Communicating Uncertainty

Lessons from Risk Communication

Charlotte Boys
Scientific Computing MSc

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Abstract
In this seminar report, our focus is on communicating uncertainty as scientists to nonspecialist audiences. To do so, we will lean heavily on lessons learned over recent decades in the field of risk communication, as the two fields are inevitably connected. We will start by considering the definitions and sources of uncertainty given by Prof. David Spiegelhalter in his 2017 review "Risk and Uncertainty Communication". We'll see some examples of how uncertainty has been miscommunicated, touch on some philosophical ideas about trust and information, and work through some practical ways of communicating uncertainty to a lay audience, before looking at two current case studies. The ideas we'll cover are not only relevant to the field of uncertainty communication, but many are more widely applicable to communicating risk and indeed statistical information in general.

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Introduction | 1

1.1 Sources of uncertainty

Before discussing how to communicate uncertainty, let us first consider how uncertainty arises in the scientific process in the first place. We look to Prof. David Spiegelhalter's 2017 review of Risk and Uncertainty Communication [1] , where he refers to three sources of uncertainty. The first two categories are the types of uncertainty regularly referred to in the wider literature around Uncertainty Quantification [2] :

[1]: Spiegelhalter (2017), 'Risk and uncertainty communication'

[2]: Eldred et al. (2011), 'Mixed aleatory-epistemic uncertainty quantification with stochastic expansions and optimization-based interval estimation'

Aleatoric Uncertainty
Inevitable unpredictability of the future due to unforeseeable factors, fully expressed by classical probabilities.

Epistemic Uncertainty
Modelled and quantified uncertainty about the structure and parameters of statistical models, expressed, for example, through Bayesian probability distributions or sensitivity analyses.

Epistemic
Relating to knowledge or the study of knowledge.

Finally, Spiegelhalter includes a third category which is less often discussed:
Ontological Uncertainty
Uncertainty about the ability of the modelling process to describe reality, which can only be expressed as a qualitative and subjective assessment of the model, conveying with humility the limitations of our knowledge.

Ontological
Relating to the part of philosophy that studies what it means to exist.

As indicated in the above descriptions, different types of uncertainty can be expressed in different ways, and so naturally they can be communicated using different means. These means will be discussed in upcoming chapters, but first, and following the name of the seminar, we'll take a look at some motivating examples of how uncertainty can be *mis*-communicated.

1.2 How to Lie with Uncertainty

In 1969, the tobacco industry was facing a growing body of evidence linking their product with the development of lung cancer in smokers. In response to a looming advertising ban, the Brown and Williamson Tobacco company released an internal memo. A much-quoted section reads:

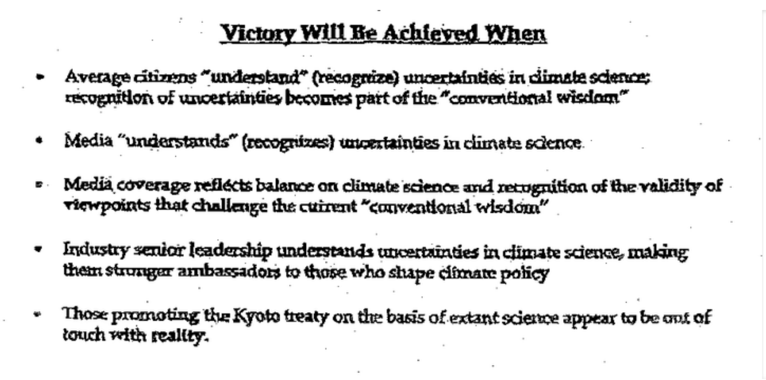
> *Doubt is our product, since it is the best means of competing with the 'body of fact' that exists in the mind of the general public. It is also a means of establishing controversy.* [3]

[3]: (),

In other words, the company wished to leverage the uncertainty around the causal link between smoking and lung cancer to play down worries and bring the evidence into dispute. This was a strategy readily recycled by the fossil fuel industry. Indeed, as early as the 1950s, both industries hired the same public relations firms, the same institutes and the same researchers [4] . Figure 1.1 shows part of an internal document stating an aim to make the public and the media 'understand' the uncertainties in climate science. Of course, the note goes on to reveal that the concern over public understanding of uncertainty is primarily so that the industry might be better placed to shape climate policy and assert the promotion of the 1992 Kyoto treaty as "out of touch with reality". Such a strategy successfully allowed the fossil fuel industry to keep profiting from oil and gas extraction while 'debate' over the science of climate change continued, resulting in decades of lost time and an ever smaller window of opportunity to keep global heating to below 1.5C [5, 6] .

[4]: Hulac (2016), *Tobacco and Oil Industries Used Same Researchers to Sway Public*

[5]: Rich (2018), *Losing Earth: The Decade We Almost Stopped Climate Change*
[6]: McGrath (2018), *Final call to save the world from 'climate catastrophe'*



Victory Will Be Achieved When

- Average citizens "understand" (recognize) uncertainties in climate science; recognition of uncertainties becomes part of the "conventional wisdom"
- Media "understands" (recognizes) uncertainties in climate science
- Media coverage reflects balance on climate science and recognition of the validity of viewpoints that challenge the current "conventional wisdom"
- Industry senior leadership understands uncertainties in climate science, making them stronger ambassadors to those who shape climate policy
- Those promoting the Kyoto treaty on the basis of extant science appear to be out of touch with reality.

[7]

Figure 1.1: An internal memo from the American Petroleum Institute, 1998.

