE was taken as evidence of the historicity of the patriarchs. It was with this ***circular reasoning*** that the historicity of the patriarchs was "proven" to the satisfaction of Biblical Archaeologists.

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[1] Date: March 2018
Key words and phrases: logical fallacy, circular reasoning, model validation, data analysis, mathematical models, learning set, test set, climate change, global warming, field data, statistics, scientific method.
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Finkelstein offers a similar account of circular reasoning in the effort by Biblical Archaeologists to establish the historicity of the story of David and Solomon and their grand united monarchy. In the case of David's conquests and also for the lavish kingdom of Solomon, the archaeological data are interpreted and dated in terms of the Biblical accounts of these events – and then used as evidence to support the historicity of the same Biblical accounts. The use of ***circular reasoning*** in these cases was completely missed by researchers and peer reviewed journals and the claimed archaeological evidence for the historicity of David and Solomon's grand united monarchy stood as textbook history for more than eight decades (Finkelstein, 2002). These accounts show that the use of circular reasoning in research and the acceptance of the findings are not unusual.

A unique circular reasoning issue in climate change research is that the use of climate models in empirical test of theory (Rahmstorf, 2007) (Rowlands, 2012) compromises the independence of the empirical test of theory from the theory itself. Climate models are an expression of theory. They execute the mathematics to spell out what results we might expect to see if the theory is correct. Therefore, the practice of utilizing climate models in empirical tests of theory is a form of circular reasoning because the empirical test is no longer independent of the theory that is being tested (VonStorch, 1995) (Hodges, 1992) (McDonald, 2013.) (Harper, 2008) (Enright, 1989) (Mehta, 2004) (Krueger, 2001) (Freedman, 1991) (Vul, 2010).

A related issue in climate change research is that the design and interpretation of empirical tests often subsume certain aspects of the theory. For example, in the test of whether changes in atmospheric carbon dioxide levels are anthropogenic, the observed change in atmospheric CO2 is converted into gigatons of carbon equivalent (GTC) and its ratio with total fossil fuel emissions in GTC over the same period is interpreted as the fraction of the increase in atmospheric CO2 that was caused by emissions. This so called "airborne fraction", taken as evidence of anthropogenic increase in atmospheric carbon dioxide, subsumes the relationship that it purports to prove (Munshi, 2017).

A recurring pattern of circular reasoning in climate science involves the discovery that the hypothesis being tested is true only in a portion of the time span of the time series being used for the test. The finding is then published as empirical evidence in support of the theory with the added "discovery" of the shorter time span where the effect is most evident (Huber, 2011). These research findings contain circular reasoning because in the end the hypothesis is proven with data from which the hypothesis was derived. In all such cases the research finding is readily accepted by the researcher and the research community by way of confirmation bias because the result are reasonable in the context of the AGW theory that has gained wide acceptance as "settled science".

We now present examples from the literature to demonstrate the use of circular reasoning in three broad areas of climate change research. They are tropical cyclones, sea level rise, and uncertainties in measurements of natural flows in the carbon cycle. Other areas of climate research will be presented in future extensions of this study.

(1) Increasing Destructiveness of Tropical Cyclones (Emanuel, 2005)

Sea surface temperature (SST) is the link that connects AGW research with tropical cyclone research. Rising SST is observed (Hadley Centre, 2017) and thought to be an effect of AGW (Hansen, 2005)[2]. At the same time, the theory of tropical cyclones holds that cyclone formation and intensification are related to SST (Vecchi, 2007) (Knutson, 2010). Testable implications of the theory for empirical research are derived from climate model simulations (Knutson, 2010) and also from sedimentary evidence of land falling hurricanes over a 1500-year period (Mann, 2009). These studies suggest the following guidelines and testable implications for empirical tests of the theory that AGW affects tropical cyclone activity[3] (Knutson, 2010):

1. Globally averaged intensity of tropical cyclones will rise as AGW increases SST. Models predict globally averaged intensity increase of 2% to 11% by 2100.
2. Models predict falling globally averaged frequency of tropical cyclones with frequency decreasing 6%-34% by 2100.
3. The globally averaged frequency of "most intense tropical cyclones" should increase as a result of AGW. The intensity of tropical cyclones is measured as the ACE (Accumulated Cyclone Energy).
4. Models predict increase in precipitation within a 100 km radius of the storm center. A precipitation rise of 20% is projected for the year 2100.

Complications of empirical tests in this line of research are (Knutson, 2010):

1. Extremely high variance in tropical cyclone data at an annual time scale suggests longer, perhaps a decadal time scale which in turn greatly reduces statistical power.
2. Limited data availability and poor data quality present barriers to research.
3. Limited theoretical understanding of natural variability makes it difficult to ascertain whether the variability observed in the data is in excess of natural variability.
4. Model projections for individual cyclone basins show large differences and conflicting results. Thus, no testable implication can be derived for studies of individual basins. It is necessary that empirical studies have a global geographical span.
5. Advances in data collection activity, methods, and technology create trends in the data that must be separated from climate change effects (Landsea, 2007) (Landsea, 2010).

