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Wild Fires and Climate Change-Nowcasting and Forecasting Climate Change Using Advances in Machine Learning Methods

Christoph Kohlhepp[1*]

[1]Principal Data Scientist, Fulcrumbright Ltd., Queensland, Australia. E-mail: chris.kohlhepp@gmail.com

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Abstract

This paper seeks to address many questions on climate change. Some questions may be deemed answered conclusively already, such as are we as humans changing the global climate? More interestingly perhaps, this paper seeks to establish conclusive causal links between climate change and its effects, in particular the large wildfires that swept the United States and Canada as well as the bush fires that ravaged Australia in the lead-up to the covid pandemic. There are many ways to build climate models. Ours are built using a bespoke Artificial Intelligence (AI) pipeline. This AI pipeline was built to model the complexities of our global climate and the many noisy interactions within it. A key goal of our model has been to be accessible. This means we have tried to show trends and probable outcomes in the lifespan of the average person, built on data inputs of the lifetimes of present-day generations. People cannot relate to the medieval warm period. They were not there. Instead, we aim to build models from what is and has been playing out right in front of our own eyes. The aim has been to build actionable data within the horizon of decision makers of around 5 to 10 years—or one or two election cycles. How often have we heard about projections for the end of the century? Once we get there, it will be too late. What is needed are models for the "here and now". And based on our models, individuals might choose where to purchase a house, what country to live in, or fire fighters might direct their resources to better combat wildfires. We have combined our global climate model with city level data across four countries: Australia, the United States, Canada and New Zealand.

Keywords: *Climate change, Wildfires, Mechine learning, Data sets*

1. Introduction

The author has always been a sceptic, always prone to ask questions. The climate story is no exception. Just before the covid pandemic, that climate story became close and personal. As an Australian living in Australia, the author witnessed the colossal destruction inflicted upon the Australian landscape during the fire season

* *Corresponding author: Christoph Kohlhepp, Principal Data Scientist, Fulcrumbright Ltd., Queensland, Australia. E-mail: chris.kohlhepp@gmail.com*

of 2019/20. Parliamentary data shows that 17 million hectares were burnt across the state of New South Wales alone (Lisa *et al.*, 2020). The fires claimed the lives of an estimated one billion mammals, birds and reptiles (Lisa *et al.*, 2020). Seventy-one human lives were lost (Lisa *et al.*, 2020). It was time to submit scepticism to mathematical scrutiny.

Adding to the woes of the covid pandemic then under way, residents of Western Australia found themselves threatened by another wave of bush fires in February 2021—in the midst of a covid lockdown (Julia, 2021). While the pandemic had the center stage the world over, the relevance of climate change and wildfires was only elevated.

This paper seeks to make sense of an experience then shared by many Australians, Canadians and Americans and enable decision making for the future.

Our gratitude goes out to the families in the United States, Canada, New Zealand and Singapore who sent their loved one to our shores to help during the bush fires of 2019/20.

2. Technical Vision—A Generative AI Pipeline

Our AI pipeline is built using the MIT programming language Julia and its eco-system. Broadly, this ecosystem combines elements of machine learning to carefully construct what we call "Causal AI" Our eco-system excels over traditional statistical approaches in that it allows modeling complex, non-linear relationships in dynamical systems while it is explainable and can be trained on sparse data sets much smaller than what is typically required to train many deep learning models. Strategically, the choice of a high-performance programming language Julia (over Python) means that larger data sets can be handled also. This enables the swift construction of models from heterogeneous and alternative data sets on commodity hardware to achieve what customarily requires larger data centers.

3. Technical Vision—Dynamical Systems Causality Analysis (DSCA)

A key value proposition of our eco-system is a machine learning method which we term Dynamical Systems Causality Analysis (DSCA). This permits the analysis of diverse and large data sets under conditions where traditional statistical methods and modern machine learning methods struggle. DSCA facilitates disambiguation of "Non-Granger Causality in complex dynamical systems with feedback loops, discontinuities and involving of regime shifts.

Consider two variables A and B which may exhibit statistical correlation or may exhibit a "dependence probability." Both correlation and "dependence probability" are non-directional concepts meaning they are agnostic to causation. If two variables A and B are dependent, then A might cause B or B might cause A. In a dynamical system the two might reinforce one another through a feedback loop. Finally, a common forcing variable C might cause A with certain delay and B with a longer delay, leading an observer of A and B to falsely conclude that A causes B because the two are correlated and A precedes B (Granger Causality). Moreover, relationships may hold over varying timelines and not beyond these. Indeed, such timelines may eventually differ for in-sample and out of sample data. Traditional statistical approaches and most modern machine learning approaches will struggle in the aforementioned setting, miss important relationships or identify false positves. Please refer to CO_2 and C13 Discussion and to CO_2 and C13 Causality – Dynamical Systems Causality Analysis for an elaboration of how these concepts apply in climate analysis.

4. Discussion—Climate Change; How Do We Know?

Some of the key questions this paper sets out to answer are shown below:

1. Is the world really getting warmer?
2. Is any warming causally dependent on CO_2?
3. Are humans to blame in any causally dependent relationship between CO_2 and global temperatures?
4. Can we mathematically attribute changes in weather extremes to human initiated CO_2 emissions?
5. Can we predict weather extremes so as to proactively manage them?

Although these are straightforward questions, none have trivial answers.

1) In looking towards the first question "Is the world really getting warmer?", what is a valid measurement of global temperature? While it is summer in one hemisphere and it is winter in the other. Global temperatures exhibit seasonality–or cycles. There are many such cycles. Should "global temperature" mean air temperature or ocean temperature? Oscillating ocean temperatures (El Niño, La Nina) are another cycle—as are day and night. All such cycles have different durations so a simple averaging of temperatures over one fixed period cannot fully capture what is happening. El Niño and La Nina, for instance, aren't simply annual cycles. Some drivers of global temperature exhibit varying patterns but not "neat" cyclicality–think trade winds or solar radiation. Human perception, highly subjective, is not helpful either. Who can really claim to feel a 0.5-degree temperature difference over a time span that exceeds human life expectancy?

2) In looking to answer the second question "Is any warming causally dependent on CO_2?", merely showing a rise in CO_2 with an associated rise in temperature, does not sufficiently establish causality. Experimental intervention, typically required to establish true causality, is not possible. We cannot turn back time and repeat the Industrial Revolution in a controlled experiment to establish how different actions (factors) lead to different outcomes. In a complex system, there will be many so-called factors. Data scientists refer to this as a factor model. What we really want to show is that one factor depends on another, not merely that the two are correlated. Correlations miss non-linear dependencies. Moreover, spurious correlations are ubiquitous. In dynamical systems, factors can be mutually reinforcing. We are looking to isolate genuine dependencies from an otherwise noisy and complex environment.

3) In looking to answer the third question "Are humans to blame in any causally dependent relationship between CO_2 and global temperatures? ", we will need to show that the burning of fossil fuels is a causal dependency in the change of CO_2–rather than CO_2 variations occurring naturally.

4) As to the fourth question, "Can we mathematically attribute changes in weather extremes to human initiated CO_2 emissions?" Explaining weather extremes is the casus belli of this paper. We have witnessed an increase in reports of record temperatures, wildfires from Australia to California and floods around the world. Or rather, we have witnessed an increase of news reports of such events on our personal devices. Is it we are more aware of such events now because we carry the news in our pockets or are we truly seeing more events of the kind in question?

5) The fifth question "Can we predict weather extremes so as to proactively manage them?" follows on from the forth question. If we can predict weather extremes, such as wildfires, then we can more effectively direct existing resources and more effectively target pre-emptive measures. For instance, firefighting crews and equipment are shared between California in the United States and Australia. Improved predictions mean improved scheduling of resources. Beyond simply directing resources, we might choose one mitigating action over another. For example, can we quantify the contribution of vegetation to fires in order to assess the impact of backburns or control burns? We will look at this in the context of satellite vegetation indices and wildfire impact.

5. The Data

The following is an overview of the data used to construct our global climate model.

6. Elaboration—Is the World Really Getting Warmer and Why?

6.1. Cross-Sectional Correlation Analysis – Non-Longitudinal

Figure 1 depicts hierarchically clustered correlations in the global climate model. Red depicts strong correlations. Dark blue depicts non-correlations.

6.2. Observations

Few strong correlations exist. Of note is that atmospheric C13 is strongly correlated to atmospheric CO_2. For the benefit of the reader, atmospheric C13 denotes the global isotopic CO_2 concentration, or the ratio of carbon C13 to C12. C13 is an important indicator for the following reasons: Plants prefer to absorb C12 from the atmosphere during photosynthesis, but the atmosphere contains a mix of C13 based CO_2 and C12 based CO_2. All fossil fuels

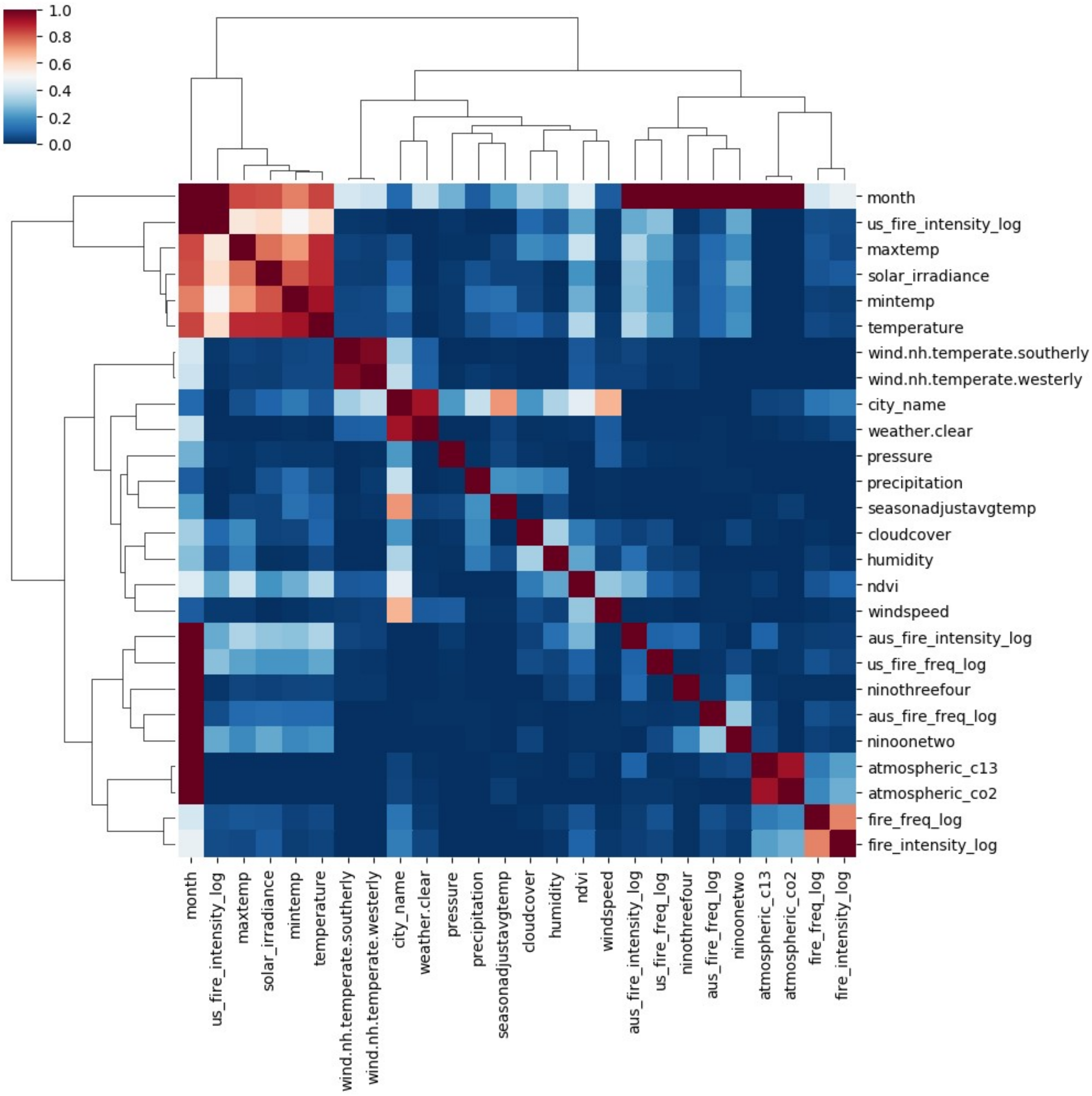

Figure 1: Global Climate Correlations - Hierarchical Cluster

Table 1: Model Data Overview

Global Temperatures, Humidity, Cloud Cover, Pressure, Wind Direction and Speed	Openweathermap.com
	[All temperatures are indicated in degrees Celsius Daily, weekly and monthly, maxima, minima]
Global Temperatures, Precipitation	NASA Power Project
	[All temperatures are indicated in degrees Celsius Daily, weekly and monthly]
Mauna-Loa CO_2 and Isotopic C13	Ourworldindata.org
Country CO_2 Emissions	Ourworldindata.org
El Nino and La Nina Ocean Temperature	National Oceanic and Atmospheric Administration
Solar Irradiance	NASA Power Project
Wildfires United States, Canada and Australia	NASA Earthdata Project
Vegetation Indices	NASA Moderate Resolution Imaging Sprectroradiometer

were, once upon a time, plant material. Hence when we burn oil, coal or gas, we chiefly emit C12 based CO_2, leading to a relative decline in C13. If we can (a) show correlation between the two factors; (b) demonstrate strong dependence probability (discounts spurious correlation); and **(c)** demonstrate causality, then we can hypothesise that humans, rather than natural climate change, are driving changes in atmospheric CO_2 (Table 1).