[7]: Admin (2019), *1998 American Petroleum Institute Global Climate Science Communications Team Action Plan*

A third example of uncertainty miscommunication can be seen in a 2013 article from the UK publication The Daily Mail. Figure 1.2 shows a somewhat loose adaptation of a graph originally published by researcher Ed Hawkins [8] . Firstly, the graph misquotes the uncertainty ranges as being 95% and 75% rather than the true 90% and 50% respectively. Secondly, it and extrapolates from a short-term trend to assert that the IPCC projections of mean global surface temperature increase were a "spectacular miscalculation". In the article, they write:

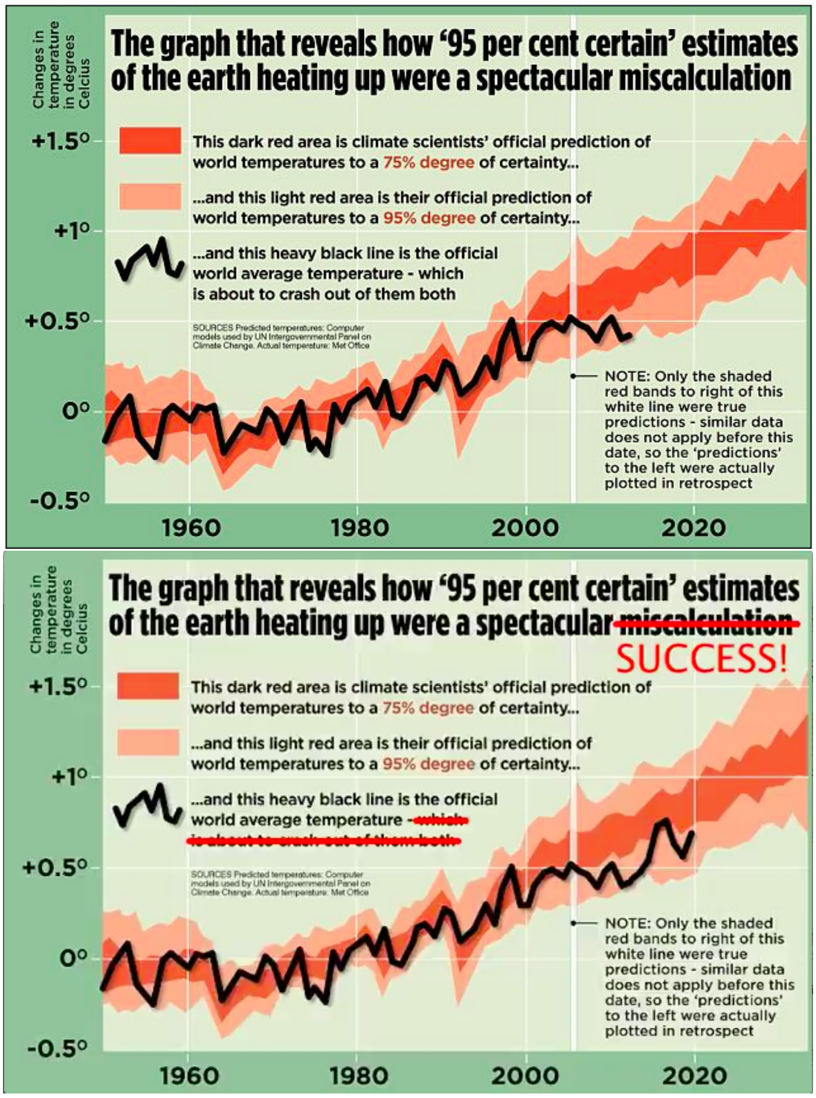
[8]: Hawkins (2013),

> *The graph shows a world stubbornly refusing to warm. Indeed, it shows the world is soon set to be cooler.*[9]

[9]: Rose (2013), *The great green con no. 1: The hard proof that finally shows global warming forecasts that are costing you billions were WRONG all along*

In fact, the graphic demonstrates that the uncertainty ranges given by the IPCC are well-calibrated; for instance it can be seen that in the 50 year period from 1950 to 2000, the yearly temperature measurements leave the 90% uncertainty range on five occassions - or 10% of the time - as should be expected. As for the second claim, updating the graph to include data from recent years shows that temperatures have remained within the projected range after all.

Uncertainty communication can also found to be lacking outside of the realm of industry public relations and tabloid publications. In an article reporting the latest UK labour market figures from the Office for National Statistics in January 2018, the BBC ran with the leader:



[9, 10]

Figure 1.2: Top: Daily Mail, March 16. 2013. Bottom: Updated graph. Kevin Pluck, December 17. 2019.

[9]: Rose (2013), *The great green con no. 1: The hard proof that finally shows global warming forecasts that are costing you billions were WRONG all along*

[10]: Pluck (2019), *Hey DailyMailUK I've updated your graph which shows that it was a spectacular miscalculation to publish it! pic.twitter.com/p34mIyJQ2y*

[11]: (2018), *UK unemployment falls to 1.44 million*

[12]: Clegg (), *UK labour market: January 2018*

> *UK unemployment fell by 3,000 to 1.44 million in the three months to November, official figures show [11] .*

It is only upon closer inspection of the ONS report [12] (which is not linked to within the article) that one can find information about the uncertainty surrounding this figure. The following can be found in Section 17, Quality and Methodology:

> *The estimated change in the number of unemployed people [...] was a small fall of 3,000, with a 95% confidence interval of plus or minus 77,000. This means that we are 95% confident the actual change in employment was somewhere between an increase of 74,000 and a fall of 80,000 [...] the estimated fall in unemployment is said to be*'not statistically significant'

The ONS report itself warns against focusing on changes over short time periods, reminding readers that long-term trends are more meaningful, and especially so where uncertainty is concerned. In this respect, it can be argued that although the BBC article concerned could have benefited from including information about uncertainty, the message of decreasing unemployment is not misleading as the short-term estimate from the ONS agrees with a long-term trend of decreasing unemployment in the UK.

