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Minireview

Model falsifiability and climate slow modes

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HIGHLIGHTS

- Climate models do not and cannot employ known physics fully. Thus, they are falsified, a priori.
- Incomplete physics and the finite representation of computers can induce false instabilities.
- Eliminating instability can lead to computational overstabilization or false stability.
- Models on ultra-long timescales are dubiously stable. This is referred to as the "climate state." Is it real?
- Decadal variability is understandable in terms of a specific class of nonlinear dynamical systems.

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ABSTRACT

The most advanced climate models are actually modified meteorological models attempting to capture climate in meteorological terms. This seems a straightforward matter of raw computing power applied to large enough sources of current data. Some believe that models have succeeded in capturing climate in this manner. But have they? This paper outlines difficulties with this picture that derive from the finite representation of our computers, and the fundamental unavailability of future data instead. It suggests that alternative windows onto the multi-decadal timescales are necessary in order to overcome the issues raised for practical problems of prediction.

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1. Introduction

There are many different types of climate models. Some are purely didactic, for which there is no specific expectation of prediction. The more advanced models are meteorologically based and are presented as "simulations" used for climate "projections". This common terminology about what climate models are and what they do is telling. A "projection" holds a more modest claim on the future than a prediction, and "simulation" suggests imitation rather than a representation of the thing itself-neither represents the qualities aspired to by a field rooted in rigorous physics. Even "model" is used in a manner different from other fields of science. The standard model of physics, for example, is subject to falsification. If it fails to make correct predictions in controlled experiments, it is false. Projections are not good enough there. Even in astrophysics, models explain phenomena that are normally subject to falsification through broad questions asked about multiple occurrences of similar physical circumstances, even in highly data-starved contexts.

What makes climate models fundamentally different is that they are presented as being unfalsifiable. Even when they deviate from actual observations, they are not superseded by a better competing model. Deviations simply invite some retuning. Moreover instead of replacement by better models retuning leads to all models becoming more alike.

There are many reasons for this. Some are fundamental features of the field, such as having comprehensive measurements for only a minute time slice of a single realization of the system under study. Controlled experiments are impossible, so falsification in terms of them is also impossible. There is no prospect of a climate analogue to meteorological skill, given only a single, as yet unfulfilled, realization for any prediction. Also contributing is the nature of the specificity of questions being asked about a physical system that is nonlinear and complex, spanning far too many scales of space and time to be directly treated either computationally or theoretically. Moreover the meteorological theory we begin with calls for data that we do not actually have, but which we optimistically infer (e.g. reanalysis) from substitutes extracted from other copious data sources not properly suited to the task.

There are many more reasons that could be discussed, but they miss the key question, which is whether climate models are actually falsifiable. Here we do not refer to matters where climate models differ from observations, say, on cloud amount or rainfall. These are, in principle at least, correctable for reasons we discuss below. This question is also not to be confused with "model validation" efforts either. We ask instead are there propositions that contemporary models make, crucial to their own objectives, that are falsifiable? Is there any physical test possible that would force us to conclude that they are unable to achieve their own objectives, thus requiring a rethinking of basic assumptions?

This paper addresses this question. But it is a question that cannot be comprehended in the face of many widely-held misconceptions about the direct meteorologically based projection modeling of climate. Foremost among these misconceptions is that climate models are full implementations of known, mature physics. This false conception can lead to the conclusion that falsification is irrelevant because models are simply an execution of previously known correct physics.

Thus we must address a variety of misconceptions about the nature of computers, physics, and climate itself. First among these is discussed in Section 2 which explains why all projection climate models must be empirically based and not direct implementations of the known physics, because of the scale of the problem and the finite representation of computers. It develops the notion of falsifiability and models.

Section 3 introduces an example of a potentially unfalsifiable proposition; namely, that the long term white spectra of climate model output represents a state of climate, depicting timescales far longer than we have direct observations. There is no empirical or theoretical way for an empirically-based model to directly distinguish this behavior from a computational artifact such as computational over-stabilization.

But is there anything else that could happen on such timescales physically that could make for something other than a white spectrum? There are certain known phenomena, which are discussed in Section 4. The existence of such ultra slow modes suggests short-term climate or long-term meteorology is a matter of low dimensional dynamics, rather than thermodynamics, which represents a very different context for sensitivity. Section 5 discusses how changes in a dynamical system are not simply a matter of energy and temperature. Change can happen without changes in energy or averages over temperatures.