The principal modeling method shown here is cross categorization (Figure 2). An element of Exploratory Data Analysis of our pipeline, this method produces query-able clusters of related information which allows inferring what characteristics of the data are associated with what other characteristics of the data and with what probability.

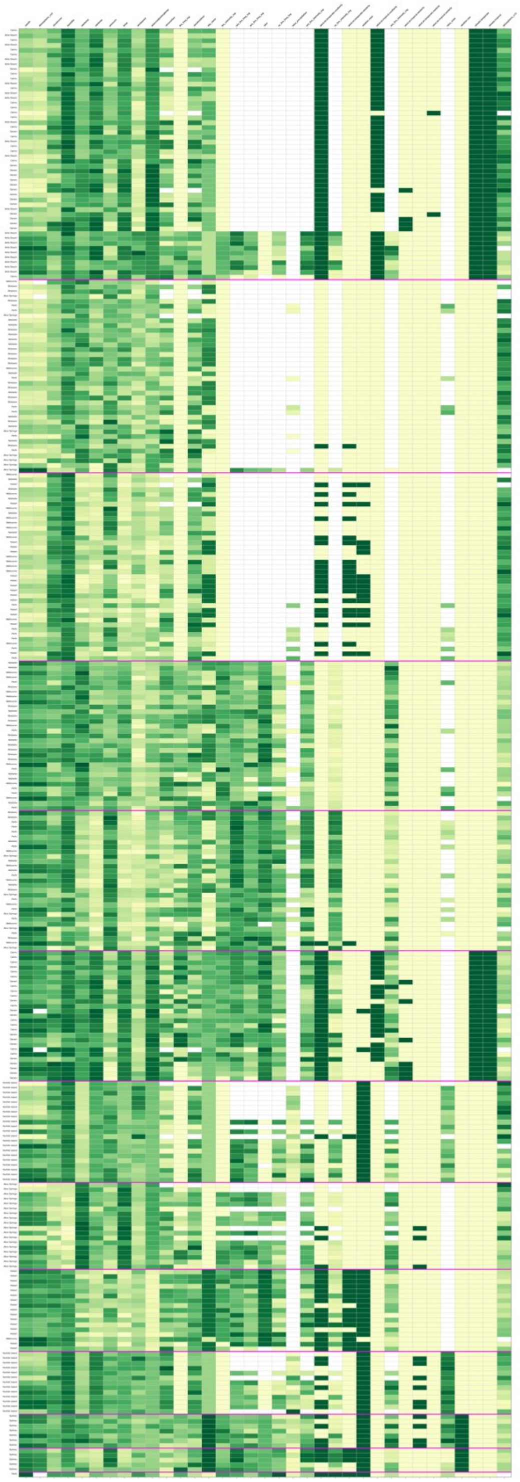

Figure 2: Cross Categorization Visualized - Australian Climate Model

6.3. Legend

6.3.1. Notes

The model, as above described, is a so-called cross-sectional model. It spans samples collected across time slices and across different locations/regions. Hence, when we say "humidity," we mean humidity recorded over time and at a location (city_name). The same applies to all parameters except CO_2 concentrations which are global and except regional parameters, e.g. United States wildfire frequency. The latter is recorded at a country level (Table 2).

This is a static, non-longitudinal model: samples are collected over time but no weight is given to recent time values over non-recent values. Later models will be longitudinal. In keeping with the aim of sourcing data from a period that generations alive today can remember, data has been collected from January 1, 1979 to the present, or approximately forty years.

Table 2: Model Parameters

Item Abbreviation	Description
month	Month of the year
us_fire_intensity_log	Fire frequency, United States, logarithmic
maxtemp	Maximum surface temperature
solar_irradiance	Solar radiation
mintemp	Minimum surface temperature
temperature	Surface temperature
wind.nh.temperate.southerly	Northern hemisphere southerly winds
wind.nh.temperate.westerly	Northern hemisphere westerly winds
city_name	Cities and more broadly locality names
weather.clear	A variable describing if the weather was clear
pressure	Air pressure
precipitation	Rain and/or snow
seasonadjustavgtemp	Annually season adjusted surface temperature
cloudcover	Cloud cover index
humidity	Humidity index
ndvi	Vegetation index in proximity to a location (GIS satellite data)
windspeed	Wind speed
aus_fire_intensity_log	Australia bush fire intensity, logarithmic
us_fire_freq_log	United States, wildfire frequency, logarithmic
ninothreefour	El Nino and La Nina ocean temperature, oceanic regions three and four
aus_fire_freq_log	Australia, bush fire frequency, logarithmic
ninoonetwo	El Nino and La Nina ocean temperature, oceanic regions one and two
atmospheric_c13	Isotopic Carbon13 CO_2 concentration
atmospheric_co2	CO_2 concentration
fire_freq_log	Wildfire frequency logarithmic
Fire_intensity_log	Fire intensity logarithmic

6.4. Cross-Sectional Bayesian Dependence Probability Analysis – Non-Longitudinal

Figure 3 hierarchically clustered Bayesian dependency probability in the global climate model based on mixture modelling.

6.5. Observations

We again note the strong dependence between atmospheric_co$_2$ and atmospheric_c13. We also note a strong dependence between US and Australian fire frequency and temperature as well as between US and Australian fire frequency and El Nino and La Nina ocean temperatures. Nearly all factors, except pressure have a greater 50% dependence probability on one or more other factors and are part of a cluster. No strong connection between CO$_2$ and temperature emerges in the non-temporal model – we will see this change in models accounting for time.

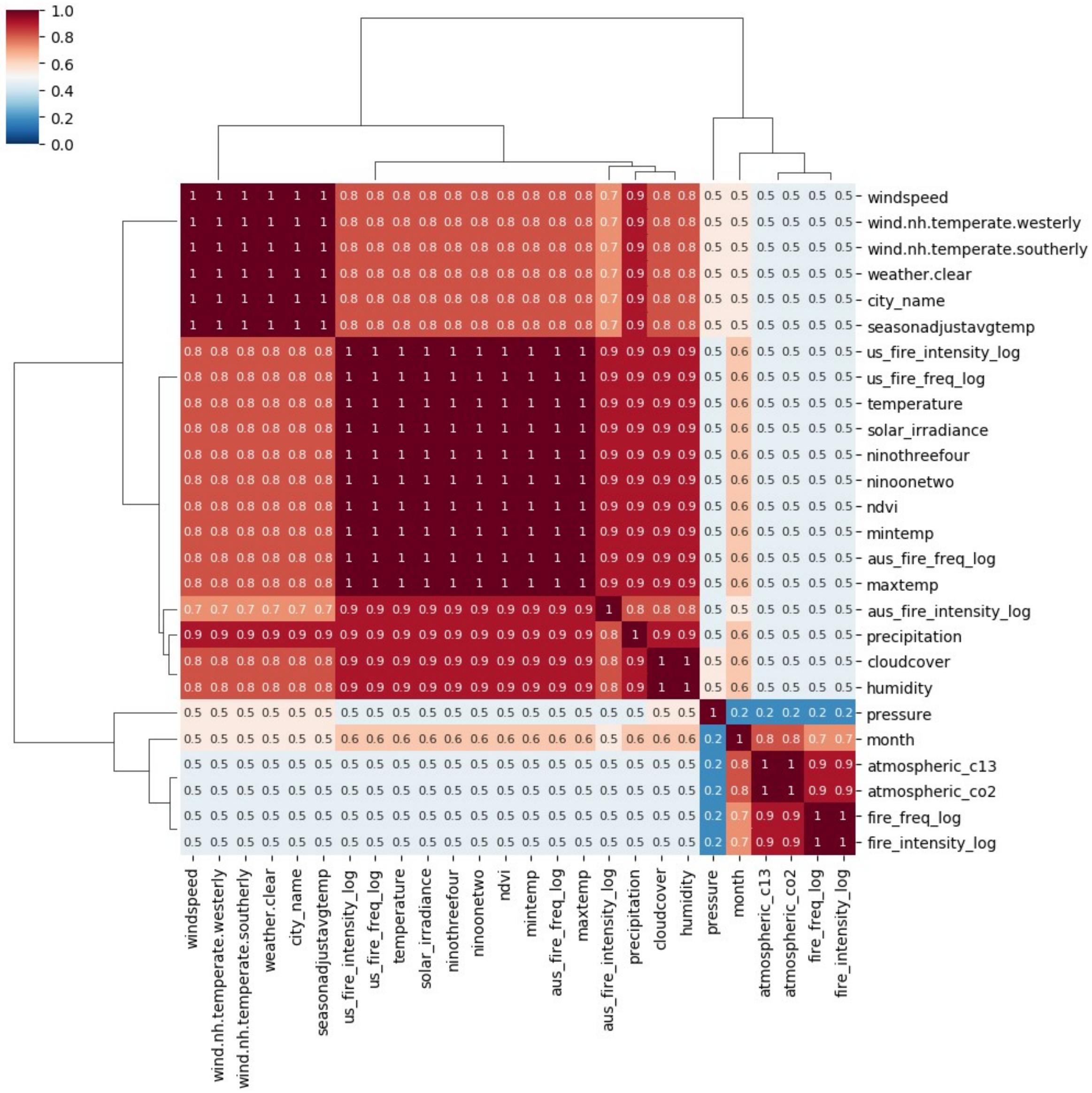

Figure 3: Bayesian Dependence Probability – Hierarchical Cluster

6.6. Bayesian Dependence Probability Analysis-Longitudinal

In the following section, we will present the longitudinal (time series) rendering of our previous models. Individual parameters are aggregated at a region level (arctic, northern hemisphere temperate, tropical, etc.) and cross-sectional parameters are "unrolled" to form parameter/section pairs. This in turn leads to a much larger matrix, which is not easily represented in a "page format" while maintaining readability (Figure 4).