A high level of interest in tropical cyclones derives from an unusually active hurricane season in 2004 when more than 14 tropical cyclones formed in the North Atlantic basin[4]. Four of these storms intensified to Category 4 or greater and made landfall in the USA causing considerable damage. The even more dramatic 2005 season followed in its heels with more than thirty depressions. Four of them intensified to Category 5 and three made landfall. The most intense was Hurricane Wilma but the most spectacular was Hurricane Katrina which made landfall in Florida and again in Louisiana. Its devastation was facilitated by a breach in a levee system that was unrelated to AGW but its dramatic consequences made it an icon of the possible extreme weather impacts of AGW.

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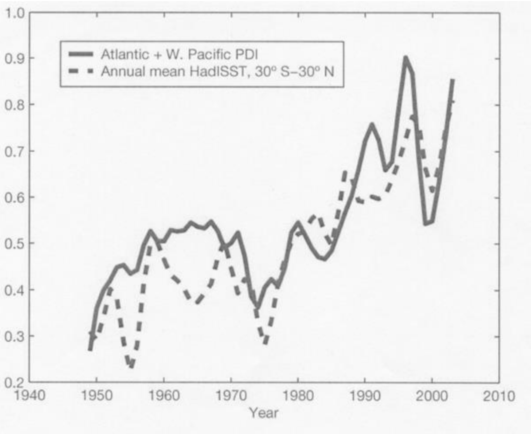
[2] The connection between fossil fuel emissions and rising SST is controversial (Munshi, 2017)

[3] Most of these guidelines are from Knutson 2010.

[4] Tropical cyclones in the North Atlantic Basin are called "hurricanes" and those in the West Pacific Basin are called "typhoons".

The Emanuel paper (Emanuel, 2005) came in the heels of these events and is possibly best understood in this context. The assumed attribution by the media of the epic devastation in the 2004/2005 hurricane seasons to AGW set the stage for climate science to claim the destructiveness of hurricanes as extreme weather effects of AGW. The Emanuel 2005 paper was one of several published in the heels of these hurricane seasons. The paper presents a new measure of tropical cyclone intensity which the author calls "Power Dissipation Index" and to which he assigns the acronym PDI. The paper finds a statistically significant rising trend in the aggregate annual PDI of North Atlantic Hurricanes in the study period 1949-2004 in tandem with rising sea surface temperature (SST) for the appropriate zone where hurricanes form. The graphical depiction of this result is reproduced in Figure 1.

Figure 1: Emmanuel 2005 finding.



The usual measure of tropical cyclone activity is the ACE or Accumulated Cyclone Energy. It is computed as the sum of squares of the maximum sustained wind speed in each 6-hour window during the life of the cyclone. It represents the total amount of kinetic energy generated by a tropical cyclone and this energy has been related to the energy in the ocean surface as measured by surface temperatures and temperature differentials such that the cyclone can be described as a heat engine (Rotunno, 1987) (Emanuel, 1987) (Goni, 2003) (Latif, 2007) (Klotzbach, 2006) (Emanuel, 2003).

When the ACE measure did not show the trend that the author was looking for he decided to cube the velocities instead of squaring them as a way of increasing the differences among years. This innovation produced the desired result and a trend became evident over the last 30 years of the 55-year study period as seen in Figure 1. Since the sum of cubes could not be called ACE, the author gave it a new name and called it the Power Dissipation Index[5] or PDI. The object variable in the hypothesis was thus changed from ACE to PDI. The PDI hypothesis was then modified to exclude the first 22 years of the study period where no trend and very little correspondence between PDI and SST are seen (Figure 1). Thus, the tailor made hypothesis to be tested was whether there is a rising trend in the PDI in the most recent 30 years[6] (1975-2004) of the study period. This hypothesis was then tested with the same data over the same time span that was used to construct it. The procedure of testing a hypothesis with the data used to construct the hypothesis constitutes ***circular reasoning*** because the methodology subsumes and ensures the desired result.

[5] It is noted that ACE has units of L^2/T^2 =energy but PDI has units of L3/T3 = L*(L2/T3) = L*power.

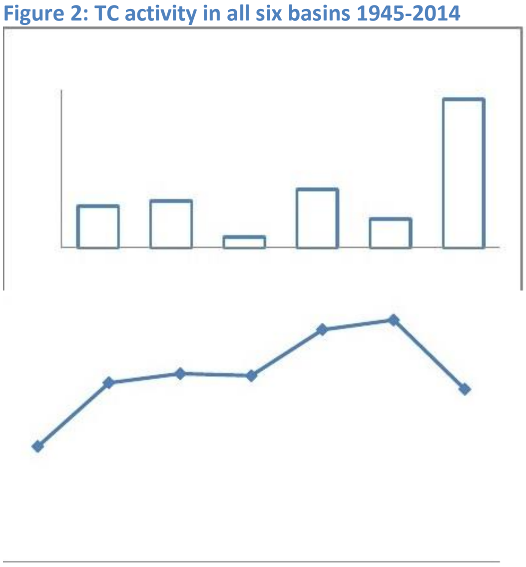
[6] The title of the paper was changed accordingly.

