Quantifying how user-interaction can modify the perception of the value of climate information: A Bayesian approach

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Article info
Article history:
Received 1 February 2017
Received in revised form 30 May 2017
Accepted 2 June 2017
Available online xxxx

Keywords:
Decision theory
Bayesian framework
Value of forecasts
Climate services

Abstract
The growing attention user relevance is receiving in the context of climate services is giving new light to engagement activities. However, while there is an almost unanimous consensus that these are important to the delivery of usable services, there is relatively little quantitative evidence of their impact on the usefulness of the service or its value as perceived by the users and decision-makers. Using a simple Bayesian decision theoretic framework, we have analysed how the perceived value of the service changes as a function of the user’s belief in the accuracy of the forecast. Based on this, we conclude, that, at least for the generic users adopted for our analysis, 30 or more repeated forecasts may be needed to ascertain the real user value of a predictive service. However, we argue that engagement between users and service providers can play a significant role in modifying the perceived accuracy and value of the service, bringing it closer in line with the objective evaluation. This requires feedback from users on both the specific climate information content and its presentation, alongside exploring the user’s attitude to risk. If appropriate engagement can be achieved, this work suggests that it has the potential to alter the overall perceived cost-benefit ratio over a relatively short period of time, enabling users to make best use of the available climate information.

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Practical Implications
The appropriate use of skilful seasonal forecasts has the potential to improve decision making across a range of sectors, and promote a proactive approach to climate adaptation, thereby providing significant societal benefits. We have here analysed how the value of a climate service changes as a function of the user’s belief in the accuracy of the forecast information. Here, users are defined to be a person or organisation which makes decisions based on the forecast information, subject to specified costs and losses, and who are influenced by the environment in which they operate, their prior beliefs and risk appetite. To study the behaviour of these theoretical users, we consider the following generic types: 1) users who initially believe the stated accuracy of the forecast, but with differing levels of scepticism; 2) users who do not initially believe the stated accuracy of the forecast, and also have differing levels of scepticism. Both types of user adjust their beliefs over time in response to the forecast performance. Our results indicate that users who are initially more sceptical of the forecast performance are correspondingly more likely to perceive its value to be lower for longer. A consequence is that such users may be more likely to discontinue using the service, which will be disadvantageous for them in the long term. For the simple, albeit realistic, cost/loss matrix used in this analysis, we also have shown that it can take at least 30 repeated forecasts for the perceived value (i.e. the value based on a user’s subjective experience of forecast performance) to converge to the objectively-defined expectation value. These results highlight the importance of suitable engagement activities, which clearly and honestly demonstrate the accuracy of the climate information in a form appropriate to the user, as well as exploring users’ attitude to risk. Doing so has the potential to shorten the time taken to adopt the service, thereby enabling users to make best use of the available climate information for making decisions.
1. Introduction

The recent international focus on climate services (e.g., Hewitt et al., 2012) has put users and their perceptions at the centre of service development. However, although a strong agreement exists on the need for closer engagement between providers and users of climate information (e.g., Goddard et al. 2010; Economou et al. 2016; van der Voorn et al. 2017), very few attempts have been made to quantify the value of such activities. Furthermore, the few studies that do exist have focused more on the importance of community engagement for climate change adaptation than on decisions which are relevant over a climate prediction time-scale (e.g., seasonal forecasting). Here, we demonstrate a flexible approach with which to assess the subjective economic value the engagement process could have for users, through the adoption of a simple Bayesian modelling framework.

It has been shown (e.g., Katz and Murphy, 1997; Richardson, 2000; Thornes and Stephenson, 2001; Mason, 2004) that the value of forecasts depends on the specific decision portfolio and associated payoffs, the risk appetite and the regulatory framework in which users operate. More succinctly, the forecast value is dependent on a user’s (interpretation of the) costs and losses in response to different combinations of decisions and physical outcomes. At the same time, it is reasonable to expect (e.g., Kirchhoff, 2013, and references therein), that a few incorrect forecasts at the beginning of a trial can disproportionately affect the uptake of a service, although some evidence may suggest otherwise (e.g., Lemos et al. 2014). In other words, the strength of user belief in the forecasts is an additional factor that will affect the perceived forecast value to any user.