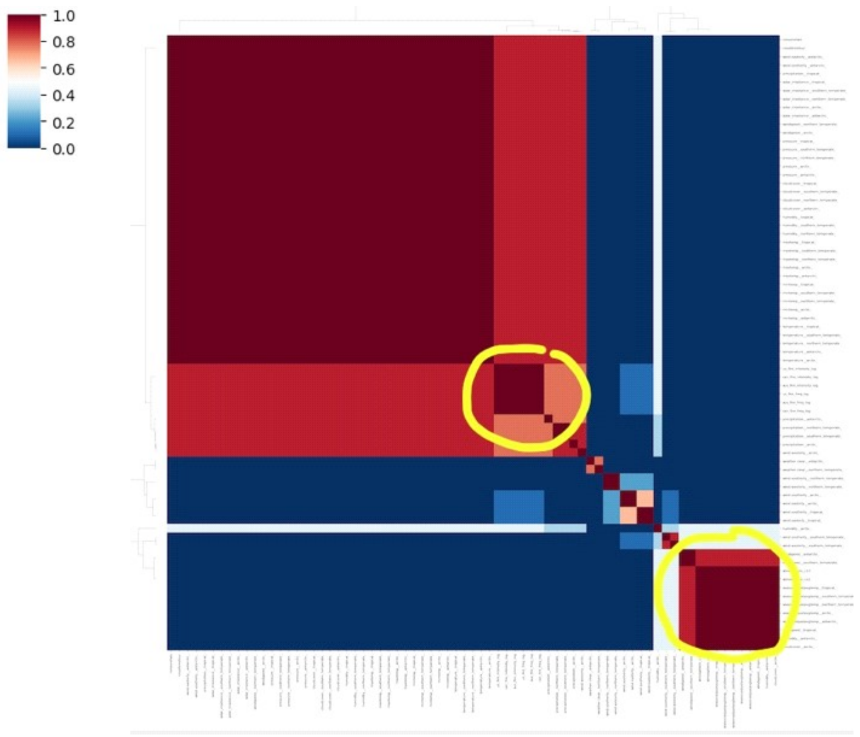

Figure 4: Longitudinal (Temporal) Bayesian Dependence Probability

As before, the diagram is hierarchically clustered, so the clusters circled in yellow are areas of interest. We will direct our attention firstly to the bottom cluster, then the center cluster.

6.7. CO_2/C13 and Seasonally Adjusted Average Temperature Cluster

The strongest temporal dependencies of atmospheric_c13 and atmospheric_co$_2$ are the annually season adjusted average temperatures of each climatic region of the globe: arctic, northern temperate, tropical, southern

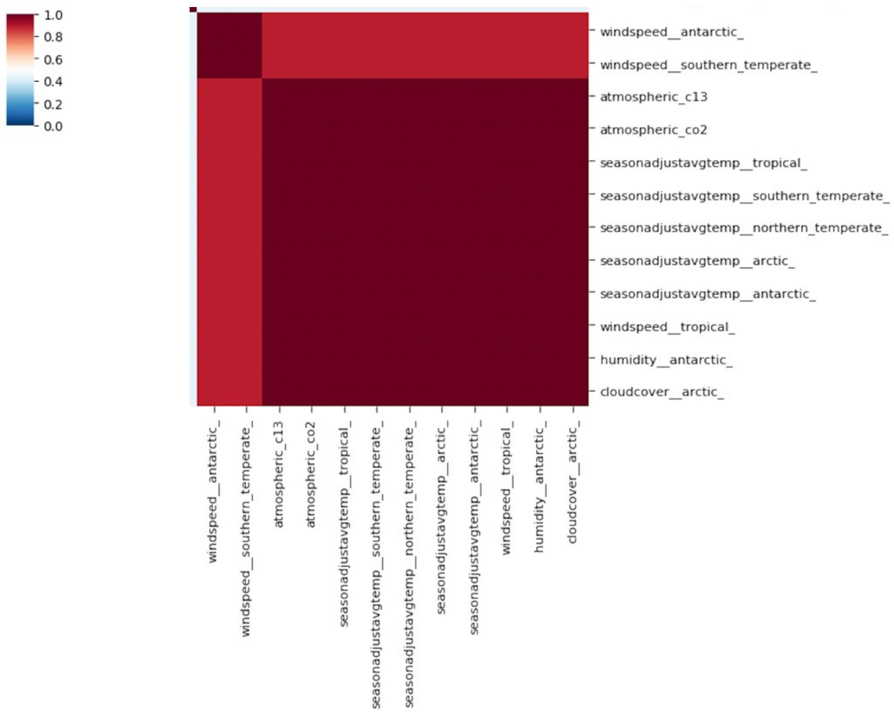

Figure 5: Seasonally Adjusted Average Temperature and CO_2

temperate, Antarctic. This is a remarkably consistent pattern. All three analyses (static correlation, static Bayesian, temporal Bayesian) informed a dependency between atmospheric_c13 and atmospheric_co_2.

This longitudinal Bayesian analysis ties atmospheric_c13 and atmospheric_co_2 with near 100% certainty to the season adjusted average temperature in all climatic zones of the globe (Figure 5).

6.8. Wildfires–Country Interdependencies Cluster and Factor Model

Figure 6 depicts probability dependencies between regional wildfires, both frequency and intensity. This strong interdependence across continents suggests a truly global underlying trend shared by all. It also suggests that fire activity in one region or continent is predictive of fire activity in another. Therefore, models predicting each region should consider the other regions.

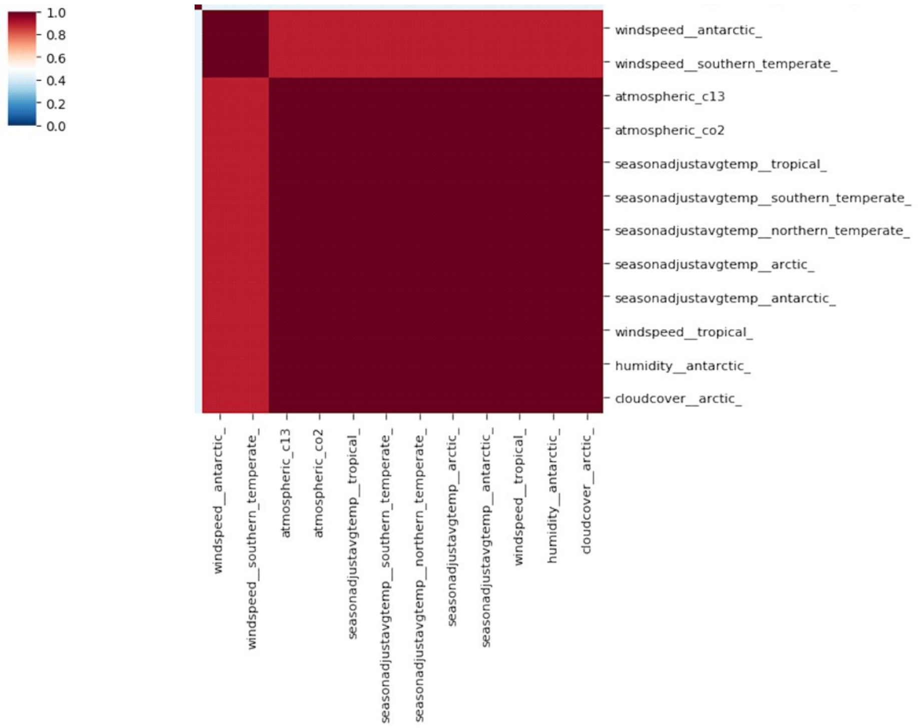

Figure 6: Wildfires–Country Interdependency Cluster, US, Canada, Australia

Further, regional fire activity depends on 39 other factors, of which 17 are water and air temperatures *("ninoonetwo", "ninothreefour", "maxtemp…", "mintemp…", "temperature…")* and a further 5 are temperature forcing variables *(solar irradiance)*. Critically, this suggests that over half the dependencies of regional wildfires are temperatures (Figure 7).

Figure 7: Regional Wildfire Factor Model

Other factors are, understandably, wind, humidity, cloud cover and precipitation. Not only are these factors intuitive but they corroborate and validate the model based on what we understand about the domain.

6.9. Climatic Region Models

For each climatic zone we present in-sample models of temperature and, as extremes are more often responsible for extreme climate events than averages, the records of temperature maxima. The blue line represents observed values. The black line represents median values, while the green confidence bands represent one and two standard deviations from the mean. The pink vertical line represents the present, i.e., now. The yellow line represents a ten-year moving average, annotated with peak and trough markers.

Each model also shows the Ordinary Least Squares (OLS) trend of observed values. All trends are positive, showing that all regions experienced consistent warming. Model fit indicators are Root Mean Squared Error (RMSE).

6.10. Note

For the benefit of the reader, OLS is a statistical method of representing a dataset with a line in such a way that trends can be estimated (Figure 8). The method produces two results: the intercept with the Y-axis (dependent variable) and the slope of the line–or the trend of the line. Since many lines are possible, the method produces that line which minimizes the overall error between actual data values (dependent variable) for all values on the X-axis (explanatory variable).

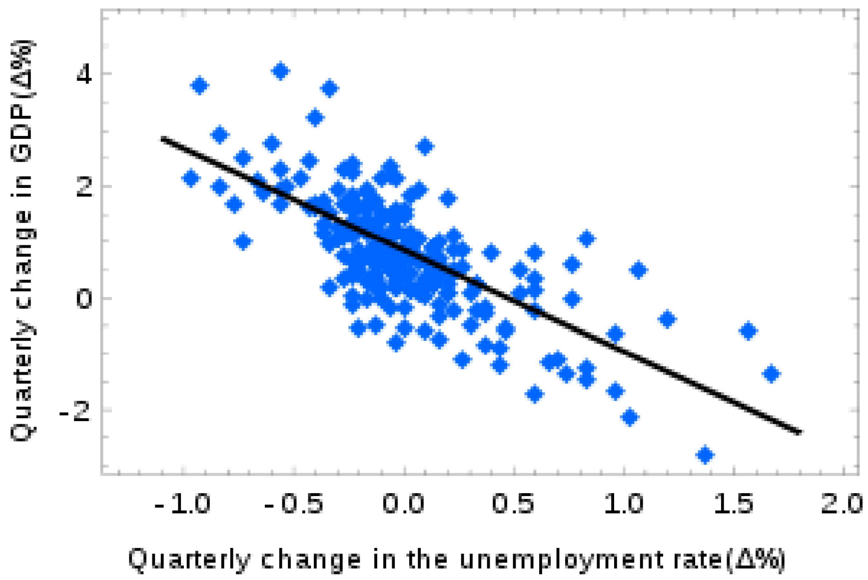

Figure 8: Visualizing OLS

Source: Wikipedia (OLS)

If the explanation above is inaccessible, one might think instead of an equal arm beam weighing scale as shown below:

Items on the scale may be irregularly distributed in the dishes on the left and right, but the scale will disambiguate if the sum of weights is heavier on the left or on the right. OLS likewise will disambiguate if the weight of the data samples on the graph trends upward or downward. In this manner, even if the data exhibits no upward or downward trend that is discernible with the human eye, we can still evaluate any trend. A very intuitive and visual explanation of Ordinary Least Squares (OLS) can be found here:

https://setosa.io/ev/ordinary-least-squares-regression/

6.11. Arctic Temperatures

In the annually season adjusted temperature model we observe a consistent warming trend. The peak value for the moving average is the present (Figures 9-11).