Lessons from Risk Communication | 2

When considering best practice in the communication of scientific uncertainty, it is helpful for us to lean on the more developed field of risk communication. When we talk about risk, we refer to the more daily usage of the term as the probability that an undesirable event will come to pass.

We also need an aim for our communication of risk and uncertainty, and since the topic of this report falls in the 'How to do better' section of the seminar series, we'll set ourselves the aim of **informing decision-making**. In view of this goal, we'll first discuss the more philosophical theory behind risk communication, whose ideas can be readily appled to uncertainty.

2.1 In Theory

We look to Leiss's Phases of Risk Communication [13] to understand the development of the field over the last few decades in meeting this goal. In the first phase, it was thought that the key to getting the public to understand the risk given an intervention or event, and make good decisions on that bases, was simply to give them more information. Unfortunately, human beings are not always rational actors and the context of such an event or intervention plays a heavy role in how we perceive risk.

[13]: Leiss (1996), 'Three phases in the evolution of risk communication practice'

So-called **fear factors** [14] are said to affect our ability to keep risk and uncertainty in perspective. These include events or outcomes which:

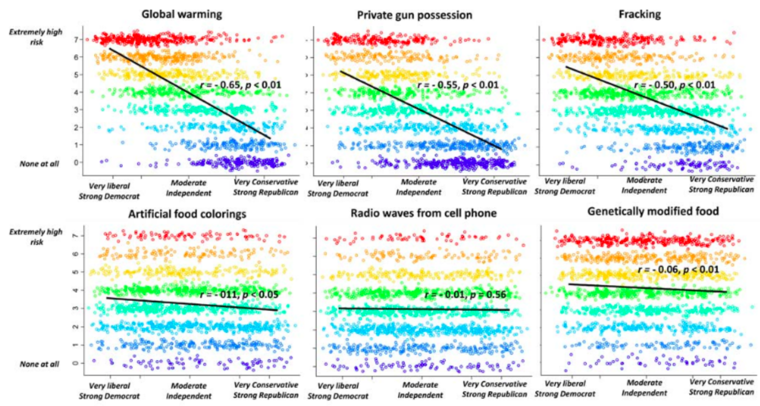
[14]: Slovic (2000), *Risk, society, and policy series. The perception of risk*

- are uncontrollable, novel or not yet understood
- have catastrophic potential or dreadful consequences such as fatality
- have risks and benefits which are unequally distributed
- are delayed in their manifestation of harm

It is instructive to think about how many of the above fear factors are fulfilled by an issue such as climate change.

In Phase II, the tools of marketing were leveraged so that information about risk was not merely communicated, but communicated *persuasively*. However, not all groups are easily persuaded to trust information: some highly politicised topics suffer a strong correlation between the politics held by an individual and their beliefs about the risks posed by that issue. Figure **??** comes from a study in the United States and shows that in the perception of risk for polemic issues such as private gun ownership are correlated with an individuals' position on the political spectrum.

As for the implications for uncertainty communication, we might expect a kind of multiplying effect, where uncertainty surrounding an issue is



[15]

Figure 2.1: Correlations between risk perception and position on the US political spectrum.

[15]: Kahan (2015), 'Climate-science communication and the measurement problem'

either used to play up or play down the associated risk, depending on the political values of an individual.

In Phase III, the search has been on for a communication approach which establishes trust between experts and target audiences. Baroness Onara O'Neill, philosopher and member of the UK House of Lords, speaks critically about the push for increased transparency as the latest attempt at building trust [16] .

[16]: (2017),

She argues that this transparency has come in the form of ever more guidelines to be met, ever more paperwork to be filled out by professionals (taking them away from their work), and ever more information entering the public sphere. As such, along with 'greater transparency' there has come an expectation, either implicit or explicit, that the public have the time and inclination to search out and digest all this new information as it is released. With the 'more transparency' approach, communication efforts stop with making information available, and the onus is on the audience to understand it.

O'Neill argues that the key to trust is not *more* transparency, but rather *intelligent* transparency. Under the notion of intelligent transparency, she defines four main characteristics [17] . Information should be:

[17]: Spiegelhalter (2019), *Why I like the Code*

- **Accessible:** People should be able to get to the information easily.
- **Comprehensible:** The target audience should be able to understand the information.
- **Usable:** It should suit the needs of the target audience.
- **Assessable:** Those interested should be able to look behind the information given, or be able to access a hierarchy of greater detail and evaluate its quality.

In this way, O'Neill argues, communicators can *demonstrate* trustworthiness rather than simply demand to be trusted. They are principles to be kept in mind in the two case studies which will be discussed later. First though, it is beneficial to work through some more practical tips on the effective communication of statistics in general.

2.2 In Practice

The communication of uncertainty necessarily overlaps with the communication of statistics in general. The following section will highlight a number of pitfalls to be aware of, which will hopefully help us to illuminate good practice.

Probability words and phrases
It is important to be aware that words and phrases surrounding probability can be interpreted in a variety of ways. A recent study among 881 native Dutch speakers [18] found that there was a wide variability in the interpretation of probability phrases, even within individual cohorts of statisticians and non-statisticians, men and women. Note that this study didn't examine the effect of the politicisation of events on interpretation of probabilities, but rather the interpretation of phrases in a neutral context.

