

Air quality services on climate time-scales for decision making: an empirical study of China

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Abstract

The provision of climate services for assessing and governing environmental problems such as poor air quality requires interactions between scientists and decision-makers. Air quality information services in China mainly focus on the coming days to weeks. However, users may benefit from air quality information on climate time-scales—from months to decades; hereafter air quality climate services. We focused on key decision-makers and stakeholders that are users of air quality climate services and conducted five workshops with these identified users to ascertain their priorities for air quality climate services, and the reasoning behind these priorities. We also conducted a choice-based conjoint experiment via an online survey distributed amongst regional and local Climate Centres and Environmental Monitoring Centres to assess quantitatively the decision-makers' needs. The results from the workshops and the survey showed that the air quality climate services needs by users in China mainly relate to seasonal forecasting of winter haze events (PM_{2.5} levels and/or the meteorological conditions conducive to the dispersion of the air pollution); there is also some interest in long-term projections of haze under climate change and a growing interest in ozone pollution in summer. Spatial relevance is perceived to be important to regional and city-level stakeholders who prefer information on the city-level, whilst national-wide information is important for national government agencies. A high level of reliability of forecasts was needed for uptake. The findings on the needs for air

quality climate services by potential users can support researchers and policy-makers in developing the scientific capacity and providing tailored, effective air quality climate services in China.

Keywords: air pollution governance; decision-maker needs; climate service; China; mixed-methods

1. Introduction

Air pollution has an adverse effect on health, wellbeing and the economy (World Bank & IHME, 2016; HEI, 2019). As such, air quality has received much socio-political and scientific attention, particularly in rapidly industrialising countries such as China (He et al., 2001; Chan & Yao, 2008). The Chinese Government has been taking stricter action in reducing and preventing air pollution since the publication of the Air Pollution Prevention and Control Action Plan by the State Council in 2013 (Huang et al., 2018, Zheng et al. 2018). In addition to emission controls, such as shutting down highly polluting factories, air pollution monitoring and forecasting have been improved to provide information for advising the public on preventive measures such as avoiding outdoor activities and wearing face masks to mitigate detrimental health impacts.

The China National Environmental Monitoring Centre (CNEMC) has been providing hourly air pollution monitoring data to the public from 2013. The air pollutants monitored include sulphur dioxide, nitrogen dioxide, particulate matter less than 10 and 2.5 micrometres in aerodynamic diameter (PM₁₀, PM_{2.5}), carbon monoxide, and ozone. The CNEMC provides a future 3- to 5-day Air Quality Index (AQI) range, which predicts the pollution level of the dominate pollutant and possible health impacts. When the AQI is forecast to be severe, a heavy air pollution early warning will be triggered with actions such as restrictive operations of factories and transportation (Beijing Government, 2018).

The CNEMC also releases qualitative trends of air quality conditions on 7-10-day timescales related to regional meteorological conditions (including wind speed, wind direction, vertical temperature profiles, and humidity), since air quality is determined not only by pollution emissions but also by meteorological conditions (Wang et al. 2014; Cai et al., 2017). In addition, the CNEMC works with Beijing Climate Centre to produce seasonal outlooks for meteorological conditions related to the dispersion of air pollution (*haze* hereafter) since winter 2017 (MEE, 2018).

Previous studies have shown that close provider – user interactions play a critical role in environmental policy and decision making, since enhancing the provider’s understanding of user needs enables services tailored better to policy and decision-making needs (Totlandsdal et al., 2007; Lemos et al., 2012; Bruno Soares & Dessai, 2016; Nkiaka et al., 2019). Climate services combining scientific information and user needs have been developed and implemented in several climate service projects in China (Hewitt et al., 2017). For example, seasonal forecasts of rainfall for the Yangtze River Basin, China (Bett et al., 2018) were initially developed (2015-2016) following scientific findings (Li et al., 2016) and user engagement (Golding et al., 2017a, b). The scope of these forecasts was revised following further user feedback (Golding et al., 2019) and scientific developments (Liu et al., 2018), and a new seasonal rainfall forecast product that was more regionally-focussed was implemented in 2019.

The provision of air quality forecasts has been largely focusing on short time-scales as introduced above. In recent years, air quality predictions and projections on seasonal and climate time-scales have been improving (Wang et al., 2018). We refer to research underpinning projections and predictions as air quality climate science. It represents the interaction between air pollution and climate, and the forecasting and projections of air quality as influenced by variations in climate on seasonal and longer time-scales (Wan et al., 2020). The term ‘air quality climate science’ does not consider the impact of

emissions controls (Sun et al., 2016), however, refers to the impact of changes in the weather and climate on air quality (Xu et al., 2017).

The provision of air quality forecasts on climate time-scales through close science-policy interactions (in short “air quality climate services”) may assist in controlling and reducing air pollution levels, for example, by informing early mitigation actions for emissions control including setting air pollution reduction targets (Wan et al., 2020). This may in turn provide public health and economic benefits, especially for regions with serious air pollution problems combined with large populations such as the Beijing-Tianjin-Hebei region and the Yangtze River Delta region (Wang et al. 2014; Xu et al., 2017). The term “service” is used to take a holistic view of both service providers and users and emphasise the importance of a two-way interaction between them.

