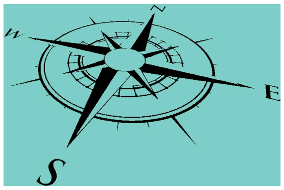
Five ways to ensure that models serve society: a manifesto - Pandemic politics highlight how predictions need to be transparent and humble to invite insight, not blame.

Here we present a manifesto for best practices for responsible mathematical modelling. Many groups before us have described the best ways to apply modelling insights to policies, including for diseases ... We distil five simple principles to help society demand the quality it needs from modelling.

The COVID-19 pandemic illustrates perfectly how the operation of science changes when questions of urgency, stakes, values and uncertainty collide — in the 'post-normal' regime.

Contents



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Description:

Nature Research is here to serve the research community by publishing its most significant discoveries—findings that advance knowledge and address some of the greatest challenges that we face as a society today. Our journals publish not only primary research but also reviews, critical comment, news and analysis.

Stakeholder(s):

Statisticians :
Well before the coronavirus pandemic, statisticians were debating how to prevent malpractice such as p-hacking, particularly when it could influence policy.

Politicians :
Now, computer modelling is in the limelight, with politicians presenting their policies as dictated by 'science'.

Researchers :
Yet there is no substantial aspect of this pandemic for which any researcher can currently provide precise, reliable numbers. Known unknowns include the prevalence and fatality and reproduction rates of the virus in populations. There are few estimates of the number of asymptomatic infections, and they are highly variable.

Complex Societies :
We know even less about the seasonality of infections and how immunity works, not to mention the impact of social-distancing interventions in diverse, complex societies.

Modellers :
Mathematical models produce highly uncertain numbers that predict future infections, hospitalizations and deaths under various scenarios. Rather than using models to inform their understanding, political rivals often brandish them to support predetermined agendas. To make sure predictions do not become adjuncts to a political cause, modellers, decision makers and citizens need to establish new social norms. Modellers must not be permitted to project more certainty than their models deserve; and politicians must not be allowed to offload accountability to models of their choosing.

Decision Makers

Citizens

Weather Forecasters :
This is important because, when used appropriately, models serve society extremely well: perhaps the best known are those used in weather forecasting. These models have been honed by testing millions of forecasts against reality.

Mariners :
So, too, have ways to communicate results to diverse users, from the Digital Marine Weather Dissemination System for ocean-going vessels to the hourly forecasts accumulated by weather.com.

Picnickers :
Picnickers, airline executives and fishers alike understand both that the modelling outputs are fundamentally uncertain, and how to factor the predictions into decisions.

Airline Executives

Fishers

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Vision

Models serve society

Mission

To set forth best practices for responsible mathematical modelling

Values

Questions: Questions not answers -- Mathematical models are a great way to explore questions. They are also a dangerous way to assert answers. Asking models for certainty or consensus is more a sign of the difficulties in making controversial decisions than it is a solution, and can invite ritualistic use of quantification.

Openness: Models' assumptions and limitations must be appraised openly and honestly.

Honesty

Process: Process and ethics matter as much as intellectual prowess.

Ethics

Sociability: It follows, in our view, that good modelling cannot be done by modellers alone. It is a social activity. The French movement of statactivistes has shown how numbers can be fought with numbers, such as in the quantification of poverty and inequalities.

Activism: A form of societal activism on the relationship between models and society is offered by US-based engineer-entrepreneur Tomás Pueyo. He is not an epidemiologist, but writes about COVID-19 models and explains in plain language the implications of uncertainties for policy options.

Frankness: We are calling not for an end to quantification, nor for apolitical models, but for full and frank disclosure.

Disclosure

Mathematics: Following these five points will help to preserve mathematical modelling as a valuable tool.

Modelling

Output: Each contributes to the overarching goal of billboarding the strengths and limits of model outputs. Ignore the five, and model predictions become Trojan horses for unstated interests and values.

Responsibility: Model responsibly.

1. Assumptions

Be aware of assumptions.

Mind the assumptions — Assess uncertainty and sensitivity. Models are often imported from other applications, ignoring how assumptions that are reasonable in one situation can become nonsensical in another. Models that work for civil nuclear risk might not adequately assess seismic risk. Another lapse occurs when models require input values for which there is no reliable information. For example, there is a model used in the United Kingdom to guide transport policy that depends on a guess for how many passengers will travel in each car three decades from now.