[18]: Willems et al. (2019), 'Variability in the interpretation of Dutch probability phrases-a risk for miscommunication'

Further, data shows an asymmetry between terms, with English speakers holding *unlikely* and *probable* as synonyms of *low chance*, but ***very*** *likely* and ***very*** *probable* as synonyms of *high chance*. Meanwhile, the above study showed that Dutch speakers, like English speakers, give *unlikely* as a synonym for *low chance*, but put *high chance* somewhere between *likely* and *very likely*. This shows that not only is there a perhaps unexpected asymmetry when we interpret probability phrases, but also that there is variation when that information is translated between different languages. There are further studies comparing English with French, German and Chinese [19–21] , providing more evidence that interpretation of verbally-provided probabilistic information differs between languages.

[19]: Davidson et al. (1994), 'Translations of uncertainty expressions in Canadian accounting and auditing standards'
[20]: Doupnik et al. (2003), 'Interpretation of uncertainty expressions: a cross-national study'
[21]: Harris et al. (2013), 'Lost in translation? Interpretations of the probability phrases used by the Intergovernmental Panel on Climate Change in China and the UK'

Naturally, there is more consensus around words on the extremes: always, certain, never, impossible. This is to be expected as these words leave little room for interpretation compared to words like *likely* and *unlikely*. However, this insight mightn't be very helpful as it is rare that scientists have such extreme results to communicate.

When asked what percentage of people taking a drug can expect to experience a 'common' side effect, the mean estimate given in a study of 120 people was 34% [1] . In fact, the true pharmacological definition is that a common side effect is one that affects $1 - 10\%$ of patients, and the recommended formulation for communicating this risk is: *"Common: may affect up to 1 in 10 people"*.

[1]: Spiegelhalter (2017), 'Risk and uncertainty communication'

Key advice

The advice is clear: reporting probabilities verbally can lead to misinterpretation, especially in the case of translation between languages, so numerical values or a combination of representations is preferable.

Numerical probabilities
It is important to be aware that comparisons between natural frequencies (*1 in x*) can easily cause confusion. Amongst 1000 respondents for the following question:

> *Which of the following numbers represents the biggest risk of getting a disease? 1 in 100, 1 in 1,000, or 1 in 10?*

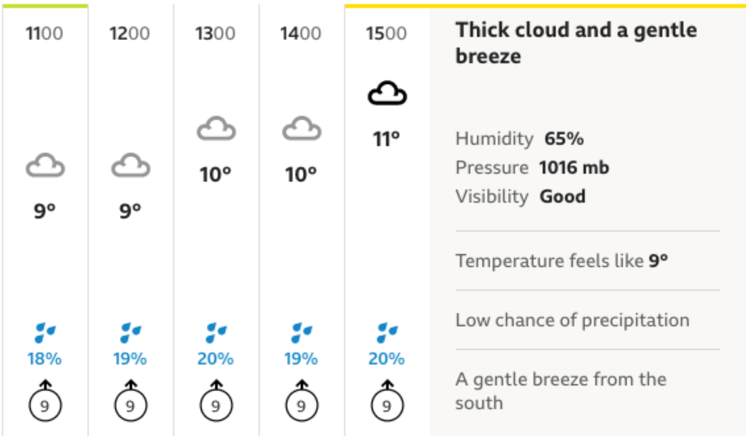
only 72% of participants in the US and 75% of participants in Germany could answer the question correctly. Trevena et al. conclude that risks should either be compared with simple percentages or by using a frequency format where the denominator is kept fixed [22] .

Although natural frequencies are preferred in the field of medical risk communication (although there is still some dispute)[1] , for chance of rain forecasts, conditional probabilities (10%) are preferable [23] . A good example, which combines conditional probability with a phrasal interpretation and a pictorial illustration can be seen in Figure **??**.

[22]: Trevena et al. (2013), 'Presenting quantitative information about decision outcomes: a risk communication primer for patient decision aid developers'

[1]: Spiegelhalter (2017), 'Risk and uncertainty communication'

[23]: Joslyn et al. (2009), 'Probability or frequency? Expressing forecast uncertainty in public weather forecasts'



Absolute risk vs. relative risk
Yet another thing to keep in mind is the *framing* of risk. In his review, Spiegelhalter gives the example of a BBC article from 2015, seen in Figure 2.2.

Here, the **absolute** risk framing provides an eye-catching statistic - less than two slices of bacon per day increases the chance of developing colorectal cancer by 18% - but in its **relative** framing the result is much less alarming: the relative increase turns out to be just 1%. That is to say, of 100 people who don't eat bacon, 6 can be expected to develop bowel cancer over the course of their lifetimes. Of 100 people who eat 50g of bacon or some other processed meat every day of their lives, 7 can be expected to develop bowel cancer, amounting to a relative increase of 1 in 100. Such a statistic can be intuitively communicated in infographic like the one in Figure 2.3.

The graphic provides an easy part-to-whole comparison, and the random placement of the filled-in figures helps to communicate the aleatoric uncertainty of the disease.

Positive and negative framing
Another choice in the communication of probabilistic information is the use of positive and negative framing. An example of positive framing would be to say that, when using a medication, "roughly 10% of patients get a blistering rash". Whereas the negative framing would read "roughly 90% of patients do *not* get a blistering rash". Despite having the same outcome, the first framing, which states the risk of an unwanted event

Processed meats - such as bacon, sausages and ham - do cause cancer, according to the World Health Organization (WHO).

Its report said 50g of processed meat a day - less than two slices of bacon - increased the chance of developing colorectal cancer by 18%.