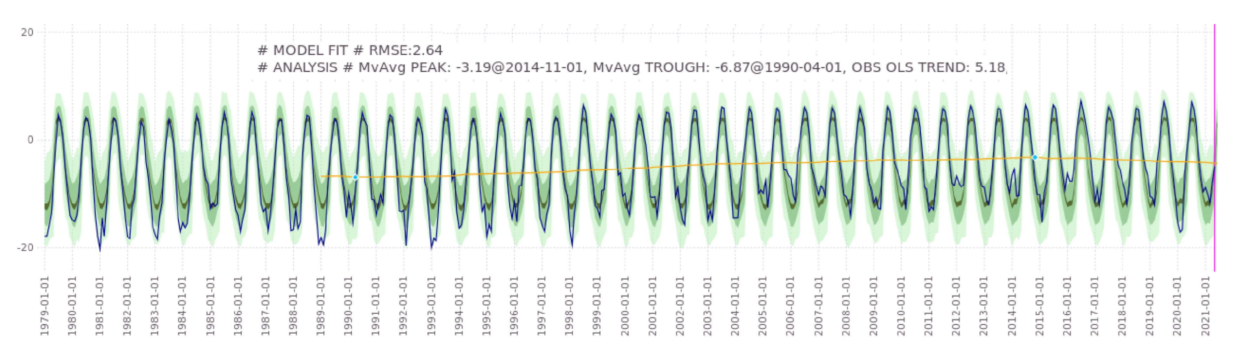

Figure 9: Temperature Arctic

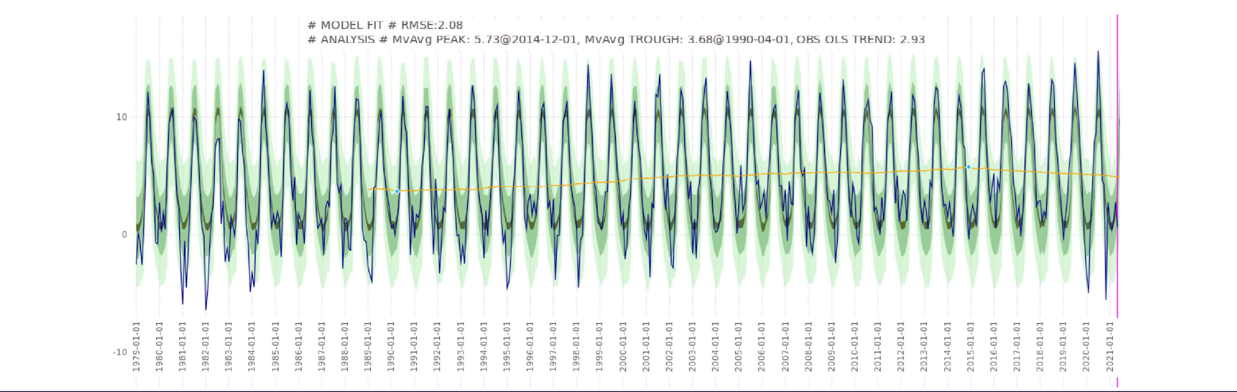

Figure 10: Maximum Temperature Arctic

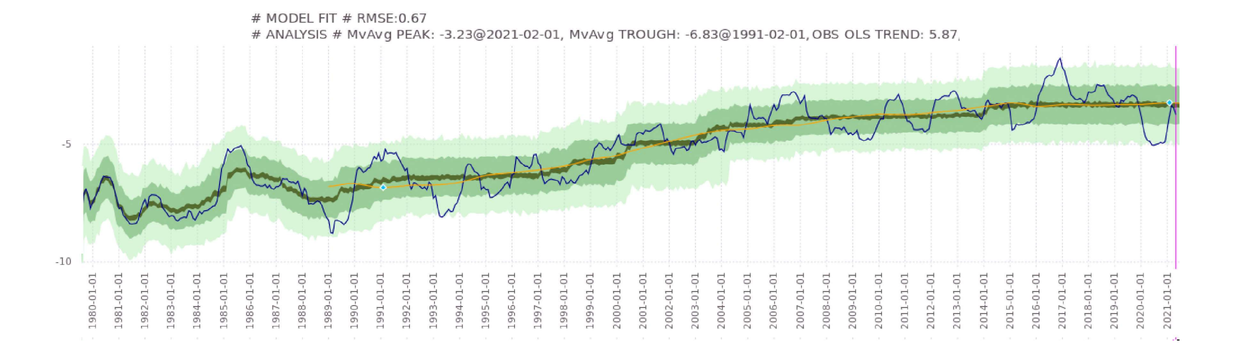

Figure 11: Seasonally Adjusted Arctic Temperature

6.12. Temperatures in the Northern Hemisphere Temperate Zone

In the annually season adjusted temperature model we observe a consistent warming trend. The peak value for the moving average is the present (Figures 12-14).

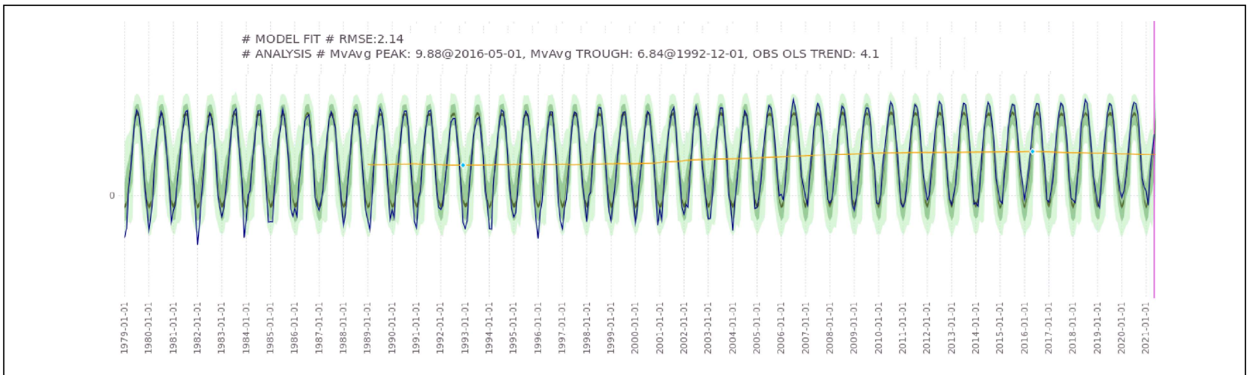

Figure 12: Temperature Northern Hemisphere Temperate

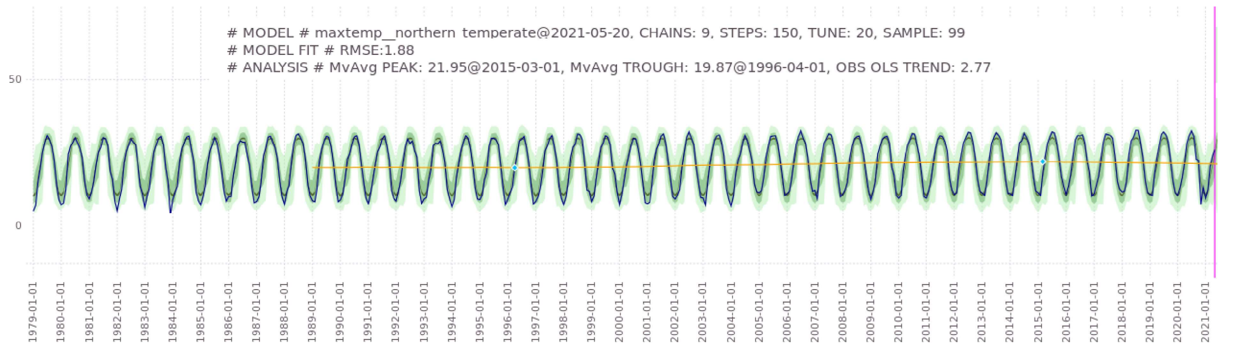

Figure 13: Maximum Temperature Northern Hemisphere Temperate

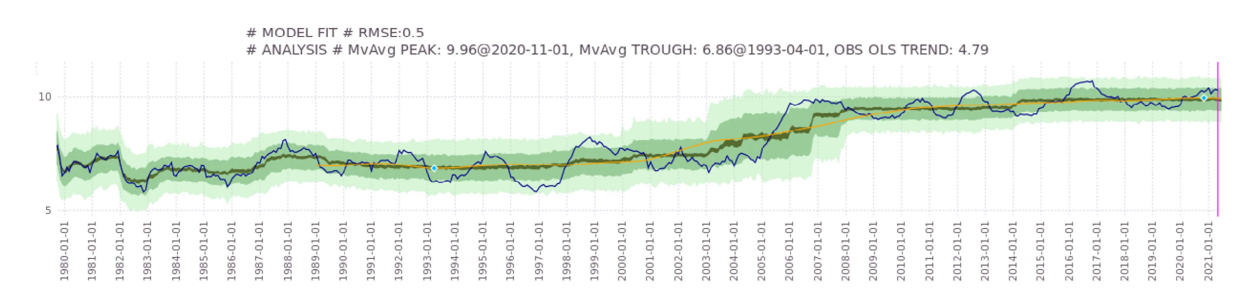

Figure 14: Seasonally Adjusted Temperature Northern Hemisphere Temperate

6.13. Tropical Temperatures

In the annually season adjusted temperature model we observe a consistent warming trend. The peak value for the moving average is the present (Figures 15-17).

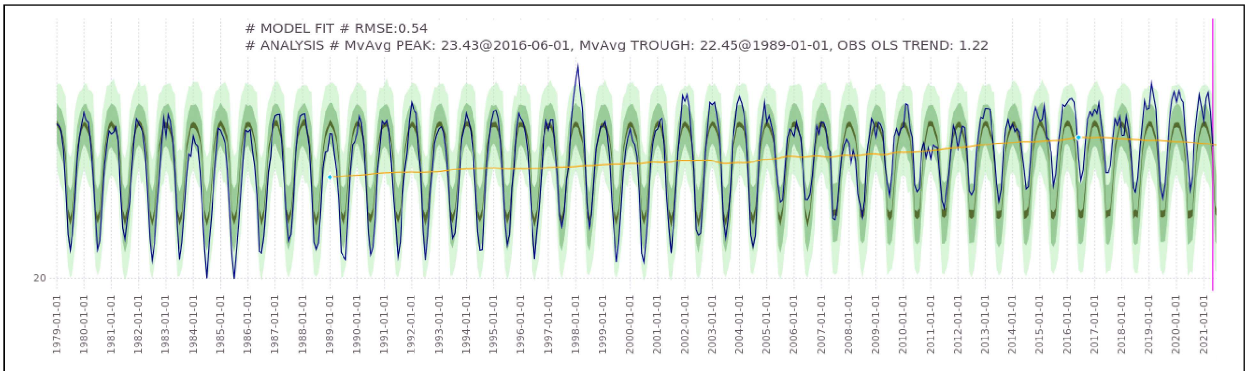

Figure 15: Temperature Tropical

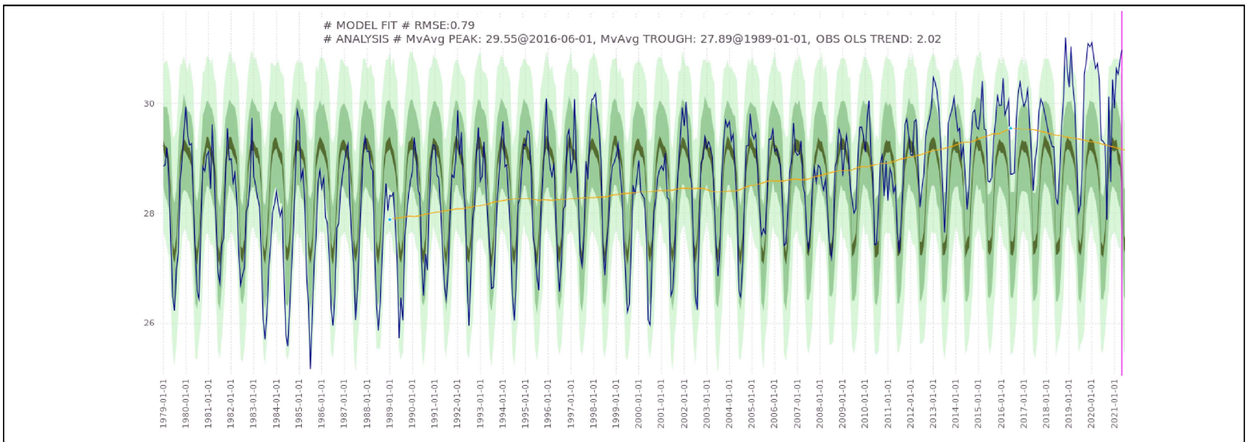

Figure 16: Maximum Temperature Tropical

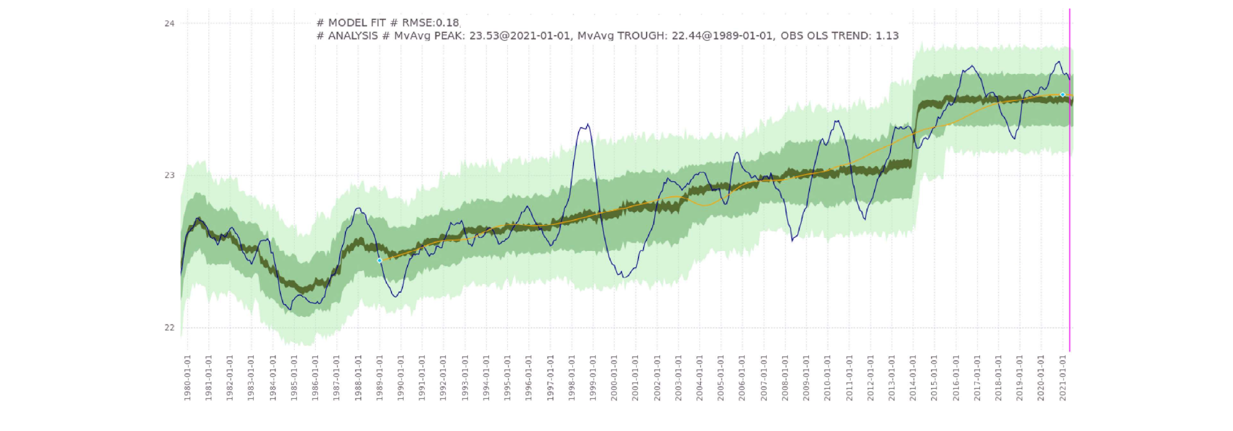

Figure 17: Seasonally Adjusted Tropical Temperature

6.14. Temperatures in the Southern Hemisphere Temperate Zone

In the annually season adjusted temperature model we observe a consistent warming trend. The peak value for the moving average is the present (Figures 18-20).