2. Climate models are empirically based

All computers have a "finite representation". That means that there are a finite number of numbers available to any computer. Because the representation is tied to physical objects, an infinite representation requires an infinitely large computer.

Finite representation is fundamentally incompatible with the differential equations of classical physics on which the rigorous basis of meteorology and potentially climate (through meteorology) are based. In order to apply a computer to these equations, the equations need to be broken apart into discrete maps. Making these maps behave as much like the original equations as possible is the business of numerical analysis. There are three types of error that emerge from breaking up the original equations to accommodate the finite representation:

1. Round off error
2. Truncation error
3. False symmetry and false invariants.

Item 3 is not entirely independent of the other two, but it pertains to the definitive feature of the climate problem: ultra long-timescale integration of equations. The invariant properties of physics built into the underlying equations are the pivots that any physically based predictions turn on. Think in terms of energy and momentum as computational invariance of some problems. See [1] for examples. Invariants are the reference against which change is measured. Capturing change over extreme timescales is thus most tied to how the dynamical symmetries are altered in the process of breaking up the original equations for use on a computer. One's ability to look into the future is increasingly compromised as integration times grow. There is no other topic that pushes direct time integration of known equations to such an extreme as the meteorological program to capture climate. It will be discussed more in Section 3.

Discrete maps exist on a denumerable grid. What happens between grid points is not, and cannot be, captured. The strategy of numerical methods is to lose as little between grid points as possible. Best practice is to arrange for grid point spacing to be smaller than any expected structure in the solutions of the original equations. Imagine a grid of 1 mm over all active fluids on Earth corresponding to the Kolmogorov turbulent cutoff for air. Below that there are no more turbulent eddies. Choosing the fluid's discrete map approximation to have time steps corresponding to one second of real time, ten variables, one floating point operation per clock cycle per variable, a cycle rate of 10^{10} Hz, yields a ten-year prediction that would take 10^{20} years to compute. The age of the Universe is believed to be about 10^{10} years.

If climate models were to ignore the sub grid scale processes, they would fail completely because the small phenomena they represent accrue to be of considerable importance (e.g. thunderstorms). Clearly a better option is needed to do any computation at all. Improper computation permits structure to be lost between grid points when mitigated by ad hoc corrections. That is, it corrects for lost phenomena below the grid scale: sub grid scale. These phenomena are treated by empirical corrections to actual physics. Improper computation is common in engineering. When backed by laboratory measurements it can be an effective alternative. But there are no laboratories to put the climate system into.

The empirical nature of large climate models can be clearly seen in their diverse outputs. If they followed the laws of physics in their entirety, they would all produce the same results under the same conditions. But they do not. In a recent study, the Climate Model Inter-comparison Project phase 3 (CMIP3) models [2] were considered and a detailed comparison at the dynamics level, using an approach involving climate networks [3] was performed. It was found that the models not only do not agree with each other when it comes to dynamics, they also do not agree with reality.

This result is confirmed in Fig. 1 using a different procedure. In this figure we asked the following simple question: What are the odds that a given month in the past 5 years was extremely warm (or cold) relative to the base period 1979–2011, for an arbitrary location in either the Northern or Southern Hemispheres? Our definition of extreme here is among the warmest (or coldest) 3 months in this period, so the base probability is $3/33 = 0.09$, which is the intersection of the lines in the figure. This is a question we can ask observations (here the ERA-Interim 2-meter temperature), as well as the CMIP3 near-surface air temperature, and compare the answers.

There appears to be an emerging confirmation bias in models. During the CMIP3 period, even though the model mean significantly over-predicts warm events and under-predicts cold events relative to the observations in both the Northern and Southern Hemispheres, some reasonable models analogs for the observed state are present. In addition, the spread between the models is rather large. For this reason the CMIP5 family of models was developed [4] in which several adjustments to the models were made. Fig. 2 is the same as Fig. 1 but for the CMIP5 models. We now see that indeed the spread between the models has decreased but the models are even more removed from the observations. While the model results are all converging on a solution that solution excludes the observed state at a $p > 0.99$ level of confidence. This strongly hints at an emerging confirmation bias, with the models evolving to resemble each other ever more closely in each progressive model generation. The disagreement between models and reality and the bias have also been identified in other more specific studies [5–8].