[24]

Figure 2.2: BBC, 26. October 2015

[24]: Gallagher (2015), *Processed meats do cause cancer - WHO*

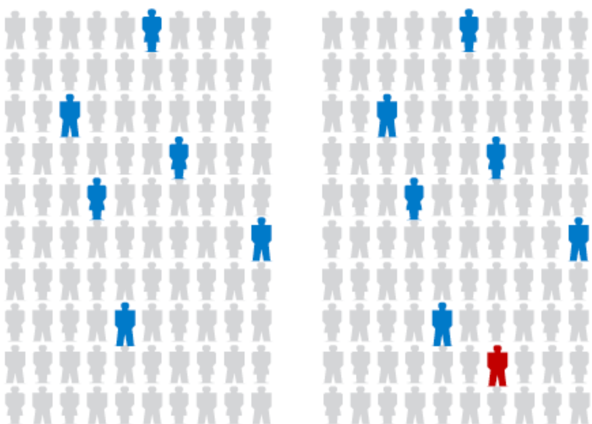
happening, is was rated higher on a risk scale of 1 - 5 (1.82 vs. 1.43)[1] . Although in this case (especially considering there is no absolute zero given on this risk scale) there was only a small increase in the perception of risk, we shall see in the a case study later on how, in the early weeks of the Coronavirus outbreak, positive framing was leveraged by one publication to create a dramatic and arguably misleading headline.

[1]: Spiegelhalter (2017), 'Risk and uncertainty communication'

Spiegelhalter argues that in the case of positive vs. negative framing, the most balanced communication method would be to present both cases. Indeed, providing both positive and negative framing not only helps avoid the varying interpretations which can arise when only one of the two is used, but also assists with the understanding of the correct **reference class**. In weather forecasting, including the chance of rain alongside the chance of no rain significantly reduced the number of people making reference class errors [25] .

The reference class

When the forecast says there's a 80% chance of rain today, what exactly does it mean? Rather than rain 80% of the *time* today, or rain over 80% of the *area* today, in fact the true interpretation is *on days with conditions like this* (that's the reference class) there is an 80% chance that there will be *some* rain. However, in this case understanding the reference class is not important as long as the forecast is enough to inform you that you might need an umbrella!



[1]

Figure 2.3: A pictorial visualisation of relative risk increase.

[1]: Spiegelhalter (2017), 'Risk and uncertainty communication'

Case Studies 3

3.1 Climate and Weather Forecasting

Climate and weather modelling hold all the sources of uncertainty we discussed in the Introduction. Of course, any real-world process has an element of aleatoric uncertainty. Meanwhile, epistemic uncertainty comes from choices of boundary and initial conditions, model parameters, as well as model structure. In this case, the model structure encompasses things like grid resolution, or whether all relevant processes are included and accurately represented in the model.

Depending on the context, some of these sources of epistemic uncertainty are more important than others. For instance, the long time scales in climate modelling mean that boundary conditions are more important than initial conditions. An example of a boundary condition in this case would be an emissions scenario, which sets the amount of greenhouse gases flowing into the atmosphere. On the other hand, the chaotic systems of weather mean that initial conditions play a greater role in this type of forecasting.

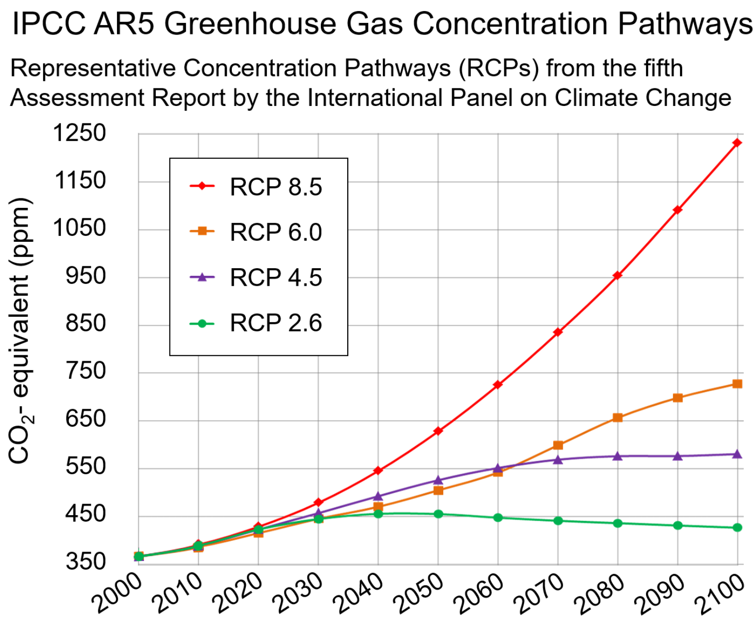
Climate modelling in particular not only has all the standard epistemic uncertainties involved in mathematical modelling, but is fundamentally indeterminate insofar as future boundary conditions depend on future behaviour and policy decisions not yet made - ontological uncertainty. As a result, we can only produce models for 'what would happen if' scenarios - provide projections, rather than predictions.

Ensemble predictions (EPs) are groups of model simulations which produce a range of predictions designed to explore the effect of one or more sources of uncertainty. There are different types of ensemble to explore different uncertainties; structural uncertainty can be explored using multimodel ensembles (MMEs) whereas parameter uncertainty is explored with perturbed parameter ensembles (PPEs).

Although, as we shall see, ensemble models can certainly help us to understand, visualise and communicate uncertainty, their use is not without challenges. Climate EPs often use the representative concentration pathways (RCPs), seen in Figure **??**, which describe several possible 'climate futures', and to which no relative probability can be assigned, thus carrying a large amount of ontological uncertainty. As a result, there is fierce debate over how such models should be interpreted and communicated.

In analogy to the four characteristics of intelligent transparency espoused by O'Neill, Stephens et al. 2012 state three properties by which efforts to visualise and communicate EPs could be evaluated:

- **Richness:** The amount of information communicated. In this respect, the needs of non-technical users must be balanced with



[26]

Figure 3.1: Wikipedia: Representative Concentration Pathways.