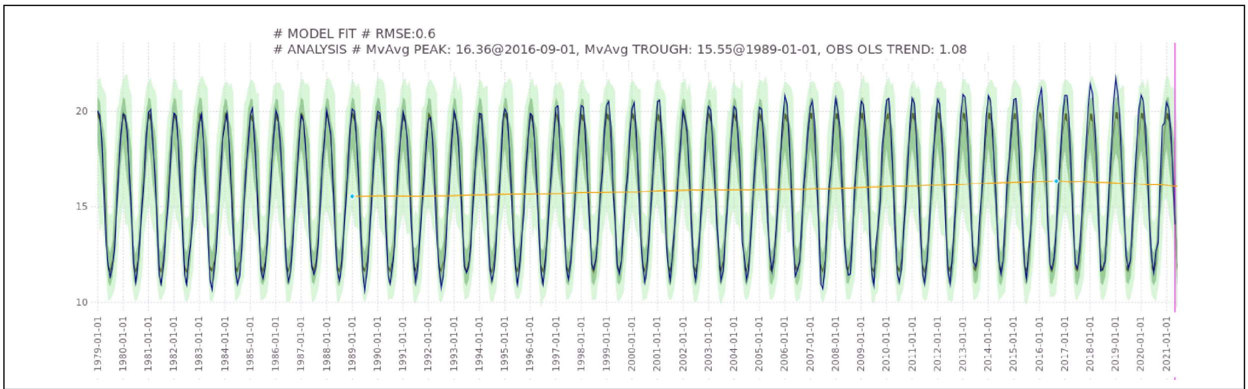

Figure 18: Temperature Southern Hemisphere Temperate

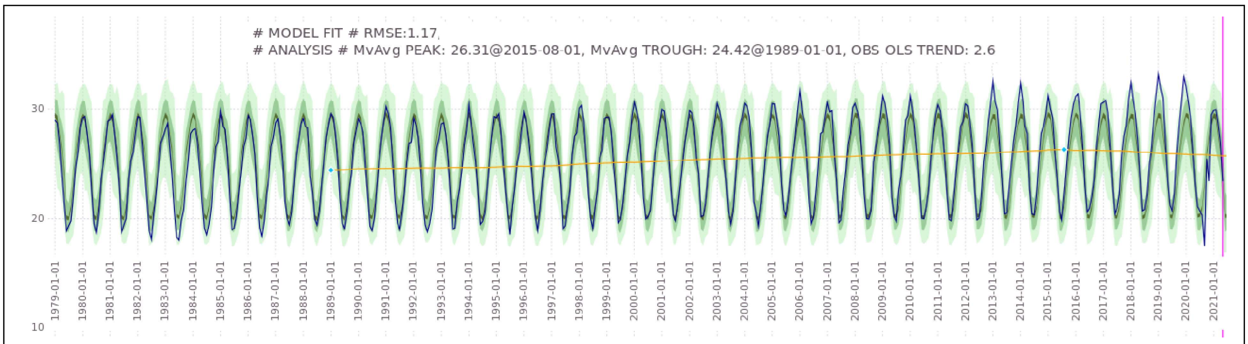

Figure 19: Maximum Temperature Southern Hemisphere Temperate

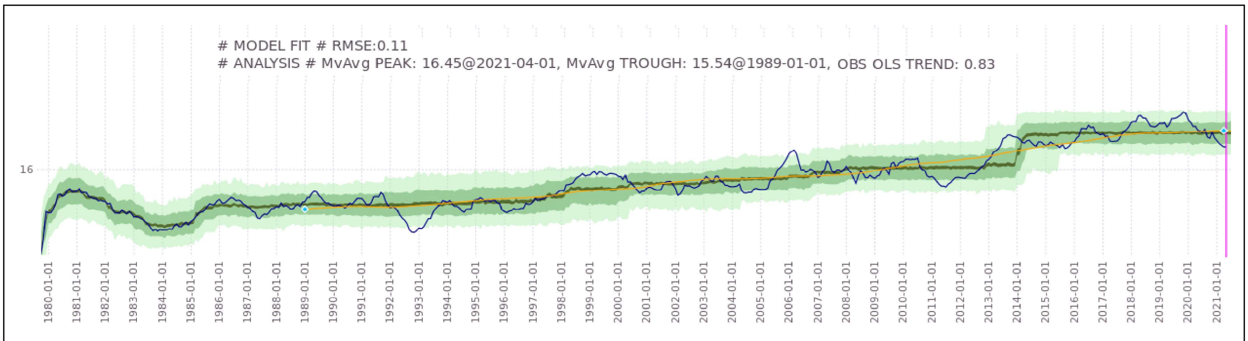

Figure 20: Seasonally Adjusted Temperature Southern Hemisphere Temperate

6.15. Antarctic Temperatures

In the annually season adjusted temperature model we observe a consistent warming trend. The peak value for the moving average is the present (Figures 21-23).

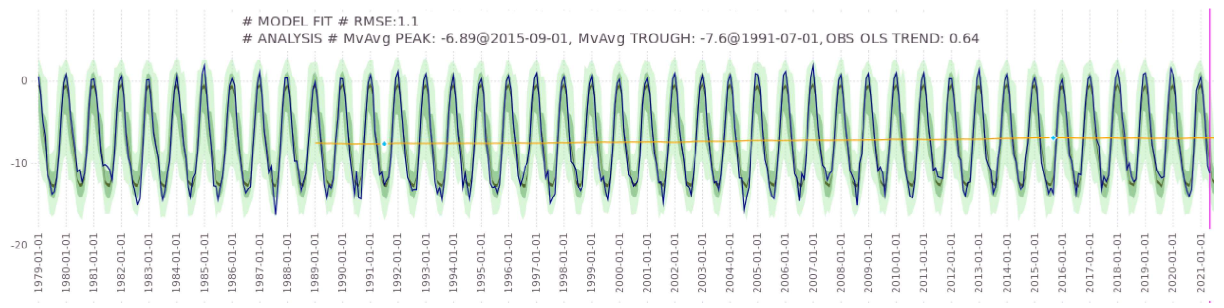

Figure 21: Temperature Antarctic

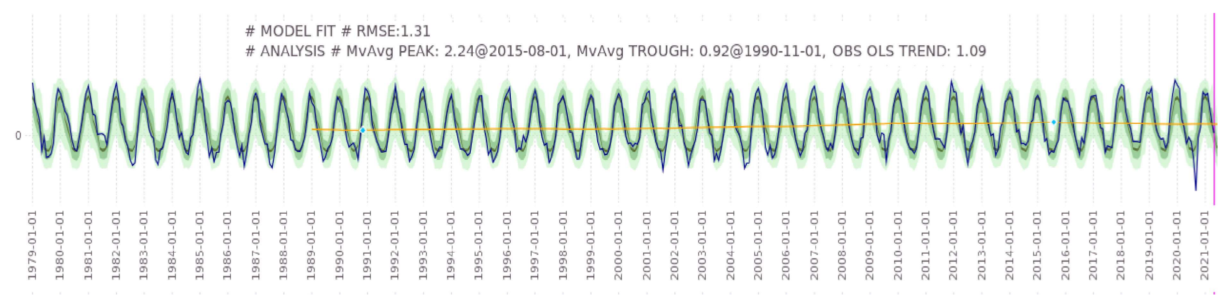

Figure 22: Maximum Temperature Antarctic

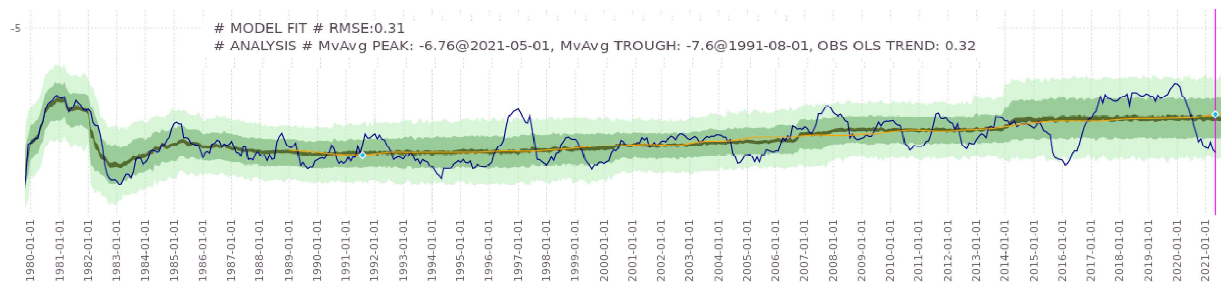

Figure 23: Seasonally Adjusted Antarctic Temperature

Crucially, we make two observations:

1) All climatic regions of the globe exhibit a consistent warming trend.
2) The warming trend is strongest in the northern hemisphere (strongest for the Arctic) and weaker for the southern hemisphere (weakest for the Antarctic). This is a known phenomenon owing to the larger land mass of the northern hemisphere (Table 3).

Table 3: Global Warming Trend by Climatic Region

Region	OLS Trend
Arctic	5.87
Northern Hemisphere Temperate	4.79
Tropics	1.13
Southern Hemisphere Temperate	0.83
Antarctic	0.32

6.16. CO_2 and C13 Discussion

To restate the significance of the role of CO_2 and C13: atmospheric C13 denotes the global isotopic CO_2 concentration, or the ratio of carbon C13 to C12. C13 is an important indicator: Plant life prefers to absorb C12 from the atmosphere during photosynthesis, but the atmosphere contains a mix of C13 based CO_2 and C12 based CO_2 (as well as C14). All fossil fuels were, once upon a time, plant material. Hence when we burn oil, coal or gas, we chiefly emit C12 based CO_2, leading to a relative decline in C13. As a trivial example, if all CO_2 were comprised of 1 part C13 and 2 parts C12 (fictional) then the C13 ratio would be 33%. If then, C12 doubled to 4 parts, C13 would represent only 1 in 5 parts, hence 20%. This is what we mean by a relative decline in C13 resulting from an increase in C12 (Figures 24 and 25).

We will now turn our attention to the final argument causality. We require causality in addition to dependency probability, because dependence probability is agnostic to the direction of the driver->response relationship. What is chicken and what is egg? In the context of the climate discussion, this is an important consideration.

We shall begin with a broad examination of the data.