Empiricism is not bad, but it means that deviations from observations can always be subjected to (non-unique) correction, and hence cannot be shown to be fundamentally wrong. However if complex enough a simple fix may prove challenging, as we see from the peculiar clustering of Fig. 1.

3. Does computational overstabilization occur in models?

Speaking simply, physical systems may be either stable or unstable. When representing them on a computer, it is well known that numerical methods can exhibit false instability [1], but it is not universally appreciated. Lesser known is a fourth possibility: the numerical treatment of an unstable system can exhibit false stability [9]. Stability falsely emerging from numerics is *computational overstabilization*. The two erroneous scenarios of the four are easily linked because over-correcting false instability can easily lead to false stability.

Clearly, long-term integrations can be problematic even in linear systems with positive eigenvalues. The risk of such instability is aggravated for nonlinear systems. The logistic equation is the iconic example. Introducing *ad hoc* mathematical structures to stand in for sub grid scale physics compounds the matter further. Thus peculiar divergences, in addition to nonphysical properties emerging from climate models such as gradual mass loss or negative densities, might be attributed to computational artifacts. In that case, altering numerical procedures to control these phenomena, such as suppressing instabilities, is understandable.

Formerly, to control long timescale instabilities false fluxes were used to suppress them, known as flux adjustments [10]. Recent parameterization technology has made such explicit adjustments unnecessary, but it is far from clear whether they

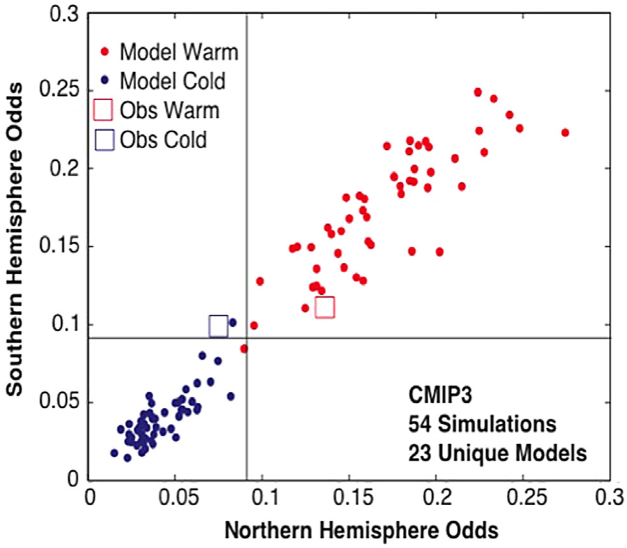

Fig. 1. A comparison between CMIP3 models and observations. See text for details.

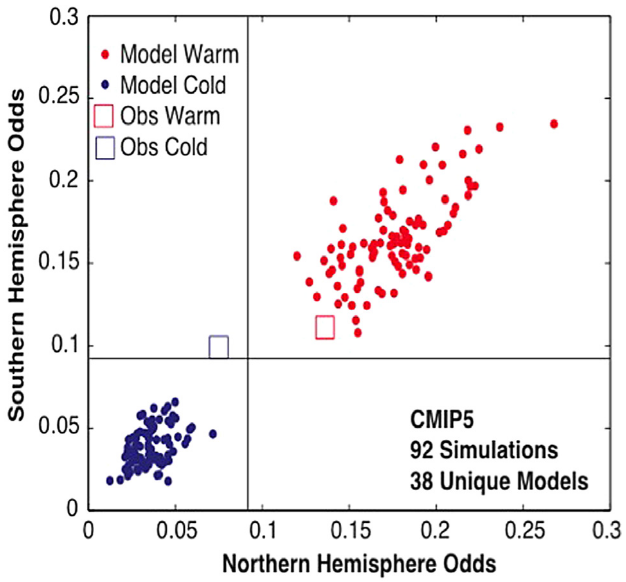

Fig. 2. A comparison between CMIP5 models and observations. See text for details.

are not just internalized into the ad hoc mathematical structures being employed. Climate models used for projections that have been stabilized exhibit white power spectra on long, extra-meteorological timescales, which implies steady long-term behavior, sometimes referred to as a "climate state".