At this point, a rising trend is seen in the PDI time series 1975-2004 at an annual time scale but the trend is not statistically significant because of extreme year to year variability in cyclone formation and intensification (Knutson, 2010). To smooth out the variance, the author took a 5-year moving average of the PDI data; and when that also failed to show a statistically significant trend, he took 5-year moving averages of the 5-year moving averages (in effect a 10-year moving average) and was finally able to find statistical significance for rising PDI over the last 30 years of the study period (Watkins, 2007). The findings presented by the paper are based on this rising trend and the visual correspondence between PDI and SST seen in Figure 1.

However, in his hypothesis test computations the author failed to correct for degrees of freedom lost in the computation of moving averages. When moving averages are computed some data values are used more than once. It can be shown that the average multiplicity of use is given by the relationship $M = (\lambda/N)*(N-\lambda+1)$ where M is the average multiplicity, N is the sample size, and λ is the width of the moving window (Munshi, 2016) (VonStorch, 1995) (Watkins, 2007). In the case of a window with λ=10 years moving through a time series of N=30 years, the average multiplicity is M=7. The effective sample size is computed as EFFN=N/M or EFFN=30/7 = 4.285 and the degrees of freedom for the t-test for trend is DF=EFFN-2 or DF=2.285. The statistical significance reported by the author at N=30 and DF=28 is not found when the sample size is corrected for multiplicity. A false sense of statistical power was created by the methodology used when decadal moving averages were taken (Munshi, 2016).

The North Atlantic basin is just one of six major cyclone basins around the world. The other five are The West Pacific, the East Pacific, the South Pacific, the North Indian, and the South Indian. The most active basin is the West Pacific. The theory of anthropogenic global warming as expressed in terms of climate models indicates that only *long term* changes in *global averages* of all six cyclone basins may be interpreted in terms of the impacts of climate change (Knutson, 2010). The study of a single basin over a brief 30-year period is unlikely to contain useful information relevant to AGW. Data for all six basins over a 70-year study period 1945-2014 does not show trends in total aggregate annual ACE that can be interpreted as an impact of warming (Munshi, 2015).

Figure 2: TC activity in all six basins 1945-2014



The top frame of Figure 2 shows the relative activity of the six basins over the 70-year study period. From left to right the basins are East Pacific, North Atlantic, North Indian, South Indian, South Pacific, and West Pacific. The North Atlantic, although close to home for many climate researchers, is not a significant source of cyclone energy in a global context. The lower frame of Figure 2 does not show a sustained trend in tropical cyclone activity on a decadal time scale particularly when the decade 2005-2014 is included.

It is likely that (Emanuel, 2005) was a product of climate activism that had reached a high level of intensity in the years leading up to 2005 by way of the push for the ratification of the Kyoto Protocol for CO2 emission reduction as well as the *European heat wave of 2003* that was claimed and widely accepted to be caused by AGW. It was a time when the extreme weather effect of AGW was given credence by the IPCC and generally taken for granted. Given the theoretical basis that connected SST to tropical cyclones, the truth of AGW driven hurricane intensity was thus taken to be a given (Emanuel, 1987) and then apparently proven by the 2004/2005 hurricane seasons. It remained for climate science only to tend to the details of presenting the data in the appropriate format.

Thus the ultimate form of ***circular reasoning*** is found in (Emanuel, 2005) in which a high level of confidence ex-ante in the truth of the proposition that AGW causes extreme tropical cyclone activity left the presentation of empirical evidence of that relationship as mere detail.

(2) Anthropogenic Acceleration of Sea Level Rise (Nerem, 2018)

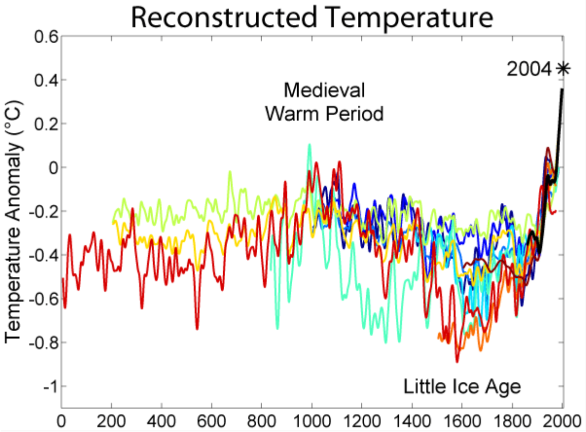
At least since 1982 and particularly so since the James Hansen Congressional testimony of 1988, a principal projected hazard of AGW has been the specter of dangerous anthropogenic sea level rise due to melting glaciers and ice sheets and also by way of thermal expansion of water (Gornitz&Hansen, 1982) (Hansen, 2007) (Hansen, 2016). The projected hazards have been described in terms of the inundation of low-lying islands and deltas such as the Maldives and Bangladesh and the greater devastation of storm surges. A much greater extent of the inundation scenario is expected in the 100-year forecast.