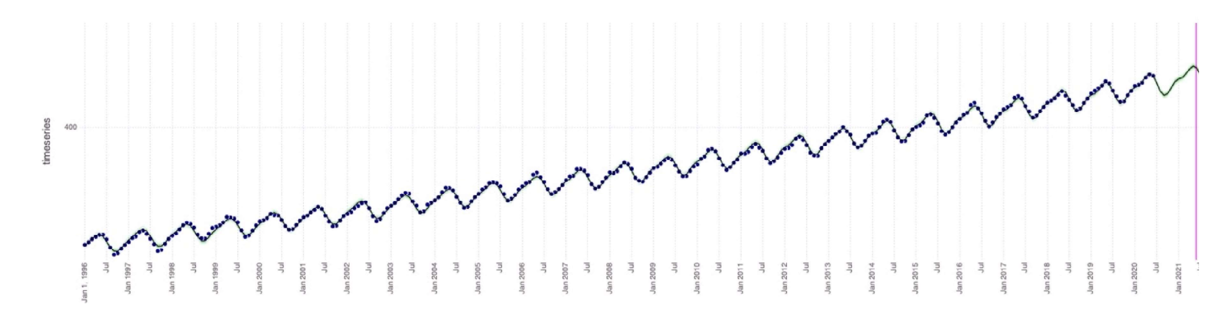

Figure 24: Atmospheric CO_2

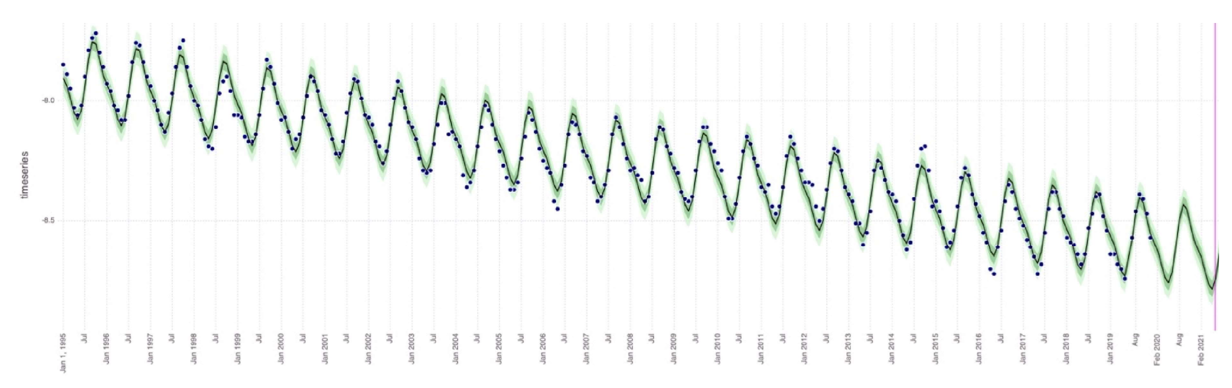

Figure 25: Atmospheric C13

One interesting exercise is to superimpose C13 onto CO_2 keeping in mind that a relative decrease in C13 represents a relative increase in C12. We therefore superimpose an inverted C13 graph over the CO_2 graph. This logically transposes increase and decrease. Although not strictly scientific, a visual analysis is always interesting and sometimes revealing.

Here we observe that the inverted atmospheric C13 graph (faded) visually exhibits the same trend as the CO_2 graph. The inverted C13 graph is neither scaled nor shifted on the time axis to fit. It simply fits (Figure 26).

We can repeat this visual data exploration experiment with global country CO_2 emissions and the CO_2 record over the same time (Figure 27).

Global (country aggregate) CO_2 emissions are shown in blue while CO_2 is shown in red in parts per million (scale not indicated). Once more not strictly scientific, a visual analysis is nonetheless interesting and revealing. Although units of measurement are different, overall variance on the Y-scale is plotted analogously by the plotting library. We may therefore observe broadly matching gradients on both curves.

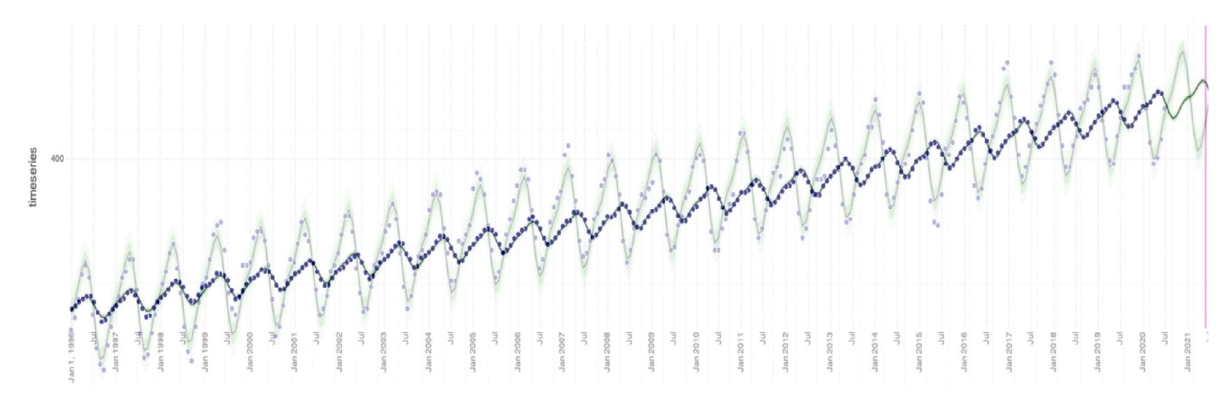

Figure 26: Atmospheric CO_2 with Inverted C13 Superimposed (Faded)

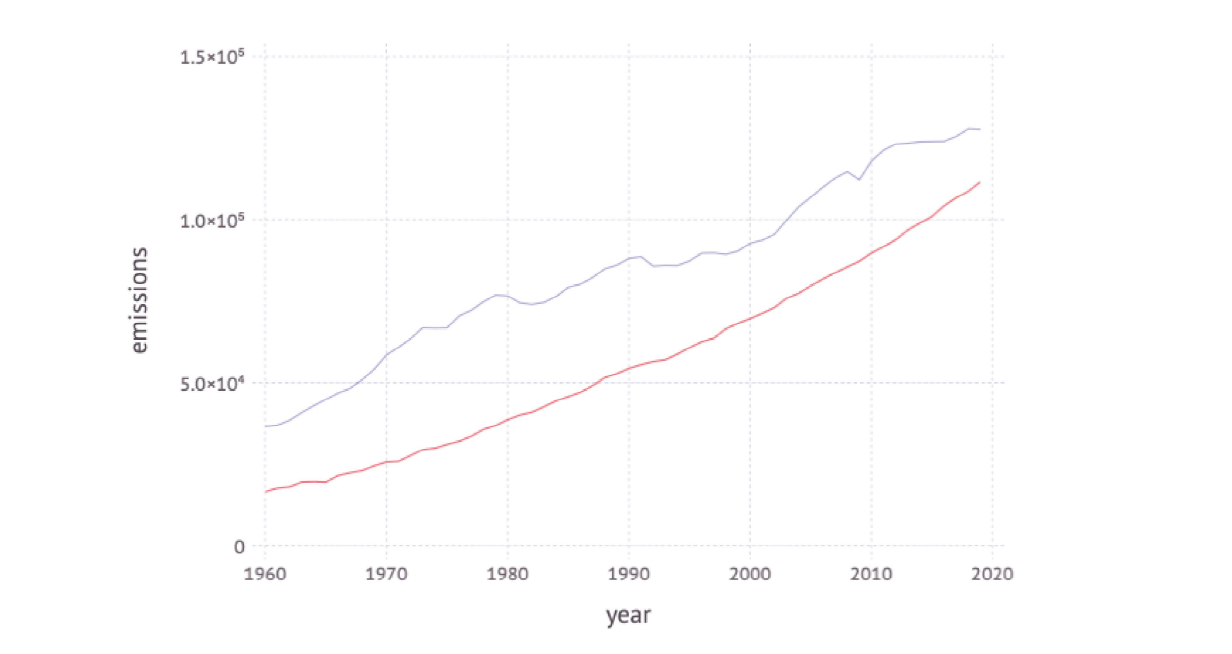

Figure 27: Global CO_2 Emissions with Atmospheric CO_2 Superimposed

The "smoking gun" we seek is a causally demonstrable *driver->response* dynamic between the human caused variable C13 and the strongest increases in temperature. We must therefore contemplate causality and what it means.

6.17. CO_2 and C13 Causality – Dynamical Systems Causality Analysis

We recall that experimental intervention, typically required to establish true causality, is not possible. We cannot turn back time and repeat the Industrial Revolution in a controlled experiment to establish how different actions lead to different outcomes. For this reason, popular statistics employs "Granger Causality." For the benefit of the reader and broadly speaking, Granger Causality (Granger Causality) posits that when two variables are correlated and one precedes the other than one is deemed to cause the other. This misses the scenario of a common forcing variable which in fact drives both but with varying time delays. The method therefore is limited in pinpointing causality.

Our AI pipeline leverages a machine learning method which we term Dynamical Systems Causality Analysis (DSCA). DSCA facilitates disambiguation of "Non-Granger Causality in complex dynamical systems with feedback loops, discontinuities and involving of regime shifts—on a system of scale. DSCA builds temporal causality graphs which may be interrogated for varying time horizons (Figure 28).

Graph-central to the causality graph is atmospheric C13. This graph centrality as a measure as a measure of relative significance is telling alone.

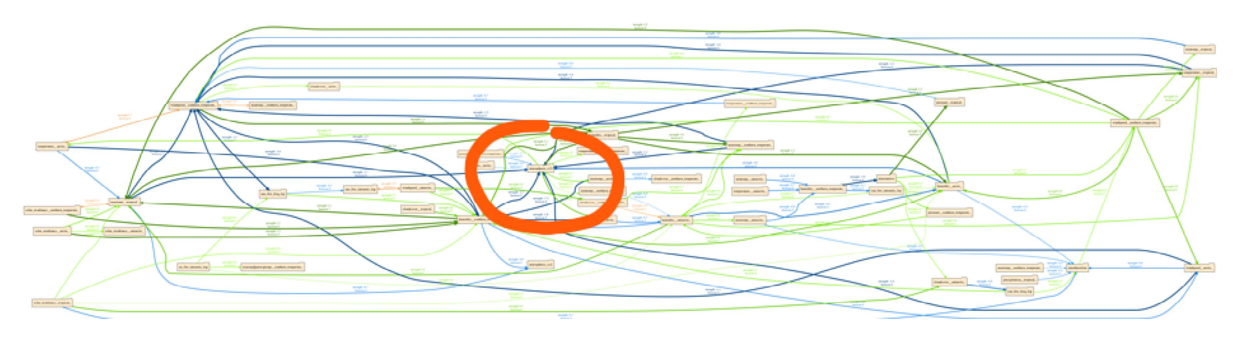

Figure 28: DSCA Model Causality Overview

We may "zoom" to different prediction horizons and causality relationship strengths as well as "drill down" on individual causality relationships. Arrows indicate the direction of causality while the thickness of arrows indicate causality strength (Figure 29).

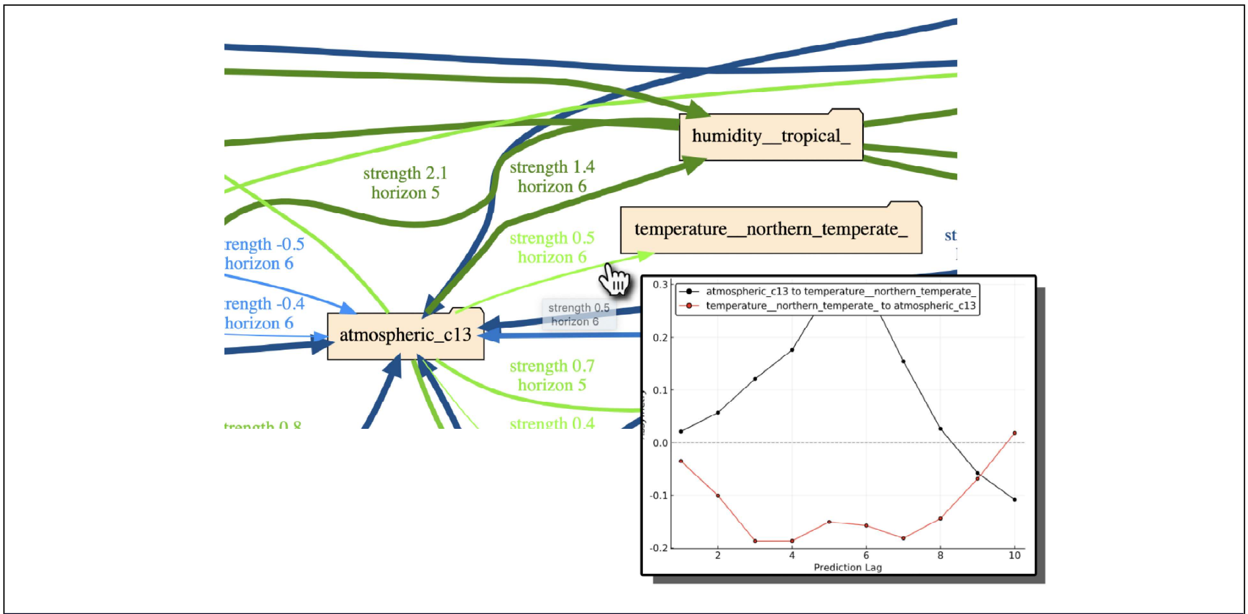

Figure 29: DCSA Causality Mapping

Shown in Figure 30 is an excerpt within the neighborhood of atmospheric C13.