But is this a true or false stability? We return to the notion of false instability. Just as one can imagine false instability, as suggested above, one can clearly imagine the reverse: natural (true) instability can be (falsely) suppressed by computational methods. In [9] this was illustrated by suppressing the chaos in the Rössler system

$$\begin{aligned}\frac{dx}{dt} &= -(y+z)\\ \frac{dy}{dt} &= x+0.2\,y\\ \frac{dz}{dt} &= 0.4+z\,(x-5.7).\end{aligned} \tag{1}$$

The largest Liapunov coefficient was confirmed as positive to demonstrate the inherent chaos for the indicated coefficient values. A backwards Euler numerical method was then employed to produce a computed solution that was a stable periodic attractor instead of an dynamically unstable strange attractor. Furthermore, the step size functioned as it were a bifurcation parameter. As it was reduced, the numerical solution exhibited period doubling bifurcations. The intrinsic instability of a known system was computationally over stabilized purely by the numerical method employed.

The notion of computational overstabilization has wide implications. The original question was to ask: is instability real or a computational artifact? But there is also (at least since [9]) a more sophisticated and equally important question to ask as well: is the stability of a computed solution real or a computational artifact? In the context of stable long-term climate model solutions, the question can be put slightly differently. Should initial instability in solutions be equated with other non-physical computational artifacts and suppressed? Is the emerging instability inherently computational, real, or some subtle mixture of the two? How could one tell the difference? Even if one could tell, how could one contrive to keep one and only suppress the other?

These are nontrivial questions, not only because the climate-model problem is so computationally extreme, but even if it were simpler, the task of separating computational instabilities from real ones is notoriously tricky. One might approach this question practically by looking at data, but even here the issue of long timescale stability in models is one of timescales over which we have sparse to no data. The importance of this issue for the utility of climate projections cannot be underestimated. If models exhibit a unique stable state over long timescales, this is key to the common claim that climate models can be distinguished from meteorological models as boundary value problems rather than initial value problems. It is central to any investigations of attribution of climate change that any long timescale change must come from external causes. The system has no ring to it and cannot change unless forced. The notion of forcing is thoroughly entrenched in the intuition of much of the research on climate. It has implications for the meaning of climate sensitivity. A dynamical system responds to external forcing in complex ways quite differently from a steady thermodynamic-like one.

If these white spectra could be proved false, our conception of many of the standard notions of climate research fall into jeopardy. Moreover, because the agenda of climate modeling is not only to capture climate in meteorological terms, but also to discover what it actually is in the process, these questions raise doubt about the agenda to discover climate through modified meteorological models itself. But there remains no way within current means to decisively falsify it.

4. Ultra slow modes versus climate state

In response to the doubts raised about the reality of the stability of solutions of climate models, a practical question can be asked: can anything be happening on these long timescales that could cause the spectra of computed model variables to be anything other than white? This is especially compelling when thought of in terms of thermodynamic timescales associated with reservoirs and flows comparable to the size of the system. The essence of a reply to this is that the system is not purely thermodynamical even on long timescales. Dynamical ultra slow modes in the ocean-atmosphere system are well known, but can they provide something that could overcome white spectra on very long timescales? Perhaps they can. Dynamical systems can lead to timescales of arbitrary duration when nonlinear coupling is involved. So the question is whether there is coupling and what is its nature?

This is difficult to answer directly because meteorological models and climate models compute a suite of thermodynamic and dynamical variables directly, while our data on such slow modes must be in terms of indices formed from incomplete meteorological data. Moreover the state of the art focusses on means over local temperature anomalies (i.e "global temperature") in order to compare to observations. More will be said about problems with this index in Section 5. Shifts in this global temperature index (known as climate shifts) are superimposed on a very long period increasing signal (often referred to as global warming). It is not always increasing however. For example, from 1880 to 1910 the trend is negative. It then changes to positive until the early 1940s. Then it shifts to negative until the mid 1970s and back to positive until 2000. And since 2000 it appears to have shifted again to a horizontal or slightly negative trend regime.

A series of papers [11–14] demonstrated that these shifts depict the ultra slow modes often described as the "natural variability" of the climate system. The ultra slow modes might be understood in the climate system (an infinite dimensional system) if there are low-dimensional sub-systems that may communicate with each other. It has been shown that a network of major climate modes (specifically, the North Atlantic Oscillation (NAO), the Pacific Decadal Oscillation (PDO), the North Pacific Index (NPI), and the El Nino/Southern Oscillation (ENSO) may synchronize intermittently. In other words, the four modes may resonate with each other in a variable manner. If during synchronization the coupling between the modes increases, the synchronization collapses and climate emerges in a new regime represented by a shift in the temperature trend. This mechanism (which is consistent with the theory of synchronized chaos) is purely dynamical and has explained all the above-mentioned climate shifts in the 20th and 21st centuries [11–14].