More than 200 years of tidal gauge data are provided by multiple sources such as the Permanent Service for Mean Sea Level and the University of Hawaii sea level data center (PSMSL, 2018) (UHSLC, 2018). A global sea level reconstruction has been synthesized from tidal gauge data by the PSMSL (Jevrejeva, 2008). Satellite measurements of global sea level on the high seas began in 1993 and are made available by the University of Colorado (CU Sea Level Research Group, 2018).

Such sea level datasets have drawn the intense attention of climate science. They are studied to find empirical support for what must seem obvious and what has already been seen in the climate simulation models – that warming causes land ice to melt and that in turn causes the sea level to rise. However, sea level rise (SLR) does not by itself imply an effect of AGW. Paleo records shows that both temperature and sea level have been mostly rising since the last glacial maximum (LGM) and more recently, since the so called Little Ice Age (LIA) (Huybrechts, 2002) (Grinsted, 2010) (Moberg, 2005) (Kemp, 2011). It is therefore necessary to determine what the appropriate metric should be to distinguish anthropogenic sea level rise from natural sea level rise.

Climate models that relate warming to sea level rise by way of ice melt suggest that the appropriate metric is the *acceleration* of sea level rise (Douglas/Kearney/Leatherman, 2000) (Hansen, 2005) (Rockström, 2009) (Dangendorf, 2016) (Rignot, 2011) (Rahmstorf, 2007). In empirical research, a second order polynomial regression is normally used to detect acceleration. If a statistically significant positive quadratic coefficient is found in rising sea levels, a finding of acceleration is confirmed and the observed SLR is declared as anthropogenic (Douglas, 1992) (Church, 2006) (Jevrejeva, 2009) (Jevrejeva, 2014) (Slangen, 2016) (Nerem, 2018).

Figure 3: Temperature recovery from the LIA to present[7]



This procedure of detecting anthropogenic forcing of sea level rise contains ***circular reasoning***. The presence of acceleration implies only that SLR is being forced but it does not identify the forcing agent. The interpretation of acceleration as anthropogenic forcing contains the presumption of anthropogenic cause in an empirical test carried out to determine whether the cause is anthropogenic. It is further noted that the anthropogenic cause proposition derives from anthropogenic fossil fuel emissions by way of GHG warming and consequent ice melt. This causation theory implies an appropriate relationship between emissions and the rate of SLR. No such correlation has been presented in the sea level literature (Munshi, 2017).

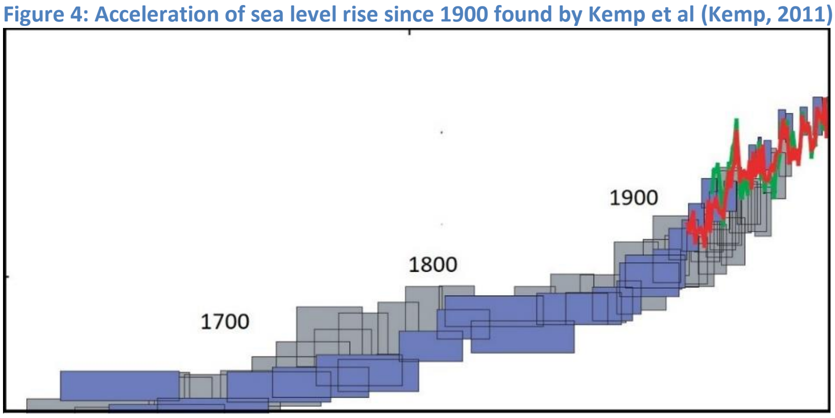
There is yet another layer of circular reasoning normally found in sea level acceleration research. It has to do with post hoc selection of the appropriate time span in which acceleration of SLR should exist if AGW theory is true. The theory of AGW states that warming since "*pre-industrial times*" has been caused by emissions from fossil fuels used to power the Industrial Revolution. The time span for the empirical test of theory should be set accordingly.

The Industrial Revolution began in the early 18th century with the invention of the steam engine. The Bessemer process for steel manufacture in the mid19th century was followed by the invention of the internal combustion engine in the late 19th century and the mass production of automobiles in the early 20th century (Allen, 2009). Possibly because the phrase "Pre-Industrial" is vague in this historical context, climate science uses a narrow 50-year range defined as 1850-1900 as the demarcation between Pre-Industrial and Post-Industrial periods (IPCC, 2007).