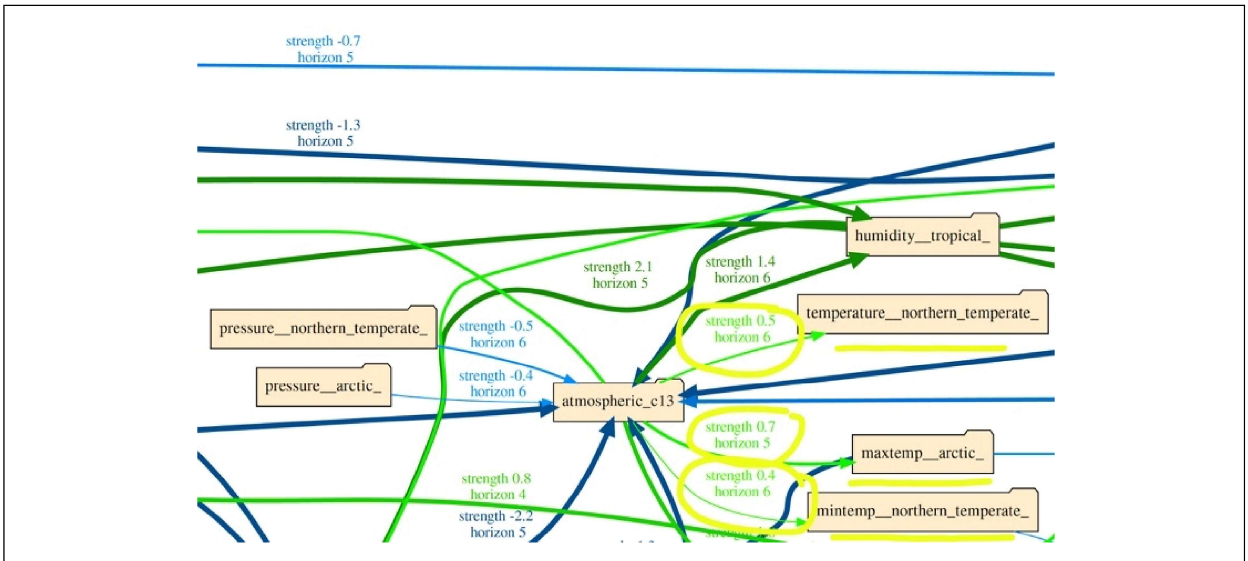

Figure 30: DSCA Causality Graph

What is immediately apparent is that causation in the graph proceeds straight from human initiated "*atmospheric_c13*" as a common driver behind a number of temperature variables.

We can now "*drill down*" on the relationships between atmospheric C13 based CO_2 and a number of the temperature records. We are interested chiefly in the regions where we now understand the global warming trends to be most pronounced the Arctic and the northern hemisphere temperate climate regions (Figures 31-33).

By way of explanation, the curve in black in the upper half of the graph is the driver. The curve in red in the lower half of the graph is the response variable which measures the predictive power from one variable to another with varying time lags.

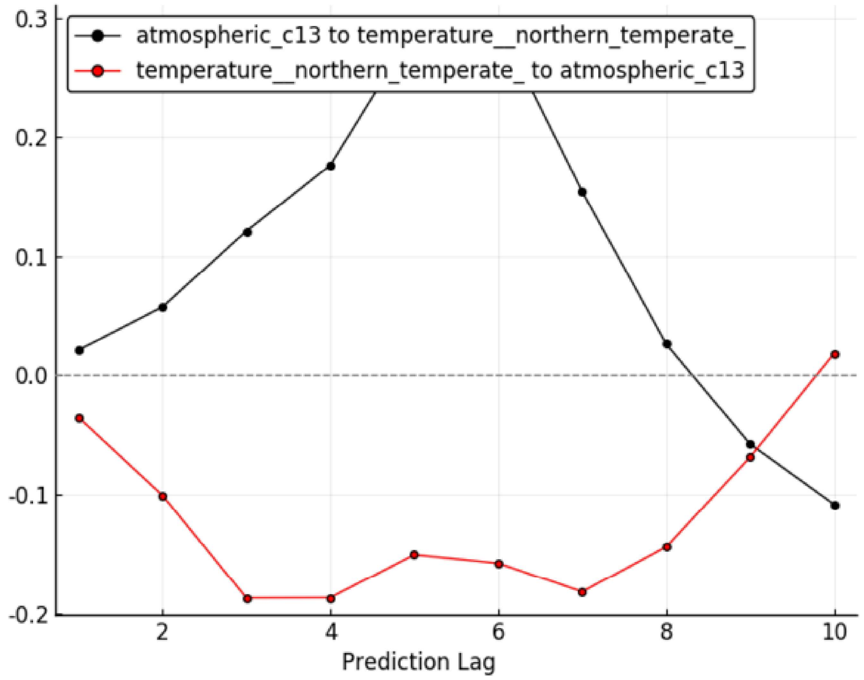

Figure 31: Causation: Atmospheric C13 -> Temperature Northern Hemisphere

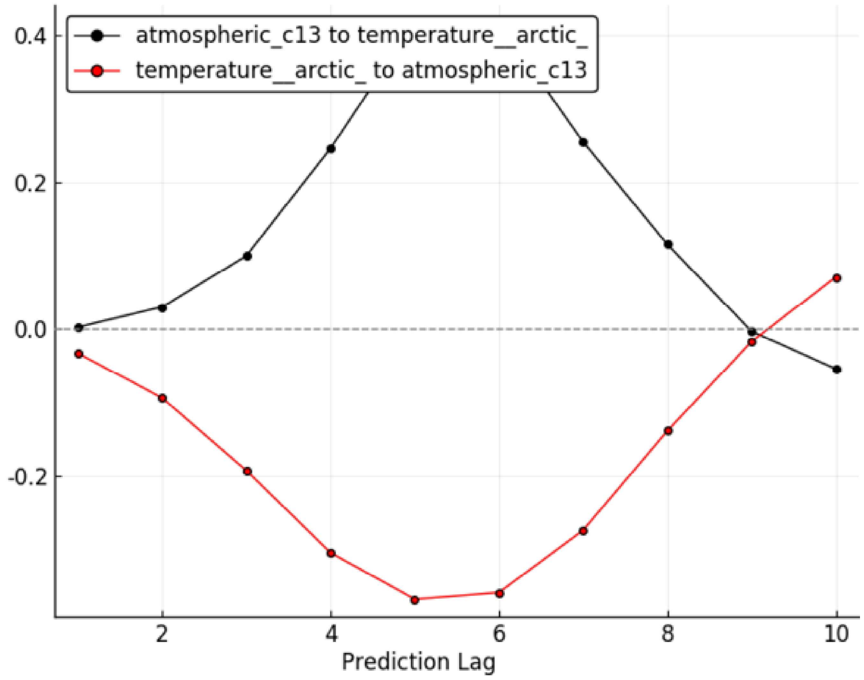

Figure 32: Causation: Atmospheric C13 -> Temperature Arctic

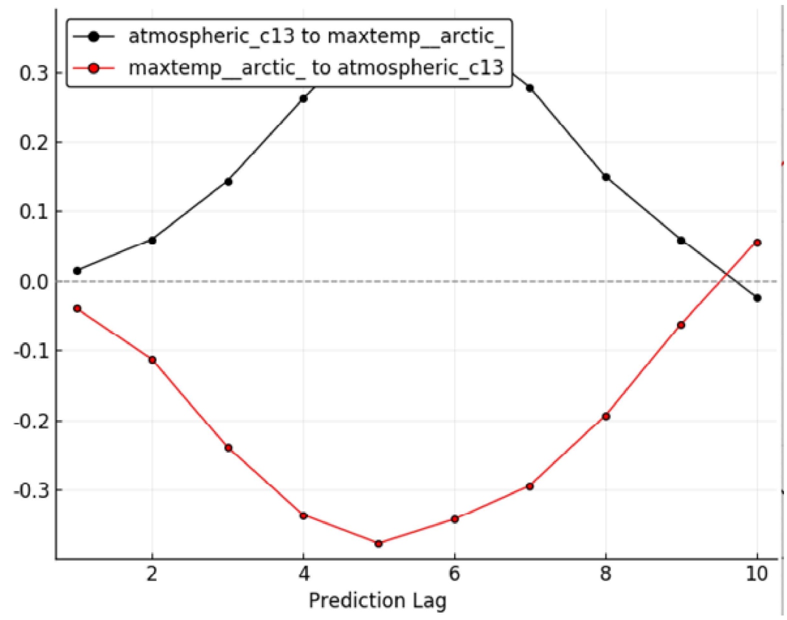

Figure 33: Causation: Atmospheric C13 -> Maximum Temperature Arctic

This is the "*smoking gun*" we have been seeking: a direct causal link between rising temperature and the relative lowering of atmospheric, isotopic C13 based CO_2 relative to C12 based CO_2 as results from the emissions of fossil-based fuels. Importantly, demonstrating a direct causal link obviates the need to seek larger overarching cycles to explain global warming in different ways.

As with any dynamical system, we expect other interacting variables: It is not immediately apparent what role pressure might have specifically upon isotopic C13 based CO_2, except that since air is compressible pressure will directly induce variations in the measured concentration of the constituent gases within the air. Further, he ability of the oceans to absorb and correspondingly release CO_2 might be modulated by pressure. We have not investigated this further.

If you are interested in details on DSCA as a machine learning method, please contact us for more details.

6.18. Fires Need Fuel - Vegetation Indices and Wildfires

Our country level models are augmented by NDVI data from NASA's Moderate Resolution Imaging Spectroradiometer (MODIS Vegetation Indices). NDVI is a Normalized Difference Vegetation Index (Figure

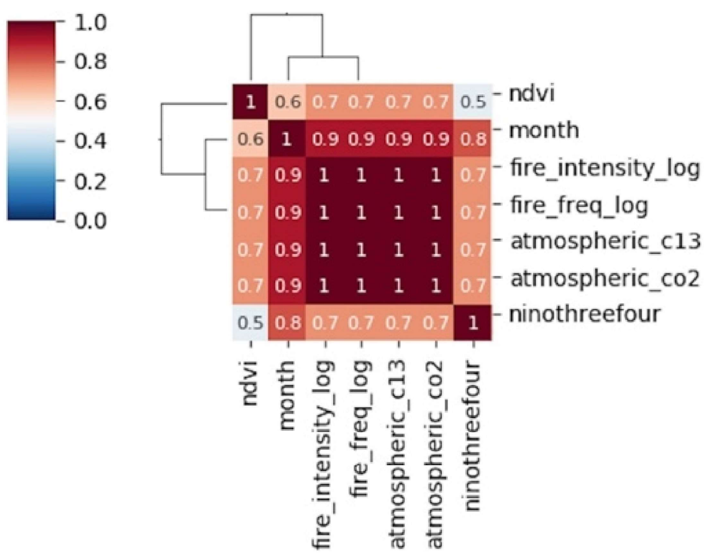

Figure 34: Vegetation/Fuel Load and Wildfires

34). This NASA dataset provides consistent spatial and temporal comparisons of vegetation canopy greenness, a composite property of leaf area, chlorophyll and canopy structure—hence allows modeling fuel load as well as the effects of control burns by fire departments as well as areas burned by wildfires.