The question we are trying to answer here is whether, and if so by how much, early engagement with the user can alter the uptake of the service by affecting the a priori expectation of the service value. For the purposes of this investigation, the users under consideration are assumed to be individuals or organisations which make decisions that are informed by climate services. For this reason, the terms “user” and “decision-maker” are used interchangeably throughout this work. As outlined below, the salient characteristics of these theoretical users are defined by their cost/loss function and interpretation of forecast accuracy. By applying this framework to a sequence of forecasts, we can quantify the theoretical user’s subjective perception of forecast value. In application to real users, these characteristics will be influenced by the environment in which they operate, their risk appetite and prior beliefs.

2. Value of information

Although many users are keen to use the best and most accurate data available, experience suggests that the minimum level of forecast accuracy required to inform a specific decision depends significantly on the context of that decision. In addition, optimal decision-making, based on forecasts, requires a clear understanding of both the costs and losses associated with different outcomes and decisions, as well as the accuracy of the forecast. It is unlikely that users will ever share this highly sensitive information with climate service developers; however, in some cases, it is possible to infer the relative ratios of costs and losses, based on users’ decisions. This is particularly evident in a climate service prototype developed for the UK transport sector, as part of the FP7 EUPORIAS project (Hewitt et al., 2012; Palin et al., 2016; see also Bruno Soares and Dessai, 2015). During early engagement with stakeholders from across the transport sector, it became clear that there was interest in the provision of winter impact forecasts. However, these potential users were not, in general, prepared to make explicit use of seasonal prediction in their decisions, partly because of scepticism about forecast accuracy, and partly because the penalty (due to regulatory instruments and risk appetite) of failing to adequately prepare for one significant icy/snowy event would have been much greater than the potential savings achieved through preparing for a warmer than average winter.

These observations are broadly consistent with previous work (e.g., Richardson, 2000, 2012) which demonstrates that, given a certain level of skill (however defined), the only users who could benefit from a prediction are those for whom the cost of undertaking a mitigation action is in some sense close in magnitude to the potential loss. Accordingly, it follows that trivial options, such as either taking action at all times, or never, can easily become the optimal strategy for those users characterised by a highly skewed cost-loss function.

However, even if we limit ourselves here to those users whose cost/loss function means they can gain value from climate forecast information, the real value they can achieve is less than this theoretical maximum, even when accounting for limitations in the predictive ability of the forecasting system. This is because of subjectivities in the way in which users interpret the climate information; for example, their personal interpretation of the information, based on their innate scepticism and prior experiences, as well as a potential reluctance to fully adopt new practices.

Assuming the behaviour of a decision-maker can be modelled through a Bayesian (probabilistic) framework, we show here that the subjective value of the climate/weather prediction (a priori belief) can have a measurable impact on its real (e.g., monetary) value. We demonstrate this behaviour using two paradigmatic examples: 1) users who initially believe the stated accuracy of the forecast, but with differing levels of scepticism; 2) users who do not initially believe the stated accuracy of the forecast, but who also display differing levels of scepticism. We then study the evolution of the subjective value over time and its reaction to the occurrence of positive (successful predictions) and negative (wrong predictions) experiences.

We conclude that, while the long-term perception of the forecast value must correspond to its real value irrespective of the initial a priori belief, the transient perception can be quite different between the two cases. This means that service providers that are genuine about their evaluation of the forecast accuracy, should put as much care as they can into the user engagement as this can significantly affect the transient value of the predictions.

3. Methods

The Bayesian framework, mentioned above, is used to describe key influences on users’ decisions-making, and consists of two main parts: firstly, a decision theoretic framework which captures user decision-making based on a cost-loss (utility) matrix that quantifies consequences for each decision-outcome combination; secondly, the Bayesian probabilistic framework, which describes the user’s belief or perception of the forecast accuracy given its running performance. These are discussed in more detail below.