[7] Wikipedia

Study of sea level rise from the paleo record from as early as 1500 show an abrupt acceleration that begins sometime during this period just prior to 1900 (Figure 4) and these results have been interpreted as an impact of the Industrial Revolution on SLR in terms of acceleration (Kemp, 2009). The time span for testing the effect of AGW on SLR is therefore guided by these considerations. Arbitrary time span selections are likely to be a *time span of convenience* selected post hoc so that the acceleration hypothesis is formed and then tested with the same data.

Figure 4: Acceleration of sea level rise since 1900 found by Kemp et al (Kemp, 2011)



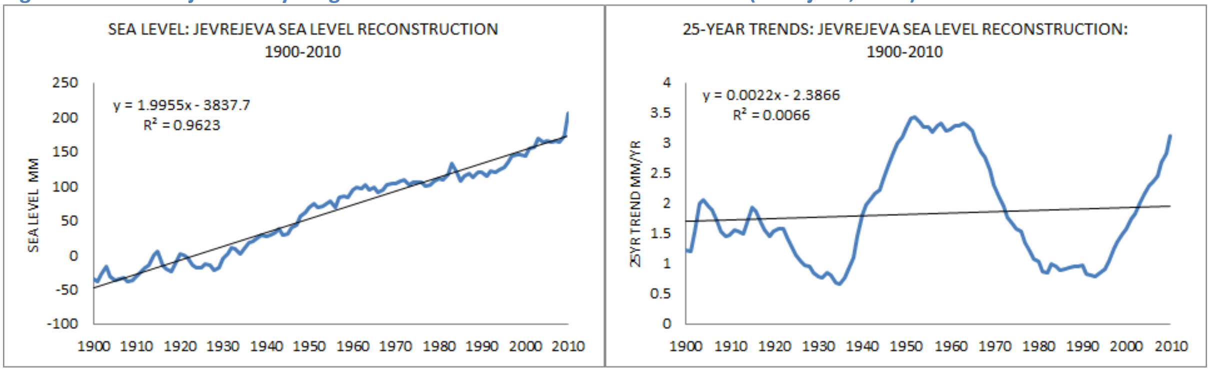
We now present the (Nerem, 2018)[8] findings and methods in light of the foregoing structure, methods, and issues in sea level acceleration research.

In Nerem2018 the authors test the SLR acceleration hypothesis with satellite altimetry data for global sea level measured on the high seas. At the time of their work these data were available for the 25-year sample period 1993-2017. They state that their motivation for the selection of this dataset is that the data are more accurate than older tidal gauge data and should therefore yield a more reliable and realistic estimate of acceleration. For the 25-year study period 1993-2017 they found an average SLR of 2.9 mm/y with acceleration in SLR of 0.084 mm/y^2. Because of the brief study period of 25 years the authors adjusted the computed values for climate anomalies imposed by ENSO and the Pinatubo eruption and known ice sheet losses.

After thus validating their findings, the authors extrapolated the quadratic curve that contained the acceleration parameter forward by 83 years to make the forecast that by the year 2100 the sea level will have risen another 615 mm from 2017 levels. The authors state that this projection is consistent with climate model forecasts for <=2C warming found in the IPCC AR5 as 400-600 mm rise from the 2013 level (Horton, 2014). The authors claim that their results show that the observed SLR and its acceleration in the study period 1993-2017 are driven by AGW and that the amount of the rise corresponds with observed ice sheet and glacial melt in Greenland and Antarctica. These results and conclusions are drawn from a very brief 25-year *time span of convenience* that does not conform to the theoretical demarcation of time for the study of anthropogenic sea level rise. To interpret these results in context, we compare them with SLR rates and accelerations observed in the post-industrial portion of a 203-year global sea level reconstruction 1807-2010 (Jevrejeva, 2014) shown in Figure 5.

[8] In the following discussion we will refer to this work as Nerem2018

Figure 5: The Jevrejeva 200-year global sea level reconstruction 1807-2010 (Jevrejeva, 2014)



The left panel of Figure 5 shows the Jevrejeva sea level reconstruction in mm from 1900 to 2010 and the right panel shows the rate of sea level rise in mm/y in a moving 25-year window moving one year at a time from the one that ends in 1900 to the one that ends in 2010. In the left panel, the slope of the curve at any point indicates the rate of SLR but in the right panel the slope indicates the rate of change in the rate of SLR or the *acceleration* in sea level rise in a 25-year window. The right panel shows that the mean rate of SLR in a moving 25-year window varies over a large range from a low of 0.66 mm/y to a high of 3.44 mm/y. The average of all 25-year mean rate of SLR is 1.84 mm/y, close to the full span average SLR≈2 mm/y shown in the left panel of Figure 5 and not very different from SLR≈1.7 reported by Church for the same sample period (Church, 2011).