[26]: (2020), *Representative Concentration Pathway*

the risk of oversimplification.

- **Robustness:** Refers to the fidelity of the EP and the extent to which this trustworthiness is communicated. Robustness of communication can be increased by adding information richness, as in examples we'll see later where colour grading is added to visualisations of EPs to indicate quality of prediction.
- **Saliency:** The interpretability and usefulness of communication for the target audience.

Setting aside the complexity of communicationg uncertainty in climate modelling (which could be an entire report in itself) we will instead demonstrate the communication of uncertainty using EPs by looking at the example of tropical storm forecasting.

Figure 3.2 shows the shows the US National Hurricane Center's famous cone of uncertainty. The correct interpretation of the cone is as follows:

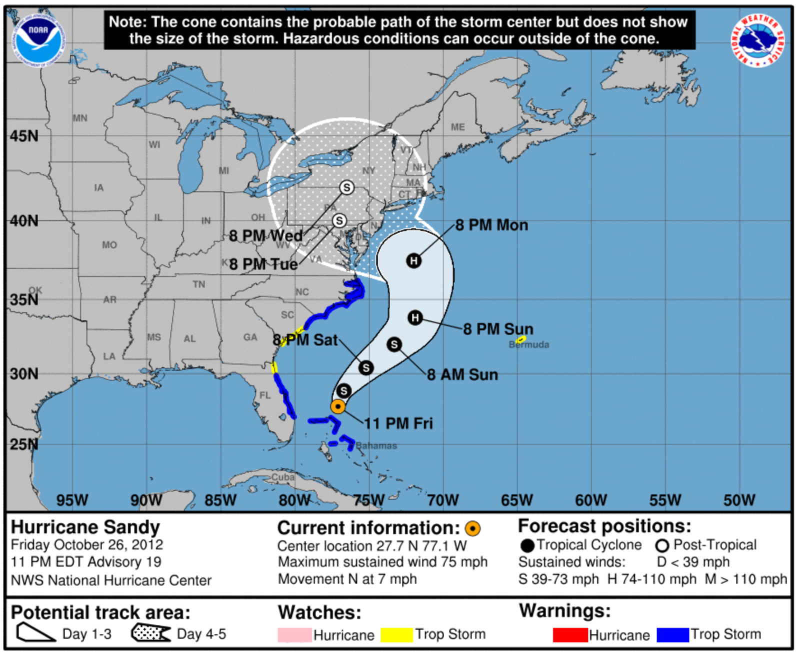
The tropical cyclone can be expected to remain within the cone roughly $60 - 70\%$ of the time [27] .

[27]: (), *About the Cone*

Some viewers misunderstand the graphic, thinking themselves to be out of harm's way if they reside outside of the cone [25] . However, the cone merely represents the uncertainty range for the path of the tropical storm, and gives no information about wind speed, storm surges or the wider area outside of the path which might feel the effects, and in particular gives no guidance on who should or should not evacuate.

[25]: Stephens et al. (2012), 'Communicating probabilistic information from climate model ensembles—lessons from numerical weather prediction'

One alternative, for better saliency of communication, is to use so-called **spaghetti plots**, which more clearly show the variety of possible paths a tropical storm might take. A spaghetti plot showing 50 realisations



[27]

Figure 3.2: National Hurricane Center, US.

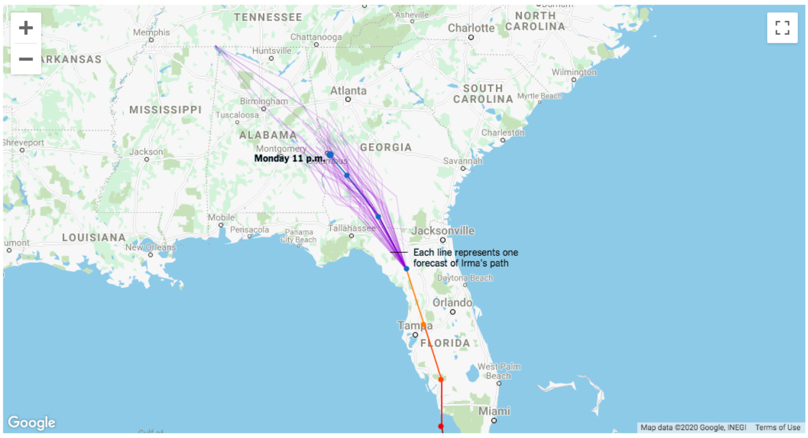
[27]: (), *About the Cone*

of path predictions for Hurricane Irma in September 2017 is shown in Figure 3.3.

Increasing the robustness of uncertainty communication can be done by adding richness of information in the form of heatmaps and colour grading. Heatmaps are useful for indicating areas where many model realisations are concentrated. Colour grading can be utilised for more subjective, qualitative uncertainty information, such as if there were two sets of EPs from two research institutes, one of which has an excellent track record of producing accurate predictions. The predictions of the more trusted predictions could be shaded darker. An example of heatmaps and colour grading can be seen in Figure 3.4.

Tropical storm and weather forecasting are topics with great potential for visualising uncertainty. In fact, it has been shown that greater richness of information about uncertainty leads to forecasts which are rated as more trustworthy than deterministic forecasts alone [30] , meaning good uncertainty communcation can in turn inform good decision-making.