3.1. A decision theoretic framework for user action

For simplicity, a 2-by-2 cost/loss matrix is considered (Katz and Murphy, 1997; Mylne, 2002; Richardson, 2012). In this approach there are only two outcomes: a specific uncertain (weather) event (denoted as θ) will occur with probability P(θ) or it will not occur (denoted as θc) with probability P(θc) = 1 − P(θ). Similarly, there are only two decisions: to either take action before the event (D=1) at some cost, or not (D=2) with associated losses if the event occurs. Table 1 shows the associated cost/loss matrix where
We now consider forecast information which is not perfect and, therefore, provides only “partial information”. The value of this partial information will, of course, be determined primarily by the forecast accuracy.

To illustrate this, we consider a deterministic, binary forecast (e.g. representing an ensemble mean). Let $X_i$ denote a forecast of the event $\theta_i$ occurring, with $X_i$ denoting a forecast of the event not occurring (i.e. $\theta_i$). The “forecast accuracy” can then be defined by the conditional probabilities $P(\theta_i|X_i)$. One simple way of quantifying this conditional probability is to calculate the frequencies from a 2-by-2 contingency table of historical data (see Table 2). For instance, $P(\theta_i|X_i)$ could be derived from the quantity $N_{11}/N$, as

$$P(\theta_i|X_i) = \frac{N_{11}}{N}$$  

In this context, $P(\theta_i)$ represents the “base rate” probability ($\sum_{j=1}^{h} P(\theta_j)/N$) and the Expected Value of Partial Information (EVPI) is given by:

$$EVPI = ECVI - \sum_{k=1}^{2} \min_{\theta_j} \sum_{j=1}^{2} U_{\theta_j} P(\theta_j).$$  

We also define the “base rate” probability ($\sum_{j=1}^{h} P(\theta_j)/N$) and the Expected Value of Partial Information (EVPaI) is given by:

$$EVPaI = ECVI - \sum_{k=1}^{2} \sum_{j=1}^{2} U_{\theta_j} P(\theta_j|X_j).$$

where the first term is the expected loss of just using the climatological forecast for $P(\theta_i)$. The second term is the expected loss from using forecast information: the innermost sum reflects the fact that the decision to take action is made based on $P(\theta_i|X_i)$, and the outermost sum is the expectation over the possible values that the forecast $X_i$ might take. Following Richardson (2000), we present the value of the forecast in relative units; according to the definitions given above this corresponds to EVPal/EVPI.

Given the example of a deterministic, binary forecast, each individual forecast must be either correct (i.e. hit or correct rejection with corresponding probabilities: $P(\theta_i|X_i)$ and $P(\theta_i|\bar{X_i})$ respectively), or incorrect (i.e. false alarm or miss with respective probabilities: $P(\bar{\theta_i}|X_i) = 1 - P(\theta_i|X_i)$ and $P(\theta_i|\bar{X_i}) = 1 - P(\bar{\theta_i}|X_i)$). For clarity of exposition, we assume $P(\bar{\theta_i}|X_i) = P(\bar{\theta_i}|\bar{X_i})$, and call this probability the “forecast accuracy”. We also define $P(\theta_i)$, i.e. the statistic of bias is the same. The extension to the case where these conditions are no longer valid (i.e. $P(\bar{\theta_i}|X_i) = P(\bar{\theta_i}|\bar{X_i})$) would require three probabilities to be specified, rather than one. This would involve a non-trivial extension of our framework and is left for future work as it is outside the scope of this paper.

For a given loss matrix ($U_{\theta_1} = U_{\theta_2} = 5$, $U_{\theta_2} = 30$, $U_{\theta_2} = 0$) with $P(\theta_i) = 1/3$, we can compute Equation (4) for a range of forecast accuracies, shown in Fig. 1 (see also Benton et al., 2017 for another application). For this particular cost/loss table, forecast accuracy needs to exceed ~0.75 before the forecast becomes of appreciable value to a user over the long term.

As highlighted above, it is important to note that EVPI and EVPal are expectations. As such, over a long time-scale, the value of a forecast will asymptotically tend towards this limit. However, over short timescales, the forecast value can differ significantly, as determined by the performance of the forecast event by event. Below, we explore this effect using stochastic simulations. For example, assuming that the forecast is typically correct 4 times out of 5, means that the accuracy is $P(\theta_i|X_i) = P(\bar{\theta_i}|\bar{X_i}) = 0.8$. From

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**Table 1**

Generic cost/loss matrix.

