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Adapting Statistical Science for a Fast-Changing Climate.

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Adapting Statistical Science for a Fast-Changing Climate

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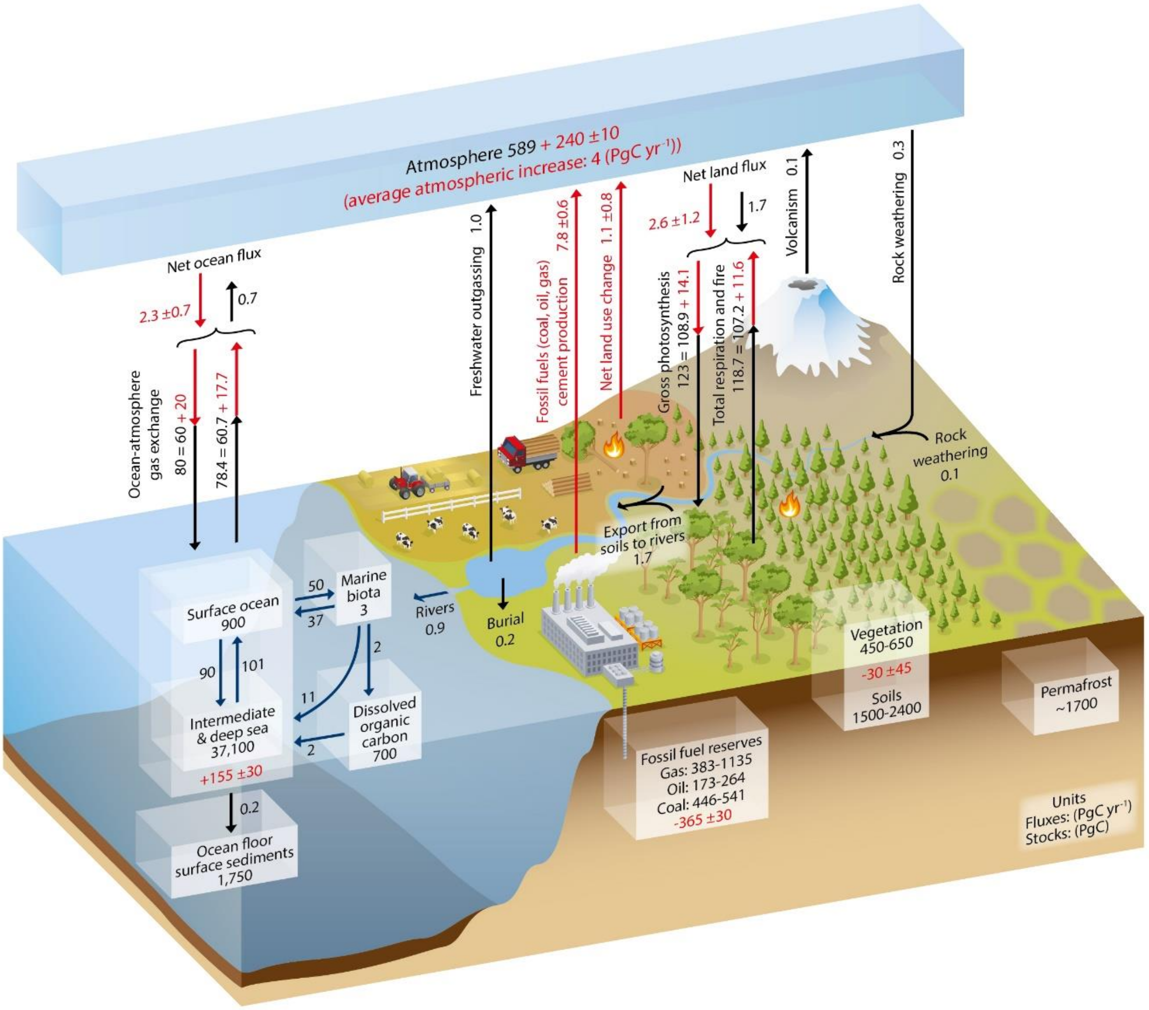
Abstract:

We have been looking up at the stars for millennia, trying to figure out our place in space, making small steps out and sending probes out even further. We are space travelers and, for the foreseeable future, Earth is our "mother ship." To sustain our voyage through space, we need to look out for stressors, overheating and, particularly, new energy sources for our ship. We need to monitor its integrity, repair components that are broken, and establish long-term maintenance protocols. That is, *mitigation* is needed at scale, and we need to plan and action it now! We have scientific knowledge about different parts of the ship with differing degrees of certainty, but the message is clear that it is in peril from overheating. Unfortunately, there are many captains to report to, with different priorities. While they demur, deflect, and disagree, Earth is rapidly approaching a waypoint where mitigation will not be enough, and *adaptation* for a fast-changing climate will be part of our future.