What the model tells us, unsurprisingly, is that vegetation depends on Carbon Dioxide (Samson, 2016) and that wildfire intensity and wildfire frequency in turn depend on vegetation. Being able to capture these relationships successfully, on a global scale, suggests we can use this data to predict wildfire activity and suggests where and when control burns will be most effective.

6.19. Nowcasting ad Event Prediction over Keyhole Markup Language

Nowcasting is the prediction of the present. For example, we might ask "where is a wildfire in the state of New South Wales most likely now?" This can take the form of predicting the present state of variables which are known drivers of a response variable where the reporting interval of the driver is at intervals which are unsuitable to the problem. For instance, MODIS NDVI values are produced at 16-day intervals, but we might predict the current NDVI time series values midway through an interval and then ask the system what the impact on wildfire risk at a specific location is given that predicted value. Our A.I. pipeline supports this type of what-if analysis and is able to generate Global Information System (GIS) (Global Information System) integrated predictions of forecasted hotspots. In particular, our system is able to generate Keyhole Markup Language (KML) (Keyhole Markup Language) prediction files which may then simply be imported into Google Earth (https://www.google.com/earth/) and indicate the probability of an event at a particular location (Figure 35).

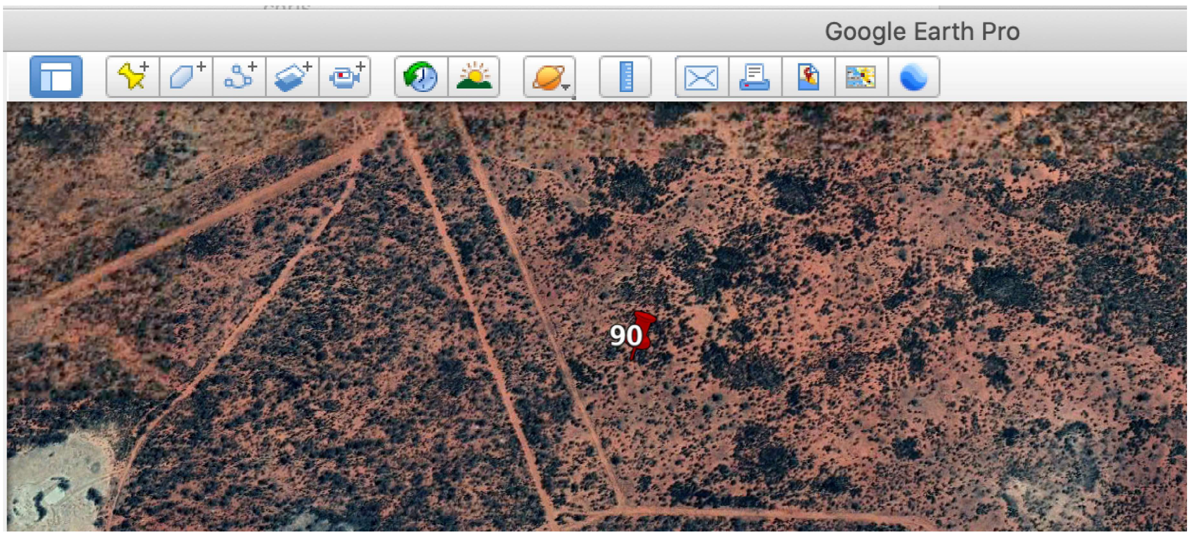

Figure 35: Google Earth Event Nowcasting and Forecasting

Likewise, one might engage in what-if analysis of the type: "If we control-burned here, what would the resulting, marginal fire risk in this area be?" Being able to quantify this would facilitate justifying control burns in one area or dismissing control burns in another area.

6.20. Forecasting

Models are built for a variety of reasons. One reason it to explain phenomena. Another reason is to predict the future. Shown in Figures 36, 37, 38 and 39 is a small selection of general model predictions.

The temperature forecast exhibits a notably higher probability of upward temperature change than downward temperature change—without a certain change in central tendency.

N.B.: Event Prediction over Keyhole Markup Language need not involve the probability of a wildfire event, but may denote any modelled event in space time, e.g., the likelihood of specific mineral deposits. In general, what is facilitated here is to predict when and where any given event is likely to occur. More poignantly in current affairs, this could likewise be the probability of an engagement by opposition forces with field commanders being updated in their phones pinpointing likely sites of engagement with hostile forces in Google Earth.

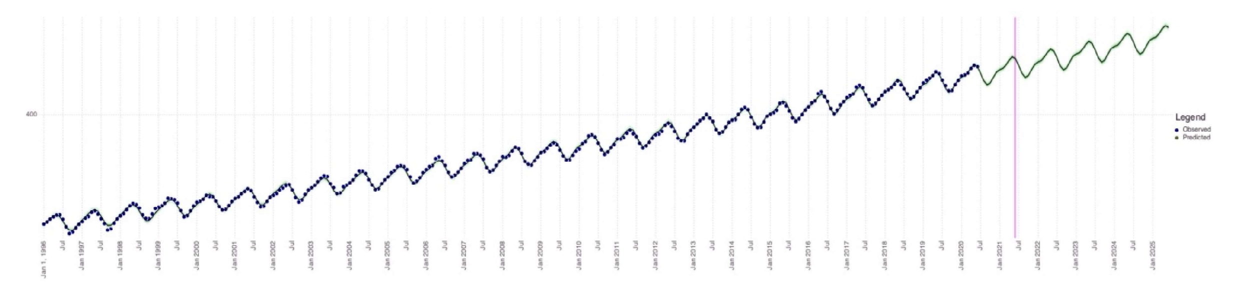

Figure 36: Forecast Atmospheric CO_2 to Mid-2025

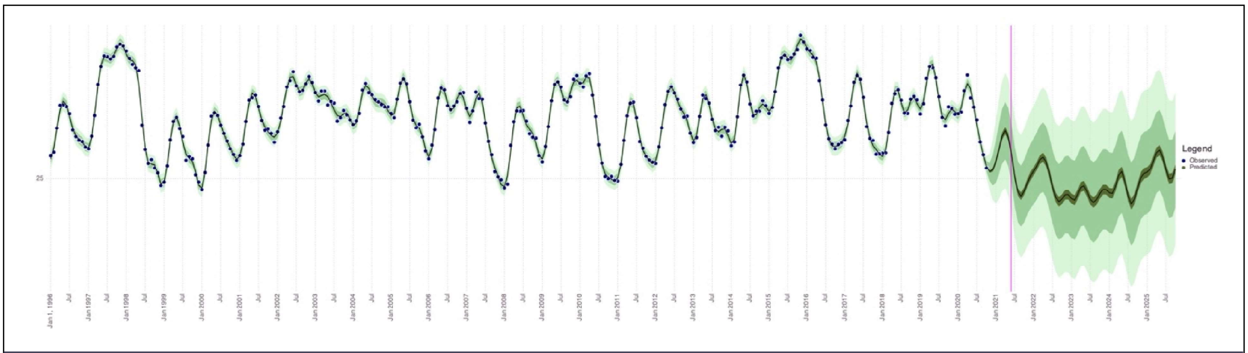

Figure 37: Forecast El Nino and La Nina Ocean Temperature to Mid-2025

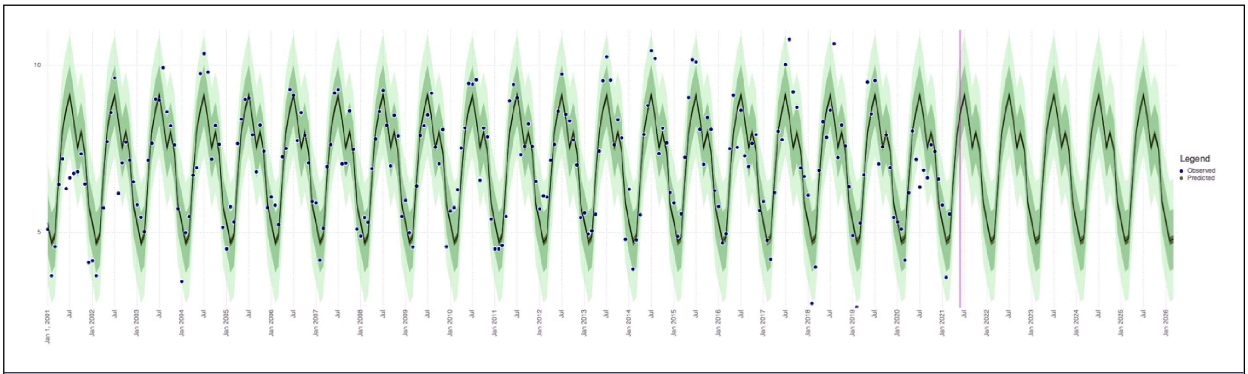

Figure 38: Forecast Canada Wildfire Frequency (Logarithmic) to Mid-2025

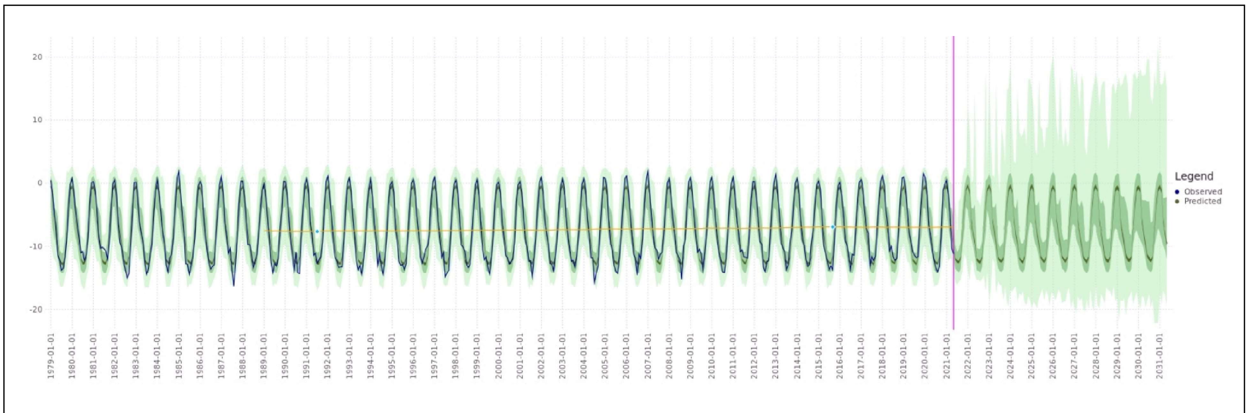

Figure 39: Forecast Antarctic Temperature to 2031

As with nowcasting, the use case for forecasting is to assist both planners and responders with reaction, mitigation and ultimately pre-emption.

If you are interested in specific city or location forecasts, please contact us for more details.

7. Conclusion

We have shown, with the help of machine learning models, a picture that paints a consensus among tools regarding the relationship between isotopic, atmospheric C13 and atmospheric CO_2 and temperature. The mathematical tools are:

1) Traditional statistical correlation

2) Dependence probability both static and longitudinal (time series)

3) Apparent Granger causality

4) Dynamical Systems Causality Analysis

Humans are contributing to changes in atmospheric, isotopic C13 in that the ratio of atmospheric C13 to atmospheric C12 is lowered through the release of isotopic C12 because of the burning of fossil fuels (ERIC, 2004) On the basis of that premise, we have further demonstrated a relationship between atmospheric C13, atmospheric CO_2 and global temperature and then demonstrated a relationship between temperature and both wildfire intensity and frequency.

Our approach is unique because it does not rely on long historical records and proxy data such as tree rings or ice core records, but rather on data that anyone can readily obtain on the internet today and verify using commodity computing equipment. This opens doors to citizen scientists the world over to monitor our climate and, by extension, hold their governments to account. Our temperature records are obtained, simply, from Openweathermap.com (https://openweathermap.org) and public NASA archives (https://power.larc.nasa.gov).

We then demonstrated a capability to help predict wildfire activity using nowcasting and forecasting, with the hope that this can assist both planners and responders with reaction, mitigation and ultimately pre-emption. We look forward to working with both planners and responders to achieve this.

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