<table>
<thead>
<tr>
<th>$\theta_1$ (e.g. icing occurring)</th>
<th>$\theta_2$ (e.g. icing not occurring)</th>
</tr>
</thead>
<tbody>
<tr>
<td>$D = 1$ E.g. taking de-icing action</td>
<td>$U_{\theta_1} (\text{correct action})$</td>
</tr>
<tr>
<td>$D = 2$ E.g. taking no action</td>
<td>$U_{\theta_1} (\text{incorrect action})$</td>
</tr>
</tbody>
</table>

$U_{\theta_j}$ quantify the costs or losses for each decision $D = 1, 2$ and outcome $\theta_j$ ($j = 1, 2$). Note that a similar matrix is used to quantify the performance of the forecast in terms of numbers of hits, misses, false alarms and correct rejections.

It is important to note here that, in the most general case, the penalties are a subjective combination of the true economic costs of the decision/outcome, as well as the user’s own attitude to risk. For example, a more risk averse user will tend to assume a higher penalty for forecast misses or false alarms, than a user with preferences for lower risk aversion. In either case, the methodology outlined below applies, while noting that the costs and losses for other than climatological frequencies, it is not worth them spending more than the value of the EVPI.

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**Table 2**

Contingency table of historical occurrences of the event $\theta_i$ and associated forecasts $X_i$.

The total number of events is $\sum_{j=1}^{h} \sum_{k=1}^{2} N_{j,k} = N$.

<table>
<thead>
<tr>
<th>$\theta_1$ (e.g. icing occurring)</th>
<th>$\theta_2$ (e.g. icing not occurring)</th>
</tr>
</thead>
<tbody>
<tr>
<td>$X_i$ (icing forecast)</td>
<td>$N_{11}$ (hit)</td>
</tr>
<tr>
<td>$X_i$ ( icing not forecast)</td>
<td>$N_{21}$ (miss)</td>
</tr>
</tbody>
</table>
this, an artificial sequence of forecast successes and failures can then be simulated using a Bernoulli distribution with probability of success \( p \).

3.2. Subjective assessment of forecast accuracy

The analysis above is based on an objective calculation of the forecast accuracy, as defined here, but applies equally well for a subjective analysis as a way of estimating user perceptions of the value of climate information. In this case, we can gain an important understanding of the motivations behind characteristically different types of user behaviour. For example, why do some users continue to use forecasts while others do not? One qualitative scenario is that an individual user may perceive a forecast to be less accurate than prescribed, because of short-term poor performance. Accordingly, they are also likely to consider its value to be lower and, therefore, may stop using the forecast. At the other extreme, users whose personal experience suggests that the forecast is more accurate than specified, might become overconfident in the forecast and fail to build contingency into their plans. In both cases, it is important to note that the “true”, long-run accuracy of the forecast has not changed, only the perceived or short-term accuracy. Both examples suggest a strong influence of subjective assessment of forecast accuracy combined with intuition about the value obtained from the forecast. In short, a more accurate forecast is perceived as more valuable, while a less accurate forecast is perceived as less valuable.

The arguments outlined above suggest that a user may stop using the forecast if their subjective estimate of its accuracy implies that its expected value falls below the threshold described earlier (see Fig. 1). It is, therefore, important to understand the user’s beliefs and perceptions of forecast accuracy. The need to explore this in a quantitative way motivates the Bayesian statistical model, outlined below, which provides a way of describing user response to a deterministic, binary forecast. In the interests of maintaining clarity, we have not considered forecast uncertainty beyond the knowledge that the forecast is imperfect, but provide a discussion in the “Probabilistic forecasts and uncertainty” section.