The above results refer to the collective behavior of the four major modes used in the network. As such they do not offer insights on the specific details of the mechanism. For example, is synchronization the result of all modes synchronizing or of a subset of them? When the network is synchronized, does the coupling increase require that all modes must become coupled with each other? To answer these questions [12] split the network of four modes into its six pair components and investigated the contribution of each pair in each synchronization event and in the overall coupling of the network. It was found that NAO is without exception the common ingredient in all shifts and when it is not coupled with any of the Pacific modes no shift ensues. In addition, in all cases where a shift occurs, NAO is necessarily coupled to north Pacific. In some cases it any also be coupled to the tropical Pacific (ENSO) as well, but in none of the cases NAO is only coupled to ENSO. Thus, results indicate that not only NAO is the instigator of climate shifts but that the likely evolution of a shifts has a path where the north Atlantic couples to north Pacific, which in turn couples to the tropics.

The results above provide a concrete picture of how the physics may play out. NAO, with its huge mass re-arrangement in north Atlantic, affects the strength of the westerly flow across mid-latitudes. At the same time, through its twin, the Arctic Oscillation (AO), it impacts sea level pressure patterns in the northern Pacific. This process is part of the so-called intrinsic mid-latitude northern hemisphere variability [15,16]. Then this intrinsic variability through the seasonal footprinting mechanism [15,16] couples with equatorial wind stress anomalies, thereby acting as a stochastic-like forcing of ENSO. This view is also consistent with recent studies showing that PDO modulates ENSO [17,18].

Another possibility of how NAO couples to north Pacific may be through the five lobe circum-global waveguide pattern [19]. It has been shown that this waveguide pattern projects onto NAO indices and its features contribute to variability at locations throughout northern hemisphere. Finally, north Atlantic variations have been linked to the northern hemisphere mean surface temperature multidecadal variability through redistribution of heat within the northern Atlantic with the other oceans left free to adjust to these Atlantic variations [20]. Thus, NAO, being the major mode of variability in the north Atlantic, affects both ENSO variability and global temperature variability. Recently a study has shown how ENSO with its effects on the Pacific North America (PNA) pattern can, through vertical propagation of Rossby waves, influence the lower stratosphere and how in turn the stratosphere can influence NAO through downward progression of Rossby waves [21]. These results coupled with our results suggest the following 3-D super-loop: NAO $\Rightarrow$ PDO/NPI $\Rightarrow$ ENSO $\Rightarrow$ PNA $\Rightarrow$ stratosphere $\Rightarrow$ NAO, which captures the essence of decadal variability in the northern hemisphere and possibly the globe.

These results suggest an alternative way of thinking about multi-decadal climate variability, incompatible with the white spectra of climate models. The ultra slow modes can be thought of in terms of a system of a few ordinary differential equations (ODEs) in variables, x, y, z, w and functions, f_i, $i = 1 \dots 4$, to be determined in principle much as the variables in the Lorenz equations are. However in this picture we link to the indices of the slow modes in the super-loop. Taking x as the PDO index, y as the NPI index, z the Nino 3.4 index, and w the NAO index, and given the functions above, as well as the discussion in this section, the functional dependencies are set according to the system of ODEs,

$$\begin{aligned} \frac{dx}{dt} &= f_1(z, w) \\ \frac{dy}{dt} &= f_2(z, w) \\ \frac{dz}{dt} &= f_3(x, y) \\ \frac{dw}{dt} &= f_4(x, y, z). \end{aligned} \tag{2}$$

In practice such a system could be realized empirically with dynamical reconstruction techniques applied to observations, pioneered in the 1980's and 90's, but recently done through techniques such as "knowledge discovery", or "machine learning" (e.g. [22–24] and references therein). The basic approach is to assume that a time series is the result of a deterministic process or quasi-deterministic one for which the observations represent a single realization. In dynamical reconstruction the functions, f_i would typically be presumed to be polynomials. The degree of these polynomials is empirically determined by matching the values obtained from model simulations against the measured values. The empirical matching can be done through many criteria that minimize error, but conventionally they are done by summing the mean square errors (MSE) of all individual variables using the variances of individual variables as a normalization factor (normalized MSE, NMSE).