Introduction

Carbon is the fourth most abundant element in the universe. Earth's carbon cycle is a closed system, with carbon moving in and out of different "pools." Carbon causes no harm while it stays in the ground (terrestrial pool) but, once extracted and burned as a fossil fuel, it is released into the atmosphere (atmospheric pool) to bond with oxygen and become a greenhouse gas. Carbon dioxide (CO_2) is an odorless, tasteless, and invisible gas; nevertheless, it can be measured from *in situ* flasks or remote sensing instruments on planes and satellites, in units of parts per million (ppm) molecules in the atmosphere. Currently, the CO_2 concentration in Earth's atmosphere is about 420 ppm, which doesn't seem like a lot, but the last time it was at that level is estimated to be 3.6 million years ago during the middle Pliocene period. We are just 200 years into the Anthropocene period (judged to have started at the beginning of the industrial revolution), and we have seen an unprecedented 50% increase of atmospheric CO_2 concentration during that time.

The Earth system has 'cycles' (e.g., the carbon cycle, the water cycle, the nitrogen cycle) that are in motion. The complexities of the carbon cycle are illustrated in a figure given in a 2013 United Nations Intergovernmental Panel on Climate Change (IPCC) report.



Source: IPCC 2013, Working Group I, Ch. 6, Fig. 6.1 (see Further Reading)

In pre-industrial times, there was balance in the carbon cycle, when about as much carbon was being removed from the atmosphere as was being added. However, in this century, the net increase of atmospheric CO_2 was about four gigatonnes (Gt) per year (and growing), which is huge – it represents about half of what was produced by humans during the year. This excess CO_2 is transported around the planet by weather systems, mixes within just months, and adds to an ever-increasing background level. The rate of increase is increasing too; over the last 20 years, increases went from about 2 ppm per year to about 3 ppm per year.

How can we reverse the rate of increase and lower the level? ‘Net zero by 2050’ attempts to drop the rate of increase to 0 ppm per year, but that does not address the high level already in place. Global heating is baked in until CO_2 can be extracted from the atmosphere. We are currently relying on natural processes to hold back the CO_2 flood, but of 100 CO_2 molecules emitted today, as many as 50 remain in the atmosphere over time scales of centuries to millennia!

Global atmospheric CO_2 and global near-surface temperatures are in a very close dance, best explained through their incremental effects. When CO_2 leads upwards this year, temperatures follow about a decade later. The climate anomalies we see this year may be due to natural variation or they may be attributable to the anthropogenic indulgences of ten years earlier. When many more extreme anomalies are observed in a short amount of time than expected from natural variation, statistical methodology can be used to attribute them to human-induced change. Droughts, bushfires, floods, and tornadoes illustrated here are becoming all too familiar and more extreme in intensity. Five years ago, scientists would describe Climate as being like your personality and Weather as being like your mood. Now it appears that Climate has a ‘Mr Hyde’ side to its personality and its Weather can be volatile and deadly.

(a) Droughts

(b) Bushfires

(c) Floods

(d) Tornadoes

Sources: (a) API Images, (b), iStock, (c) Getty Images, (d) iStock

In this written version of my presentation at the American Statistical Association’s IDEA Forum in November 2022, my message is that many species on the planet are rather slow-adapting organisms (including *Homo sapiens*). Superimposing this with a comparatively fast-changing environment can have dire consequences for Earth and all who travel in her. We are moving from a mitigation paradigm to an adaptation paradigm as it is becoming clear that our ‘built Earth’ was built for a different climate.

Mitigation and adaptation to outrace a fast-changing climate

‘If you can’t measure it, then you can’t manage it,’ a principle that addresses what society must do when faced with mitigation or adaptation decisions – measure, but not any measurement will do! The measurement process (how much, where, and when), which comes from scientific knowledge (why), can in turn be used to improve that knowledge. Bayesian learning is a way to move from prior knowledge to posterior knowledge by incorporating the measurements into a Bayesian statistical model of the hidden scientific processes (‘unknowns’) and applying Bayes’ Rule.

Bayes’ Rule

Let [*A*] denote the probability distribution of variable *A*, [*A, B*] denote the joint probability distribution of the variables *A* and *B*, and [*A* | *B*] denote the conditional distribution of *A* given *B*. Using this notation, Bayes’ Rule says that posterior scientific knowledge after measurement, written as [*unknowns* | *measurements*], is given by:

[*unknowns* | *measurements*] $\propto$ [*measurements* | *unknowns*] x [*unknowns*].

Bayes’ Rule updates prior scientific knowledge, here written as the probability distribution, [*unknowns*]. It uses this prior distribution and the measurement probability model, [*measurements* | *unknowns*], to obtain the posterior distribution, [*unknowns* | *measurements*]; the formula for Bayes’ Rule is given in the side bar. Importantly, the uncertainties in both scientific knowledge and measurement errors are captured through conditional-probability distributions. How can this help society make decisions about mitigation and adaptation?