Suppose the binary sequence of successes and failures is:

\[ Y(t) = 1 \quad \text{if forecast is correct} \]

\[ Y(t) = 0 \quad \text{if forecast is incorrect} \]

where \( t \) is time. Then \( Y(t) \) is a sequence of Bernoulli trials where \( P(Y(t) = 1) = \pi \) is the forecast accuracy defined earlier (i.e. \( \pi = P(\theta_1 | X_t) = P(\theta_2 | X_t) \)). We can then generate different realisations of \( Y(t) \) of arbitrary length, and assess the response of a theoretical user to the forecast performance described by each sequence. If \( \pi = 0.8 \), in the long-run 80% of the forecasts should be successful (and 20% should be incorrect). However, due to the random nature of the sequences, there will be realisations for which the local value (in time) of the accuracy will be lower or higher than the specified long-term value. The idea behind this approach is that the user updates their belief in the accuracy of the forecast based on its performance, forecast by forecast. It is, therefore, important to consider users’ beliefs in the two main pieces of information supplied by the forecast provider:

1) the forecast
2) the forecast accuracy \( p \)

If the information provided about forecast accuracy is convincing, users may be more likely to continue using the forecast even if it is incorrect a few times. Therefore, by providing more information about the accuracy of the forecast, we can go some way to ensuring that users are able to extract more value from forecasts.

Here, users’ subjective estimates of the forecast accuracy are quantified using a Bayesian model, where the forecast accuracy \( \pi \) is perceived as “uncertain” by different users and is, therefore, modelled by a probability distribution. This prior distribution of \( \pi \) is updated according to forecast performance, event by event. The natural (conjugate) prior distribution for the probability of a binary process is the beta-distribution so that \( \pi \sim \text{Beta}(\alpha, \beta) \) with parameters \( \alpha, \beta > 0 \). The expectation or mean of the distribution is \( E(\pi) = \mu = \frac{\alpha}{\alpha + \beta} \) and the variance \( \text{Var}(\pi) = \frac{\mu(1 - \mu)}{(\alpha + \beta)(\alpha + \beta + n)} \). Thus, by varying \( \alpha \) and \( \beta \) we can express different types of user. As stated previously, we investigate the behaviour of the following: 1) users who initially believe the stated accuracy of the forecast, but with differing levels of scepticism; 2) users who do not initially believe the stated accuracy of the forecast, and with differing levels of scepticism.

For users of type 1, we assume that \( \mu \) is equal to the specified forecast accuracy \( p \), i.e. the users believe the forecaster provider’s assessment of the forecast accuracy is correct on average, but not exact. Under this assumption, we can think of the distribution in terms of the mean \( \mu \) and parameter \( \beta \) which controls the variance, given the mean, since

\[
\text{Var}(\pi) = \frac{\mu(1 - \mu)(1 - \mu)}{(1 - \mu + \beta)}.
\]

Then, decreasing the value of \( \beta \) increases the variance of the distribution, indicating a user who has less confidence in the assessment of the forecast accuracy.

Modelling forecasts in this way is extremely efficient since the beta distribution is a conjugate prior, meaning that the posterior distribution of \( \pi | Y(t) \) (i.e. after seeing the data) is also a beta distribution with updated parameters of the form

\[
\alpha' = \alpha + \sum_{t=1}^{n} Y(t) \rightarrow \alpha + np,
\]

\[
\beta' = \beta + n - \sum_{t=1}^{n} Y(t) \rightarrow \beta + n(1 - p).
\]

where \( n \) represents the total number of forecasts in the series, the limits are calculated as \( n \) tends to infinity and \( p \) denotes the long-run probability of success for the forecast (quoted by the forecast provider). Thus, as \( n \) tends to infinity, the expectation of \( \pi | Y(t) \) tends to the long-run probability \( p \).

\[
E(\pi | Y(t)) = \frac{\alpha'}{\alpha' + \beta'} = \frac{np}{np + n(1 - p)} = p.
\]

For users of type 2, we assume \( \mu \) is not equal to the specified forecast accuracy \( p \), but is instead given by \( \mu = 1/2 \). This indicates
indifference to any information about forecast accuracy provided by the supplier; however, even in this case, users can display differing levels of scepticism in their response to forecast successes or failures. For this reason, the specific cases studied here are a uniform prior, i.e. $\alpha = \beta = 1$; and the Jeffrey's prior, i.e. $\alpha = \beta = 1/2$; both reflect users that are ignorant about the accuracy of the forecast. The first, is a user who places equal chance that $\pi$ is some value between 0 and 1. The latter, reflects a user of similar beliefs, except they allow more chance that $\pi$ is close to either zero or one.