1.1. Uncertainty & Sensitivity

Perform uncertainty and sensitivity analyses.

One way to mitigate these issues is to perform global uncertainty and sensitivity analyses. In practice, that means allowing all that is uncertain — variables, mathematical relationships and boundary conditions — to vary simultaneously as runs of the model produce its range of predictions. This often reveals that the uncertainty in predictions is substantially larger than originally asserted. For example, an analysis by three of us (A.Saltelli, A. P., S.L.P.) suggests that estimates of how much land will be irrigated for future crops varies more than fivefold when extant models properly integrate uncertainties on future population growth rates, spread of irrigated areas and the mathematical relationship between the two. However, these global uncertainty and sensitivity analyses are often not done. Anyone turning to a model for insight should demand that such analyses be conducted, and their results be described adequately and made accessible.

2. Hubris

Be aware of the trade-off between the usefulness versus the breadth of models.

Stakeholder(s)

US Department of Energy :
One extreme example of excess complexity is a model used by the US Department of Energy to evaluate risk in disposing of radioactive waste at the Yucca Mountain repository. Called the total system performance assessment, it comprised 286 sub-models with thousands of parameters. Regulators tasked it with predicting "one million years" of safety. Yet a single key variable — the time needed for water to percolate down to the underground repository level — was uncertain by three orders of magnitude, rendering the size of the model irrelevant.

Mind the hubris — Complexity can be the enemy of relevance. Most modellers are aware that there is a trade-off between the usefulness of a model and the breadth it tries to capture. But many are seduced by the idea of adding complexity in an attempt to capture reality more accurately. As modellers incorporate more phenomena, a model might fit better to the training data, but at a cost. Its predictions typically become less accurate. As more parameters are added, the uncertainty builds up (the uncertainty cascade effect), and the error could increase to the point at which predictions become useless. The complexity of a model is not always an indicator of how well it captures the important features. In the case of HIV infection, a simpler model that focuses on promiscuity turned out to be more reliable than a more involved one based on frequency of sexual activity. The discovery of the existence of 'superspreading events' and 'superspreader' people with COVID-19 similarly shows how an unanticipated feature of transmission can surprise the analyst.

2.1. Complexity & Error

Find the optimum balance of complexity with error.

Complexity is too often seen as an end in itself. Instead, the goal must be finding the optimum balance with error.

Stakeholder(s):

Modellers :
What's more, people trained in building models are often not drilled or incentivized for such analyses.

2.2. Accountability

Ensure that modellers can be held accountable if their predictions are catastrophically wrong.

Whereas an engineer is called to task if a bridge falls, other models tend to be developed with large teams and use such complex feedback loops that no one can be held accountable if the predictions are catastrophically wrong.

3. Framing

Match purpose and context.

Stakeholder(s)

Modellers :
Modellers know that the choice of tools will influence, and could even determine, the outcome of the analysis, so the technique is never neutral.

US Army Corps of Engineers :
For example, the GENESIS model of shoreline erosion was used by the US Army Corps of Engineers to support cost–benefit assessments for beach preservation projects. The cost–benefit model could not predict realistically the mechanisms of beach erosion by waves or the effectiveness of beach replenishment by human intervention. It could be easily manipulated to boost evidence that certain coastal-engineering projects would be beneficial. A fairer assessment would have considered how extreme storm events dominate in erosion processes.

Mind the framing — Match purpose and context. Results from models will at least partly reflect the interests, disciplinary orientations and biases of the developers. No one model can serve all purposes.

3.1. Quality & Transparency

Commit to transparency in assessing model quality.

Shared approaches to assessing quality need to be accompanied by a shared commitment to transparency. Examples of terms that promise uncontested precision include: ‘cost–benefit’, ‘expected utility’, ‘decision theory’, ‘life-cycle assessment’, ‘ecosystem services’, and ‘evidence-based policy’. Yet all presuppose a set of values about what matters — sustainability for some, productivity or profitability for others.

Stakeholder(s):

Modellers :
Modellers should not hide the normative values of their choices.

Statistical Humans :
Consider the value of a statistical life, loosely defined as the cost of averting a death. It is already controversial for setting compensation — for the victims of aeroplane crashes, for instance. Although it might have a place in choosing the best public-health policy, it can produce a questionable appearance of rigour and so disguise political decisions as technical ones.

3.2. Social Norms

Commit to a set of social norms.