The *knowledge pyramid* is an abstraction of the levels needed. The peak of the knowledge pyramid is where decisions are made, and statistical science is usually involved at lower levels: At the base of the pyramid are measurements (think, *exploratory data analysis*); at the next level up is information obtained by exploring the measurements for structure (think, *summary statistics*); the information is then converted into knowledge at the next level by modeling the uncertainty/variability and inferring the etiology of the phenomenon (think, *inference*); and finally, at the peak, *decisions* are made. Uncertainty quantification should be involved at all levels, and the consequences of ignoring it in environmental problems can be serious. Decision makers cannot keep communities safe ‘on average,’ but they should consider the distribution and degree of loss from a mitigation or an adaptation decision. I have written about this in an Opinion piece in the journal, *Environmetrics*, and it is included in Further Reading.

More attention should also be given to the foundations of the knowledge pyramid. Underneath “measurements,” a *design* level should be recognised that provides support to the levels above. A strong design is needed *before* measurements are taken, and this will depend on prior scientific knowledge or will need an investment in a pilot study to inform the prior. That study could be done on a ‘digital twin,’ built from code by scientists and software engineers to act like the physical world. Observational studies based on ‘found’ measurements have value but are not able to provide the type of causal link available from a scientific study.

Design

A design, also called an *experimental design*, sets out the planning and execution of a scientific experiment. It generally follows the three principles given by R.A. Fisher, of Blocking (or Stratification), Randomisation, and Replication.

In the previous century, statistical science concentrated on the measurement process. In this new century, uncertainty in the scientific process has been recognized, and statistical scientists have developed incredible skill in developing physical-statistical models that are flexible and complex, yet computationally feasible. More recently, machine- and deep-learning methodologies have made a huge impact on predictive inference but have eschewed uncertainty modeling for computability; the importance of both is seen in an area known as *statistical learning.*

yyyyy-statistical models

The last 10 – 15 years have seen statistical scientists involved in substantial collaborations with climate scientists and meteorologists to measure, summarize, and infer various aspects of climate change. Temperature is but one dimension; precipitation, humidity, air pressure, and so forth are all part of the big picture, both near Earth's surface and in different parts of the atmosphere. There are spatial, temporal, and multivariate relationships to exploit, not only physical ones but statistical ones as well. The hierarchical statistical model presented in the previous section shows how the two may be bound together through conditional-probability models of the inherent uncertainty in models and in measurements, leading to the paradigm of a 'physical-statistical' model.

In climate science, there are highly complex, challenging, and fascinating problems where the answers are not only important for characterizing the where/when/how much/why of climate change, but also for designing mitigation strategies (e.g., planting more trees) or adaptation strategies (e.g., stratospheric aerosol scattering). Possible mitigation decisions should be weighed up against each other using notions from decision theory and its applications. For example, the agriculture sector is now at a stage where doing nothing in the face of climate change (a decision that is easy to make but has consequences like any other decision) can lead to costs that are a factor of three to four times more than the cost of mitigation.

Clearly, the so-called ‘climate problem’ comes to us in many guises, because weather’s moods are such an important part of our environment. There is a need for uncertainty modeling in all these guises, hence we can imagine yyyyy-statistical modelling, where yyyyy could be any one of, meteorological, ecological, engineering, defense, agricultural, hydrological, financial, medical, sociological, and so forth. We need to be able to understand the effect of climate change on weather, biodiversity, energy/construction/infrastructure, national defense, food security, water, wealth distribution, physical/mental health and, importantly, their *interactions*. Hierarchical conditional-probability modeling of these large interacting systems allows information to be passed from one to another through causal networks.

In 2021, before the Conference of the Parties 26 (COP26) met in Glasgow, the Royal Society (UK) developed a series of 12 Briefings under the heading, *Climate Change: Science and Solutions*, that addressed a variety of aspects of climate change, including some discussed above. A 2022 report from the IPCC also addresses impacts, and a further example is the *Lancet* Countdown that is making global annual assessments of health and climate change through to 2030. These three guises are referred to in Further Reading.

Conclusions

Juggling with the carbon cycle is a high-risk act that trades off economic well-being, jobs, and growth (and the fossil fuels that power them) with global heating of our planet. Making this trade-off requires a decision space with costs and benefits specified. It also requires a careful characterization of the scientific models, the measurement models, the parameters guiding them, and a quantification of their uncertainties. Statistical science shows how to combine the scientific and measurement uncertainties into an integrative, hierarchical, geophysical/ecological/engineering/agricultural/hydrological/financial/sociological-statistical model. It maps the path from design to measurements to information to knowledge, using a conditional-probability structure to quantify the uncertainty in the knowledge attained and to make wise decisions based on that knowledge.

The devastation of Australia's "black" Spring–Summer bushfires of 2019–2020 is but one of many illustrations of the enormous cost, ecological as well as financial, of taking little or no action. Our planet is overheating, and what our generation does or does not do now will deeply affect our children's generation and those that follow.

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Further Reading

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