4. Simulation results

For users of type 1, Figs. 2 and 3 plot the updated expectation for more confident ($\beta = 5$, dashed lines) and more sceptical ($\beta = 1$, solid lines) users for a number of different realisations and for different durations. From these figures it is evident that the subjective estimates of the forecast accuracy vary more for the sceptical user than the confident user. Both figures also show that the subjective accuracy exhibits a wide range of values during the first 20–30 forecasts of the assessment, spanning ~0.6–0.9. This suggests that there is a non-zero probability of the forecast being considered to be of low value, and potentially not used. However, in the long run with a large number of realisations (see Fig. 3), the expectation tends asymptotically towards $p$, with the standard deviation of the realisations decreasing. Nevertheless, conditional on the values chosen for $\beta$ and $\mu$, the evidence suggests that it may take 30 or more repeated forecasts for the subjective assessment of the forecast accuracy to be consistently close to the known value, $p$. When applied to seasonal forecasts, this is likely to be much longer than most individuals’ occupancy in a particular job role.

To visualise the effect of subjective assessments of forecast performance, event by event, Fig. 4 shows a time series of subjective value.

For comparison, Figs. 5 and 6 show the subjective accuracy and value as perceived by users of type 2, who were initially indifferent to information about forecast accuracy provided by the supplier. As expected, these users experience large fluctuations in their assessment of forecast accuracy, leading to an initially larger spread than for the other types of user discussed here. Accordingly, these users experience a correspondingly higher likelihood of the subjective value being zero. However, after approximately 100 repeated forecasts there is little to distinguish the users of type 1 and 2 considered here.

From this, it is clear that sceptical users tend to experience a greater period of time during which the forecast value is believed to be no better than that of climatological information. As such, there is a greater tendency for sceptical users to dismiss the forecasts. These findings suggest, that it is incumbent on forecast providers to demonstrate the accuracy of the climate information clearly, to ensure that users can be confident in the performance of the forecast. This could involve more stakeholder engagement, or providing more detailed evidence for our assessment of forecast accuracy. As such, the findings are consistent with studies (e.g. Meinke et al., 2006; van der Voorn et al., 2017) indicating the
importance of engagement activities which demonstrate the credibility of the information to a range of users.

Fig. 5. Long time series of forecast updates for 100 realisations of both type 2 users (p = 0.8; α = β = 1; α = β = 1/2; P(h) = 1/3).

Fig. 6. Time series of subjective ‘forecast value’ updated each forecast, for 5 realisations of both type 2 users (U11 = U12 = 5, U21 = 30, U22 = 0; P(h) = 1/3).

5. Probabilistic forecasts and uncertainty

As described above, this work has considered user response to deterministic, binary forecasts. In reality, most forecasts are probabilistic, which provides additional information about the likelihood of the event occurring, and may include more than two forecast categories. User scepticism of a forecast will depend on its verification attributes across the different categories, and their interpretation of the results. As such, a forecast that verifies badly (e.g. lack of resolution, sharpness, or reliability) is likely to reduce user’s belief in the accuracy of the information. However, it is important to note that the different verification measures mentioned here may provide useful information for different types of decision. For example, sharpness may be of most relevance to users who plan for extremes.

In principle, it seems plausible to hypothesise that a user’s scepticism of a probabilistic forecast will also be a function of the actual forecast probabilities, interpreted within the context of its verification attributes. Given this, a user’s scepticism could change in response to each forecast. In the framework described above, this suggests that real users are likely to exhibit a mixture of the behaviours outlined above, but with a range of priors and levels of scepticism that vary in accordance with their interpretation of the available information, based on their own beliefs and innate biases.