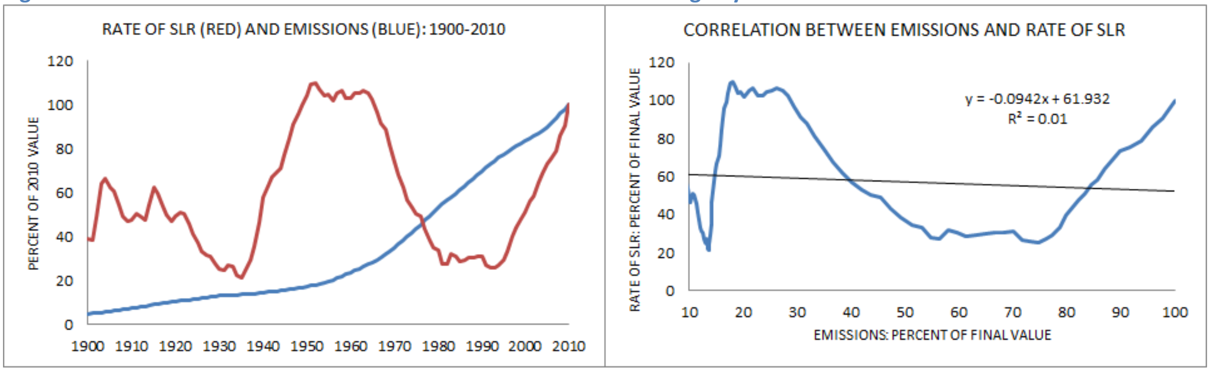
The rate of SLR reported by Nerem2018 for 1993-2017 of 2.9 mm/y falls well within and on the high end of the range of 25-year SLR in the right panel of Figure 5. Sea level rise in the most recent 25-year period in the Jevrejeva dataset ending in the year 2010 is SLR≈3.13 mm/y, also comparable with the Nerem2018 value of SLR≈2.9 mm/y. A work similar to the Nerem2018 paper but somewhat more extensive is (Church, 2011). With the same satellite altimetry data used by Nerem2018 but in a shorter sample 1993-2009, Church reports a rate of SLR≈3.2 mm/y, much closer to the our result for 1985-2010 with the Jevrejeva sea level reconstruction of SLR≈3.13.

These comparisons imply that SLR decelerated after 2010. It may be useful here to recall that acceleration of SLR means either that rising sea level is rising faster and faster or that falling sea level is falling slower and slower. Likewise deceleration of SLR means either that rising sea level is rising slower and slower or that falling sea level is falling faster and faster.

The Nerem2018 authors state that their finding of acceleration in sea level rise provides evidence of AGW and its effect on sea level. The right panel of Figure 5 shows a gradual initial deceleration until 1934 followed by steep acceleration until 1950. An equally steep deceleration is seen from 1963 to 1980. The series ends with strong acceleration from 1991 to 2010 at a rate of 0.124 mm/y^2 comparable with but higher than the acceleration of 0.084 mmy^2 reported by Nerem2018 for 1993-2017. The average acceleration for all 111 25-year windows is almost zero at 0.0022 mm/y^2 as indicated by the slope of the regression line shown in the right panel of Figure 5. This result at a 25-year time scale is much lower than the acceleration reported by Church at an annual time scale for the period 1900-2009 of 0.009 mm/y^2 for tidal gauge data.

Nerem2018 and Church2011 conclude that acceleration in SLR provides empirical evidence of anthropogenic forcing with fossil fuel emissions and that therefore the observed sea level rise presented in their work is anthropogenic. This interpretation of their results is tested in Figure 6. The left panel of Figure 6 shows 25-year SLR rates in red and 25-year fossil fuel emissions in blue as a percent of their values in the 25-year period ending in 2010. No correlation is apparent. The correlation computation in the right panel confirms this visual intuition as there is no evidence of a statistically significant positive correlation that would have to exist if higher rate of emissions cause higher rate of sea level rise in a 25-year time scale. This issue is explored more fully and at different time scales in a related work that supports this conclusion (Munshi, 2017).

Figure 6: Correlation between emissions and the rate of SLR in moving 25yr window 1900-2010



The Nerem2018 work is presented here as an example of circular reasoning in climate science research on sea level rise. The use of acceleration as evidence of anthropogenic cause of sea level rise is a form of ***circular reasoning*** because that which is to be proved by the empirical test of theory (anthropogenic cause) is subsumed in the interpretation of the data being used to carry out the test.

This relationship may be supported by climate models (Vermeer/Rahmstorf, 2009) (Rahmstorf, 2007) (Church, 2011) but models are can only yield what the theory says because they are programmed to execute the mathematics of climate change according to theory. Therefore, model results represent theory and not data and the use of models compromises the independence of the empirical test of theory from the theory itself and that in turn leads to circular reasoning.