5. Thermodynamical versus dynamical sensitivity

A climate model without ultra slow modes admits a thermodynamic-like conception of climate and climate change. In that picture, only external action can cause change, and that change can only represent a shift from one stable long-term state to another. This suggests a sensitivity in a thermodynamic-like framework—the most notable example being change in the "global temperature" (which is no proper thermodynamic temperature [25]) divided by change in carbon dioxide amount, or fluxes when processed through a radiation model. It suggests the existence of a function, where "global temperature" is a function of amount. Without long-term stability, there is little reason for such a function to exist [26]. In this picture, climate change can only be conceptually equivalent to global "warming" or "cooling" and little else. A consequence of the global thermodynamic-like picture is that local properties are integrated out or ignored (e.g. the velocity, and pressure fields), and discussion based on this tends to become speculative.

If ultra slow modes are present on the other hand, dynamics, as in system (2), emerges as a finite dimensional projection from the infinite dimensional foundation on which all of this theory is based. At best it can be approximate. Higher order terms are likely small instead of strictly zero. Climate and climate change framed in terms of such a system is inherently dynamical and not thermodynamical. It can have timescales much longer than thermodynamical ones through dynamical phenomena such as chaos or multi-periodicity. Intermittency can also produce transient behavior of any duration, depending

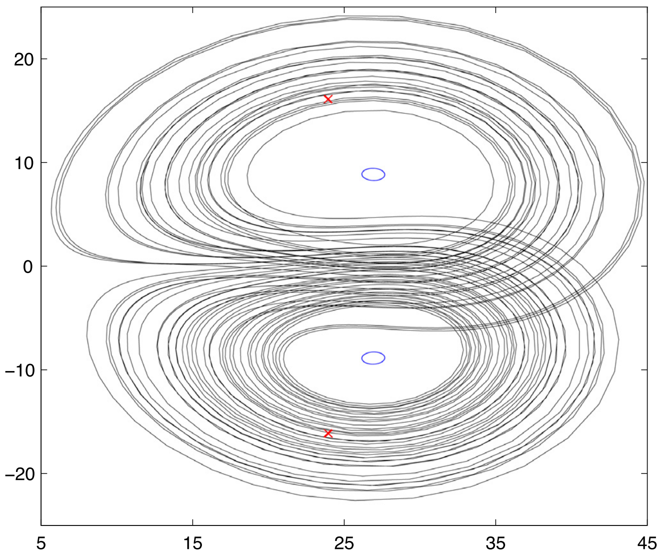

Fig. 3. $x - y$ projection of the Lorenz system perturbed with small correction term in the x Eq. (3) controlled by parameter ϵ. Clearly bifurcations take place as the attracting set changes qualitatively. Black represents $\epsilon = 0$ which is the classical Lorenz attractor. Blue depicts two limit cycles occurring for $\epsilon = 0.0314485$. Red depicts stable fixed points that the computed solutions approach for $\epsilon = 0.0315$. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

on details. Long transients might be interpreted practically as climate change, even if there is actually no qualitative change in terms of underlying properties—apparently causeless change.

External forcing of a dynamical system is very different than external forcing of a single temperature-like quantity. One imagines energetics seen narrowly as heat involved in the thermodynamic-like case, suggesting a minimal limit to the size of external forcing that can have a discernible effect. However in the dynamical case this does not necessarily apply. Changing the dynamical nature of the forcing for a dynamical system can significantly change the outcome. For example, keeping forcing level constant but changing even just the phase of a periodic forcing mechanism can vastly change the behavior of an oscillator.

Climate change need not be thought of as a change of value but as a qualitative change in dynamics. To fix ideas, imagine another example of a system known to be a lower dimensional approximation not unlike the climate system (2), the Lorenz equations. Sharp qualitative change in its solutions can occur even when they are only slightly perturbed,

$$\frac{d}{dt}\begin{pmatrix} x \\ y \\ z \end{pmatrix} = \begin{pmatrix} 10(y-x) \\ 28x - y - xz \\ xy - \frac{8}{3}z \end{pmatrix} - \epsilon \begin{pmatrix} 1 \\ 0 \\ 0 \end{pmatrix} yz. \tag{3}$$

One particular *ad hoc* perturbation, of scale ϵ, shows sharp qualitative change in solutions. Fig. 3 shows this change, where $\epsilon = 0$ (black) depicts the $x - y$ projection of the unperturbed equation.