The best way to keep models from hiding their assumptions, including political leanings, is a set of social norms. These should cover how to produce a model, assess its uncertainty and communicate the results.

3.2.1. Model Creation

Document how to produce models.

3.2.2. Uncertainty

Assess the uncertainty of models.

3.2.3. Results

Communicate results.

3.3. Guidelines

Adopt international guidelines.

International guidelines for this have been drawn up for several disciplines. They demand that processes involve stakeholders, accommodate multiple views and promote transparency, replication and analysis of sensitivity and uncertainty.

Stakeholder(s):

Infectious-Disease Modellers :
Existing guidelines for infectious-disease modelling reflect these concerns, but have not been widely adopted. Simplified, plain-language versions of the model can be crucial. When a model is no longer a black box, those using it must react to assess individual parameters and the relationships between them. This makes it possible to communicate how different framings and assumptions map into different inferences, rather than just a single, simplified interpretation from an overly complex model. Or to put it in jargon: qualitative descriptions of multiple reasonable sets of assumptions can be as important in improving insight in decision makers as the delivery of quantitative results.

Flooding Modellers :
Examples of models that have adhered to these guidelines can be found in forecasting flooding risk, and in the management of fisheries. These included stakeholders' insights and intuitions about both inputs and desired ends.

Fisheries Modellers

3.3.1. Engagement

Involve stakeholders.

Whenever a model is used for a new application with fresh stakeholders, it must be validated and verified anew.

3.3.2. Viewpoints

Accommodate multiple views.

3.3.3. Transparency, Replication & Analysis

Promote transparency, replication and analysis of sensitivity and uncertainty.

4. Judgement & Consequences

Be sensitive to potential consequences and use sound judgement.

Stakeholder(s)

Modellers :
Spurious precision adds to a false sense of certainty. If modellers tell the United Kingdom it will see 510,000 deaths if no steps are taken to mitigate the pandemic, some might imagine a confidence of two significant digits. Instead, even the limited uncertainty analysis run by the modellers — based on just one parameter — reveals a range of 410,000–550,000 deaths.

World Health Organization :
Similarly, the World Health Organization predicts up to 190,000 deaths for Africa (see go.nature.com/3hdy8kn). That number corresponds to a speculative scenario in which ten uncertain input probabilities are increased by an arbitrary 10% — as if they were truly equally uncertain — with no theoretical or empirical basis for such a choice. Although thought experiments are useful, they should not be treated as predictions.

Mind the consequences — Quantification can backfire. Excessive regard for producing numbers can push a discipline away from being roughly right towards being precisely wrong. Undiscriminating use of statistical tests can substitute for sound judgement. By helping to make risky financial products seem safe, models contributed to derailing the global economy in 2007–085. Once a number takes centre-stage with a crisp narrative, other possible explanations and estimates can disappear from view. This might invite complacency, and the politicization of quantification, as other options are marginalized. In the case of COVID-19, issues as diverse as availability of intensive-care hospital beds, employment and civil liberties are simultaneously at play, even if they cannot be simply quantified and then plugged into the models.

4.1. Openness & Explanation

Be open and provide full explanations of models.

Opacity about uncertainty damages trust. A message from the field of sociology of quantification is that trust is essential for numbers to be useful. Full explanations are crucial.

5. Ignorance

Be aware of and acknowledge one's own ignorance.

Mind the unknowns — Acknowledge ignorance.

5.1. Unknowns

Communicate what is not known.

Even today, communicating what is not known is at least as important as communicating what is known. Yet models can hide ignorance.

Stakeholder(s):

Nicholas of Cusa :
For most of the history of Western philosophy, self-awareness of ignorance was considered a virtue, the worthy object of intellectual pursuit — what the fifteenth-century philosopher Nicholas of Cusa called learned ignorance, or docta ignorantia.

5.2. Surprises & Options

Avoid inviting undesired surprises and artificially limiting the policy options.

Failure to acknowledge this can artificially limit the policy options and open the door to undesired surprises.

Stakeholder(s):

Heads of Governments :
Take, for instance, those that befell the heads of governments when the economists in charge admitted that their models — by design — could not predict the last recession.

Politicians :
Worse, neglecting uncertainties could offer politicians the chance to abdicate accountability.

Experts :
Experts should have the courage to respond that "there is no number-answer to your question", as US government epidemiologist Anthony Fauci did when probed by a politician.

Anthony Fauci

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