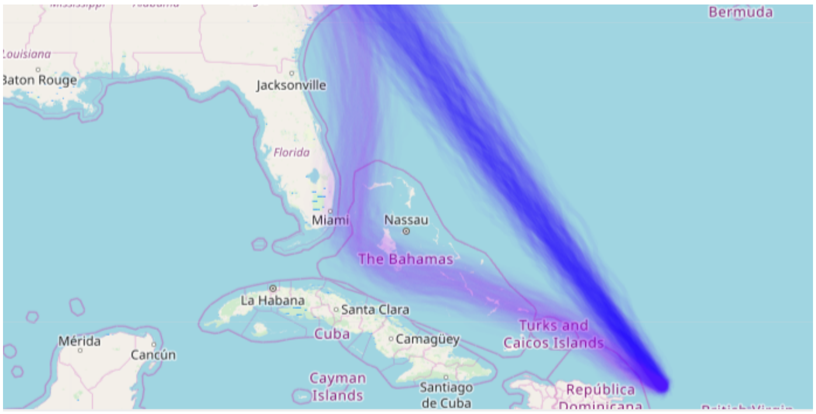
[30]: Joslyn et al. (2012), 'Uncertainty forecasts improve weather-related decisions and attenuate the effects of forecast error.'



[28]

Figure 3.3: Hurricane spaghetti plot from the New York Times, September 5. 2017

[28]: Almukhtar (2017), *Maps: Tracking Hurricane Irma's Path Over Florida*



[29]

Figure 3.4: There is potential in the use of spaghetti plots combined with heatmaps and colour grading to communicate uncertainty. Hugo Bowne-Anderson, September 18. 2017.

[29]: (), *Spaghetti Plots and Hurricanes' Paths*

3.2 Coronavirus

Our second and final case study is the recent Coronavirus outbreak. We look at epidemiological modelling from the early months of the outbreak, and how uncertainty around the number of people infected was communicated at the time.

There are several ways of communicating uncertainty around such a modelling process:

- **Precision:** Numbers can be given at a level of precision which reflects our certainty about them (20.2% implies a greater level of confidence in the figure than 20%, and likewise writing 20% rather than 22% might be appropriate depending on the level of epistemic uncertainty).
- **Confidence Intervals:** A confidence interval can be provided, or measure of statistical significance (p-value or a range within 2 or 3 standard errors).
- **Verbal qualifiers:** Verbal qualifiers such as 'best estimate' are often appropriate. If evidence is lacking, it might be appropriate to not give a number at all.
- **Qualitative scales of evidence:** An often recommended way of

communicating uncertainty arising from the scientific process, especially around health, but any public-facing area where facilitators use evidence-based interventions, is to use qualitative scales to express the strength of evidence.

- **Acknowledge limitations:** It is also recommended to acknowledge limitations, advise caution around which conclusions can be drawn from the data, model or evidence, and acknowledge unknown unknowns.

Many of these strategies can be found in the uncertainty modelling and communicaiton from the MRC Center for Global Infectious Disease Analysis at Imperial College, London, released on January 22. 2020. Figure 3.5 shows a summary table from their main report. The team used a negative binomial model to infer the number of patients infected given the number of confirmed cases internationally, outside of the Wuhan area where the virus first originated.

The table explores epistemic uncertainty by varying model parameters: giving a baseline estimate, assuming a smaller catchment population for Wuhan International Airport, shortening the virus' window of detection, as well as smaller and greater numbers of international cases. The aleatoric uncertainty is expressed using 95% confidence intervals for the estimated total number of cases. Note also the precision of the figures, which are given to the nearest 100. The analysis gives a central estimate of 4000, and an uncertainty range of 1000 - 9700. The uncertainty range is a combination of the epistemic and aleatoric uncertainties, taken from the highest and lowest confidence interval bounds across all parameter sets respectively.

The MRC summarised their report in a thread on Twitter, and we provide it here in the margin of the following page as an example of excellent uncertainty communication.

	Baseline[1]	**Smaller catchment**[1]	**Shorter detection window**[1]	**6 exported cases**	**8 exported cases**
Exported number of confirmed cases[2]	7	7	7	6	8
Daily international passengers travelling out of Wuhan International Airport[3]	3,301	3,301	3,301	3,301	3,301
Effective catchment population of Wuhan International Airport	19 million	11 million	19 million	19 million	19 million
Detection window (days)	10 days	10 days	8 days	10 days	10 days
Estimated total number of cases (95% CI)	4,000 (1,700 – 7,800)	2,300 (1,000 – 4,500)	5,000 (2,200 – 9,700)	3,400 (1,400 – 7,000)	4,600 (2,100 – 8,600)

[1]We now report uncertainty around our central estimate as the range spanned by the 95% confidence intervals of these three scenarios. [2]reported number of confirmed cases detected internationally. [3]calculated from the 3-month totals reported by [19] corrected for the travel surge during Chinese New Year (see Summary).

Figure **??**

Figure 3.5: Summary table of estimates from epidemiological models of Coronavirus from the MRC Centre for Global Infectious Disease Analysis at Imperial College, London.

The opening tweet of the thread gives the central estimate of 4000 cases, and immediately provides a link to the original report. Two of O'Neill's properties are fulfilled here: by putting the information on social media, it becomes more **accessible**. Those who wish to **assess** the information further can easily click through to read the report. The first tweet also clarifies what can **not** be concluded from the modelling - although the estimate had doubled from a previous report, there was no implication that the outbreak had doubled in size in that time.

In the following tweets, the uncertainty range is clearly stated, and the results are made **comprehensible** with further explanation. The report was provided in both English and Mandarin, making it **usable** for a larger number of people in the affected area.