6. Summary and conclusions

The expected “value” of a forecast to a user is dependent on the costs and losses associated with different outcomes and decisions, and also the accuracy of the forecast. However, the value, as perceived by a user, may be quite different, depending on their prior assumptions and interpretation of imperfect forecasts (e.g. Meinke et al., 2006; Goddard et al., 2010). To better understand how these factors can influence perceived value, we have proposed and demonstrated a Bayesian decision theoretic framework for assessing value to a user, based on the event by event performance of a synthetic deterministic, binary forecast. This approach was motivated by engagement with users across the UK transport sector which took place as part of the FP7 EUPORIAS project. It is an attempt to conceptualise the impact some factors could have on the way users respond to climate information, especially those factors that are under the service provider’s control, e.g. user engagement.

This approach also builds on current understanding of the value of “partial” information which, for any real forecast system, necessarily falls between two limiting cases (e.g. Lindley, 1985):

1) No forecast information, only knowledge of the climatological frequency of a particular event
2) Perfect information, in which a forecast is always correct

Calculations (e.g. Fig. 1) show that there is an accuracy threshold below which the forecast offers no additional value above knowledge of the climatological frequency of event occurrence, P(h). It is well known that the location of this threshold is user-dependent; for example, if the penalty for failing to act under adverse conditions is large compared to the cost of action, there is a strong incentive for users to always take action. For users subject to these, or similar constraints, only extremely accurate forecasts will provide any value above the basic understanding of the climatology. This suggests that the accuracy threshold above which the forecast becomes valuable is likely to be higher, for higher penalties. For large penalties, it is possible that the accuracy threshold is above 80–90%, making a forecast essentially redundant given plausible limitations on accuracy. However, in many cases, the threshold is likely to be considerably lower, between 60 and 80%. Under such circumstances, a skilful forecast should provide appreciable value.

It is important to note that, in the most general case, the penalties are a subjective combination of the true economic costs of the decision/outcome, as well as the user’s own attitude to risk. For example, a more risk averse user will tend to assume a higher penalty for forecast misses or false alarms, than a user with preferences for lower risk aversion. In either case, the methodology developed here applies, except that the costs and losses for a given set of outcomes and decisions are themselves also subjective. In turn, this suggests that a more risk averse user will tend to require a more accurate forecast to obtain a certain level of value (c.f.
Blench et al. 1999). Therefore, to assess the subjective nature of costs and losses, users should be encouraged to consider their individual and organisational risk appetite.

As described above, it is clear that users evaluate the performance of a forecast according to their own requirements and on an event-by-event basis. Thus, if the forecast performs badly, it is likely to be perceived to be of lower value and its use may be discontinued. According to the approach developed here, users who are initially more sceptical of the forecast performance are also more likely to perceive its value to be lower for longer and, therefore, more likely to stop using it. This scenario is potentially disadvantageous to these users.

For the cost/loss matrix used in this analysis we have shown that it can take at least 30 repeated forecasts for the perceived value to converge to the true value. Applying this reasoning to seasonal forecasts highlights the need to consider all aspects that can delay the adoption of climate predictions technologies to facilitate a rapid transition towards a climate resilient society. This suggests that it is incumbent on forecast providers to clearly demonstrate, through appropriate engagement activities, the accuracy of the climate information. In particular, effective communication of the forecasts and their accuracy, based on robust verification, will undoubtedly require feedback from users on the specific content and presentation of the climate information. Furthermore, the utility of the forecasts for decision-making will depend on a user’s self-awareness of their attitude to risk, which can also be explored during engagement activities. Given the results presented here, it would be of significant interest to compare the behaviour of real users and these theoretical predictions in future stakeholder engagement activities.

Acknowledgements

This work was supported by the Joint DECC/Defra Met Office Hadley Centre Climate Programme (GA01101). The authors wish to acknowledge all of those who contributed indirectly to the development of the EUPORIAS winter transport prototype (Seasonal Prototype: Risk of Impacts from NAO on Transport; http://sprint.euporias.eu/), through scientific discussion, review, data provision, stakeholder engagement and facilitation: Erika Palin, Adam Scaife, Anca Brookshaw, Alberto Arribas, and the UK Department for Transport-led stakeholder group.

The UK Government Department for Transport is acknowledged for providing financial support, in parallel to that received from EUPORIAS, for the SPRINT prototype.

EUPORIAS was funded by the European Commission through the 7th Framework Programme for Research, grant agreement 308291.

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