Also common in sea level research is the ***circular reasoning*** imposed by the use of a sample period of convenience in the test of a theory that implies a sample period from the 1850-1900 era to the present. In this case the dramatic results of the empirical test of theory that sea level rise is anthropogenic derives from the choice of sample period as can be seen in Figure 5. The extrapolation of the results from a 25-year sample period from 2017 to 2100 is based on the circular reasoning assumption that the SLR behavior seen in the brief 25-year period is homogeneous over all time backwards and forwards.

The shape of the curve in Figure 5 does not indicate such homogeneity and implies that the extrapolation presented and supported by model results is a creation of circular reasoning. The use of study periods of convenience is common in climate change research where great variance is seen in the sample periods used for the same research question (Jevrejeva, 2008) (Church, 2006).

(3) Anthropogenic rise in atmospheric carbon dioxide

Paleo climate data tells us that prior to the Industrial era the mean annual CO2 concentration of the atmosphere stayed in range 180-290 ppm (IPCCAR5, 2013), a difference of 234 gigatons of carbon equivalent (GTC). The range is equivalent to total global fossil fuel emissions in the 33-year period 1985-2017 but since they occurred prior to the industrial age, these changes are ascribed to volcanic eruptions which injects CO2 into the atmosphere and also to changes in solar activity which changes the flow of CO2 between the atmosphere and the oceans (IPCCAR5, 2013).

However, in the postindustrial era, these changes are shown to be much more rapid and explained in terms of anthropogenic emissions with the mathematics of the attribution presented in terms of nature's carbon cycle, renamed as the *carbon biogeochemical cycle* by the IPCC. It is described in terms of the flows among multiple sources and sinks. The atmosphere plays a role in nine of these flows. These flows, averaged over the decade 2000-2009 (Figure 7) and their standard deviations as reported by the IPCC are listed below in units of GTC/y (IPCCAR5, 2013).

Source and destination of flow	Mean	Stdev
1. Ocean surface to atmosphere	78.4	N/A
2. Atmosphere to ocean surface	80.0	N/A
3. Fossil fuel emissions: surface to atmosphere	7.8	0.6
4. Land use change: surface to atmosphere	1.1	0.8
5. Photosynthesis: atmosphere to surface	123	8.0
6. Respiration and fires: surface to atmosphere	118.7	N/A
7. Freshwater to atmosphere	1	N/A
8. Volcanoes: surface to atmosphere	0.1	N/A
9. Rock weathering: surface to atmosphere	0.3	N/A

A simple flow accounting of the mean values without consideration of uncertainty shows a net CO2 flow from surface to atmosphere of 4.4 GTC/y. In the emissions and atmospheric composition data we find that during the decade 2000-2009 total fossil fuel emissions were 78.1 GTC[9] and that over the same period atmospheric CO2 rose from 369.2 to 387.9[10] ppm for an increase of 18.7 ppm equivalent to 39.6 GTC in atmospheric CO2 or 4.4 GTC/y. The flow accounting thus shows an exact match of the predicted and computed carbon balance when uncertainties are not considered. This exact accounting balance is achieved, not with flow measurements, but with gross flow estimates constrained with the circular reasoning that assigns flows according to a balance constraint in what is termed as "net flows".

A very different picture emerges when uncertainties are included in the balance. We have the published uncertainties from the IPCC for three of the nine flows. Uncertainty for the other six flows are estimated from the blanket IPCC statement that "typical uncertainties are more than 20%" (IPCCAR5, 2013). We assume that "uncertainty" refers to a 95% confidence interval as a percent of the mean and compute the standard deviation as≈10% of the six flows without standard deviation data. We label this set of standard deviations as the "base case".

[9] Marland-Andres, Regional and National Fossil-Fuel CO2 Emissions, Oak Ridge, TN: Oak Ridge National Laboratory, 2016
[10] Scripps CO2 Program 2017 http://scrippsco2.ucsd.edu/data/atmospheric_co2/

We then carry out hypothesis tests to determine whether the system of flows at any given level of uncertainty is able to detect the presence of the relatively lower flow of fossil fuel emissions. The test is based on the proposition that an uncertain flow account is in balance as long as the hypothesis that it is balanced cannot be rejected (Munshi, 2015). The critical p-value for the test is set at the highest level found in the literature of $\alpha=0.1$ to ensure that even weak evidence of sensitivity to fossil fuel emissions is not missed.

The flow system is tested for the null hypothesis H_0: Balance=0 against H_A: Balance≠0 WITH and WITHOUT fossil fuel emissions to determine whether we can reject H_0 when the anthropogenic emissions flow is removed from the system. The results for seven different uncertainty cases are shown in Figure 8. They show that nature's system of uncertain flows of 70 to 123 GTC/y of carbon between the surface and the atmosphere is unable to detect 7.8 GTC/y of fossil fuel emissions under the base case estimates of flow uncertainties.