A single temperature-like index may not capture such change at all. That is, climate change can occur without a change in the global temperature index. Conversely, dynamical systems can be stable against outside perturbation. The classical example would be a gyroscope. Such dynamical stability implies the possibility of the absence of meaningful dynamical change even should the global temperature index change. When ϵ is raised to 0.0314485 (blue) the computed dynamics apparently has passed through bifurcation. A pair of limit cycles replace the strange attractor. When ϵ is pushed only slightly higher to 0.0315 these are replaced by apparent fixed points (red crosses).

The specific external linkage to a dynamical process in principle could be very subtle. While for example the sun has a very steady input, small perturbations in its behavior can alter how the infinite dimensional dynamics lingers on a particular finite dimensional sub-manifold. We may not even be aware of a perturbation such as in system 3 while these externalities tweak the value of ϵ. This is not to suggest that we can expect complex behaviors to be replaced by limit cycles or fixed points per se, but that modes can change due to external causes very differently than by simple discussions of energetics, or even some well-defined physical mechanism. After all, if intermittent bursts can seem like causeless change, one ultimately has to accept that the real causality is in terms of the underlying dynamical structures set by the physics. Dynamical sensitivity opens the prospect of change through mechanisms that are not so obvious such as arguments about heat: crypto-sensitivity.

6. Conclusions

Finding a theory for climate within the physics of the laboratory regime is, of course, roughly analogous to trying to extract the fluid mechanics of the laboratory regime from the microscopic chaos of kinetic theory [26,27]. Even the range of scales between the kinetic and laboratory regimes is similar in size to the corresponding range between the laboratory and climate regimes. The explanation of the laboratory scales in terms of kinetic ones has historically been fraught with deep difficulties, which inspired great endeavors in perturbation theory and even whole new fields such as ergodic theory, and it ultimately became one of the major roots of modern dynamical systems theory and chaos.

In contrast, employing meteorologically-based computer models for climate is a program to capture climate in meteorological terms. Describing those models as models of climate overlooks the central scientific problem that they must address. They are forced to search for what climate actually is within those terms. Thus there is an important distinction between the kinetic-laboratory scale problem and the meteorology-climate problem. The latter is a far more ambitious scientific problem. No matter how difficult the path leading from the kinetic regime was, there was always the clear guiding principle that the path had to end at the laboratory regime, which was and is fully known. Unlike the kinetic analogue, the meteorological path has no clear end point. There is no rigorous, physically-based regime to aim for that is known *a priori*. There is no choice but to search for what climate actually is in meteorological terms, in addition to navigating the search over a path fundamentally handicapped by a truncated physics necessitated by the finiteness of our tools.

It is beguiling to believe that the white spectra emerging from empirical meteorological models of climate achieves the central scientific objective of finding climate through meteorology. If true, it represents a fortunate windfall that cuts short a uniquely arduous, and potentially impossible, task. If true, a formal basis for discussing a prominent suite of properties, from sensitivity to attribution, becomes possible. Statistical plausibility arguments not withstanding, there is no theoretical way to prove this proposition based only on known underlying physics. But what else could cause this phenomenon in the models? Alternatively, what true dynamics could there actually be other than none at all, and why might it not appear in models? This paper provided answers: computational over-stabilization and ultra-slow modes.

So do ultra-slow modes falsify the white spectra? Perhaps. The modes represented in the suggested system (2) are not meteorological variables from the laboratory regime, but instead are more like indices; they are not rigorously set, yet. Thus they do not immediately present knowable perturbations in the meteorological variables already in play in the computer models themselves. Moreover if one were to practice some sort of empirically based reconstruction technique such as described above that could actually fit into such computer models to transform the behavior to being non-white on the multi-decadal timescale, this does not obviate the possibility of simply pushing off a white spectrum to still longer timescales. Thus knowledge of the existence of ultraslow modes and their complex behaviors does not yet decisively settle the scientific question any more than white spectra show that meteorologically based models have captured climate.

Issues like climate sensitivity, attribution, and even the nature of climate change all hang in the balance. Clearly alternatives are necessary, and any effort to re-think the problem from super models to dynamical reconstruction methods that might be able to naturally reach into the multi-decadal timescales to give an independent window into that regime is welcome.

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