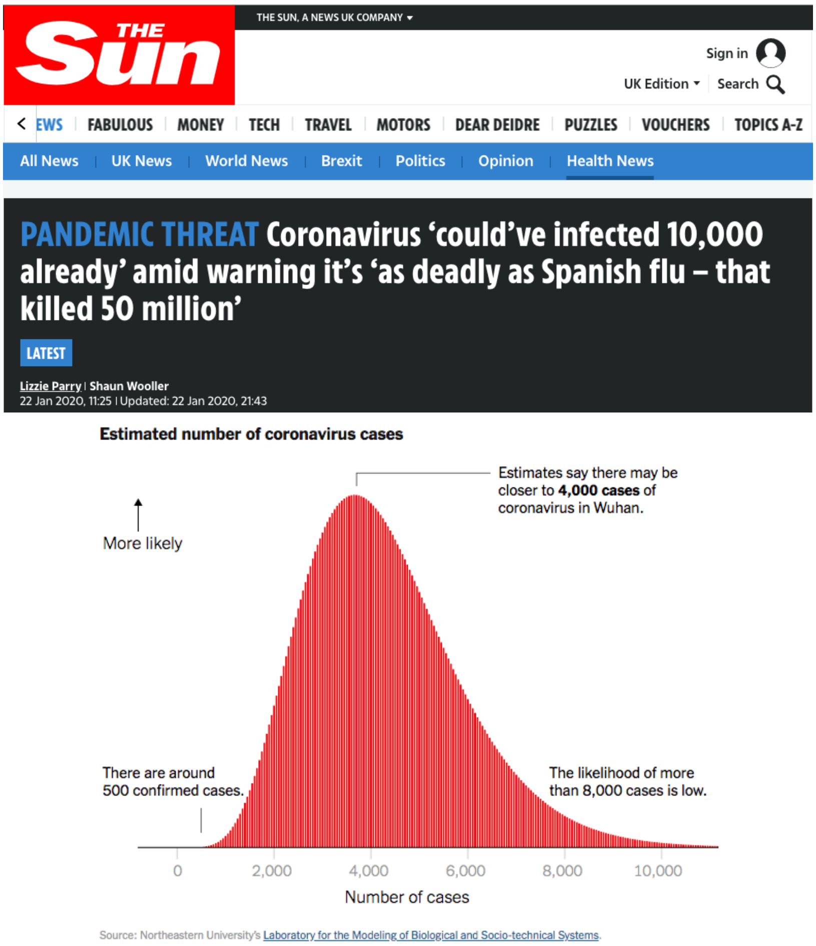
However, researchers can only do so much to influence how uncertainty is communicated. We finish this seminar report with a comparison of how epidemiological modelling of Coronavirus spread was reported in two different media publications, namely The Sun and the New York Times.

Figure 3.6 shows the headline reporting the modelling referenced above. Although the uncertainty range extended 9,700, the headline reads that the virus 'coud've infected 10,000 already'. Note the use of **positive framing** to create a more dramatic headline. A more balanced (but admittedly less catchy) framing would be to say that the number of people infected by Coronavirus could be as high as, but is unlikely to be greater than, 9700.

The New York Times reported on separate but similar modelling from the MOBS lab at North Eastern University in the United States. This team used Bayesian inference to reach their results, and Figure 3.6 shows the posterior distribution of the number of cases. The graphic is annotated to show that although it was likely the true number of cases was much greater than the number of confirmed cases at the time, the likelihood of there having been more than 6,000 cases is low. The source of the uncertainty information is also provided. Further explanation within the article advises caution in interpreting the estimates, and quotes an epidemiologist to advise that, given the uncertainties involved, the estimates were not "truth – they're just one step in trying to better understand this outbreak".

[31]

[31]: Global Infectious Disease Analysis (2020), *UPDATE: Report estimates 4000 cases*



[32–34]

Figure 3.6: Top: Headline from the Sun, January 22. 2020. Bottom: Figure from the New York Times showing the posterior distribution of the number of Coronavirus cases. January 23. 2020.

[32]: Wooller (2020), *Coronavirus 'could have infected 10,000' amid warning it's 'as deadly as Spanish flu'*
[33]: Rebecca (2020), *Wuhan Coronavirus Map: Tracking the Spread of the Outbreak*
[34]: Chinazzi et al. (2020), ‘Preliminary assessment of the International Spreading Risk Associated with the 2019 novel Coronavirus (2019-nCoV) outbreak in Wuhan City’

4 Conclusion

In this seminar report, we've explored the topic of communicating uncertainty from a number of angles. We started by discussing the Spiegelhalter's three sources of uncertainty: aleatoric, epistemic and ontological. We saw several examples of how uncertainty can be communicated *badly*, as in the example of ONS unemployment figures, or with an aim to mislead, as in the tobacco and fossil fuel industries.

In Chapter 2 we reviewed decades of research in Risk Communication, looking at the theory and practice and finding lessons which are applicable not only to the communication of uncertainty, but to communicating statistical information in general. Key takeaways are that probability phrases alone can be misinterpreted, and a combination of numbers, words and graphics can help aid understanding. We considered how statistics can be framed, finding that relative risk and the use of both positive *and* negative framing allows more balanced communication.

In Chapter 3 we looked at two case studies of uncertainty communication. The case study of climate and weather forecasting allowed us to see sources of uncertainty in context, and through tropical storm forecasts we explored best practise in visualisation as a method of uncertainty communication. In particular, we saw how heatmaps and color grading could be used in conjunction with spaghetti plots to improve the richness, robustness and saliency of uncertainty communication. Finally, in the Coronavirus case study we saw several uncertainty communication strategies put into practise: adjusting precision, providing confidence intervals and acknowledging limitations of the modelling process. A final comparison of subsequent reporting by The Sun and the New York Times ends this report on a more sobering note. When researchers communicate uncertainty well, it can certainly lead to some balanced and informative journalism. Unfortunately, not all media outlets exist for balanced and informative reporting!

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