The system is then tested with a blanket uncertainty estimate set to standard deviations of 6.5% and in increments down to 1% of mean for all flows and it is found that the flow system is able to detect the presence of fossil fuel emissions only when the standard deviation of uncertain flows is less than 3% of the mean. The Excel spreadsheet for these computations may be downloaded from an online data archive[11]. We conclude from this analysis that given the flow uncertainties in the IPCC carbon cycle balance (Figure 7), it is not possible to determine the impact of fossil fuel emissions, particularly with respect to its effect on atmospheric CO2 (Munshi, 2017).

The IPCC was able to carry out the balance by assuming that fossil fuel emissions accumulate in the atmosphere and in the oceans. They subtracted the portion of fossil fuel emissions needed to explain rising atmospheric CO2 and assuming that the rest accumulates in the oceans and explained changes in dissolved inorganic CO2 in oceans in terms of these flows and assumed rates in the flows to and from the biota and to and from the deep ocean. This procedure inserts the presumptions and biases of the researcher into the flow accounting of CO2 flows within the oceans.

The flow accounting presented in Figure 7 is the creation of ***circular reasoning***. Further evidence against the IPCC flow account for the carbon cycle is presented in a correlation analysis that does not support the conclusion that changes in atmospheric CO2 are driven by emissions (Munshi, 2017). We conclude that the uncertain system of large natural flows is not sensitive to fossil fuel emissions and that the effect of such emissions on the carbon cycle assessed by climate science is a product of ***circular reasoning***.

[11] https://drive.google.com/open?id=1LCOTLkVnMm0qWj9qaF5cN77c3v2fCaQx

Figure 7: IPCC AR5 Carbon Biogeochemical cycle: 203

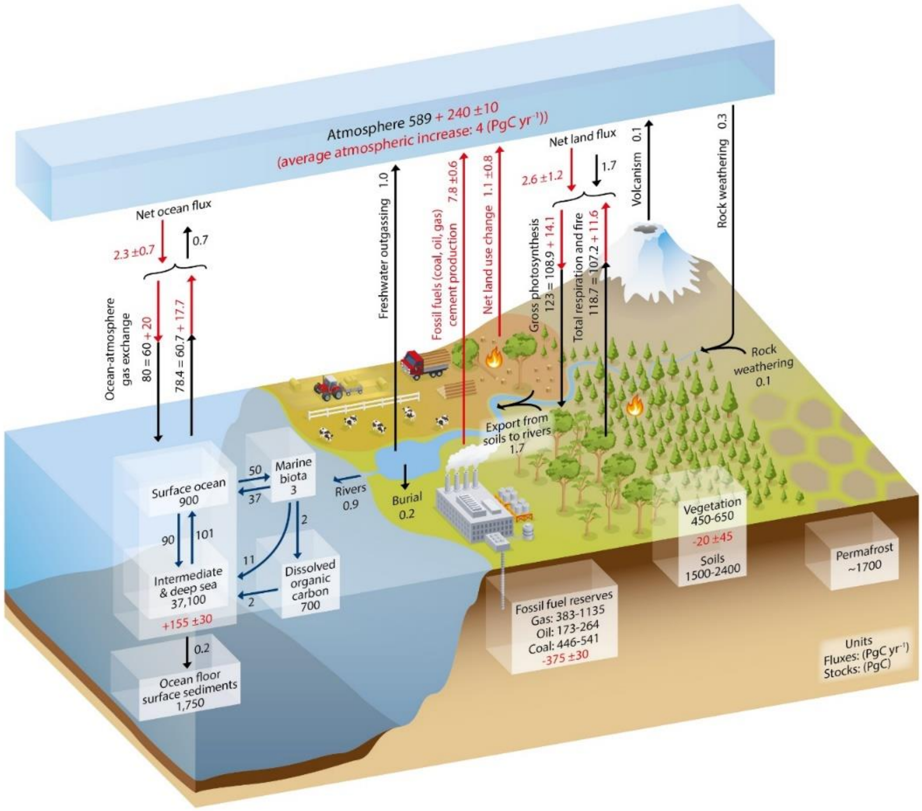
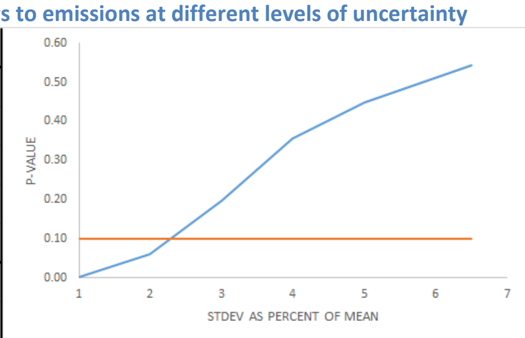


Figure 8: Sensitivity of the system of flows to emissions at different levels of uncertainty

PCT	WITH	WITHOUT
BASECASE	0.993	0.502
6.5PC	0.986	0.544
5PC	1.000	0.447
4PC	0.989	0.356
3PC	0.983	0.198
2PC	0.988	0.059
1PC	0.993	0.000



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