A lack of communication of policy needs back to the scientific community is a critical gap of the current environmental science-policy interface (Wang et al., 2021). Despite the apparent merits of improved air quality and climate forecasts, user needs related to providing air quality climate services have rarely been explored. Hence the co-production between providers and users of relevant services has not been considered. The objectives of this novel study are to investigate the main priorities for decision-makers and stakeholders in China with respect to air quality climate services, to understand the reasoning behind these priorities, and to analyse uncertainties which need to be tackled in order to implement useful air quality climate services. The aim of the paper is understanding policy and decision-maker needs. Feeding these needs to the scientific community could stimulate policy-relevant research and, in turn, improve the development of policy informed by sound science aimed at reducing air pollution levels and consequent health impacts.

In this study, the investigation of user needs regarding air quality climate services was conducted through a combination of qualitative and quantitative analysis which may allow result triangulation. This contrasts with past research on climate services and the value of air quality, where either qualitative methods such as focus groups (Bruno Soares & Dessai, 2015; Golding et al., 2017b), or quantitative methods such as choice experiments (Tang & Zhang, 2015) or hedonic pricing (Mei et al., 2019) have been used. The remainder of the paper is organised as follows. In Section 2, the methods of the study are introduced; in Section 3, we present the results; in Section 4, we discuss and summarise the results.

2. Methods

We consider potential users of air quality climate services as governmental decision-makers involved in the regulation of air pollution, and researchers who provide technical support to government departments. We focused on these user groups across China in the Beijing-Tianjin-Hebei region and the Yangtze River Delta Region.

A series of workshops were held to explore user needs related to air quality climate services from monthly/seasonal (medium-term) to climate change-related (long-term) time-scales. The themes that emerged from the workshop results were used to inform a choice-based conjoint (CBC) experiment that was implemented via a survey. The CBC survey was conducted to validate the workshop results with a wider audience, and to generate quantitative results on the prioritisation of identified user needs.

The China Meteorological Administration (CMA) and the UK Foreign and Commonwealth Office in China facilitated the identification and recruitment of participants from, primarily, the environment, climate and health sectors, who expressed the most interest in engagement and could benefit from air quality climate services.

2.1. Workshops

Five workshops were held from 12th to 20th June 2018 with identified decision-makers and stakeholders (Table 1). Appendix I provides background on the institutional relationships of the stakeholders. The structure of the workshops was: a) opening introduction and expression of interests by the research team; b) opening statements and description of main tasks undertaken by the Chinese organisations represented; c) discussion around the questions that are presented in Box One below. In several cases, the agenda of the workshops had to be more flexible, as the Chinese partners wished to devote more time on communicating on their developments in particular areas or in exploring particular issues in greater depth.

Box One: Questions guiding the workshops

- Are you interested in air quality forecasts?
- Are you interested in air quality forecasting beyond 5 days? (e.g. seasonal forecast, decadal projections, climate change projections)
- Are you already doing such forecasts? If not, do you have the capability and what development would be needed?
- What would you/policy makers use this information for?
- What spatial scales are important?
- Uncertainties
 - What information about uncertainty do you need to know?
 - How would you like the uncertainty to be communicated?
 - How do policy makers make decisions in the face of uncertainty?
- Are there any challenges for the government in starting to use longer-term air quality forecasts?

Table 1. Stakeholders involved in the workshops.

Region/City	Stakeholder organisation	Number of stakeholders	Workshop date
National/Beijing	Appraisal Centre for Environment and Engineering (ACEE)	3	12 th June 2018
	Chinese Research Academy of Environmental Sciences (CRAES)	1	
	Beijing Climate Centre (BCC)	2	13 th June 2018
Beijing	Beijing Municipal Ecology and Environment Bureau (BJEEB)	5	13 th June 2018
Shanghai (Yangtze River Delta region)	Shanghai Environmental Meteorology Centre, Shanghai Meteorological Service (SMC)	2	15 th June 2018
	Shanghai Centre for Disease Control and Prevention (SCDCP)	1	
	Shanghai Environmental Monitoring Centre (SEC)	1	
Shijiazhuang, Hebei	Hebei Environmental Emergency & Heavy Pollution Weather Forecasting Centre (HEEHPWFC)	2	20 th June 2018
	Hebei Climate Centre (HCC)	3	
	Hebei Meteorological Service (HMS)	3	

The workshops were audio recorded for analysis with given consent. Given the potential sensitivities involved, it was decided not to report any of the discussion verbatim, but to draw upon the audio recording and additional notes taken by researchers. Debriefing meetings were held after each workshop to go through the main points raised, to exchange impressions and to note any issues to carry forwards. After the workshops, one researcher combined notes from all team members into a full report and checked the accuracy by listening to the workshop audio records. A number of themes emerged from the workshop, further discussed through qualitative analyses in Sections 3.1 and 3.3.

2.2. Choice-based conjoint experiment via a survey

The core of the survey is a choice-based conjoint (CBC) experiment designed and analysed using Sawtooth Lighthouse software, which has previously been used for stated preference research in the health service sector (Cunningham et al., 2008; Molimard & Colthorpe, 2015; Moise et al., 2018), in environmental economics (Tabi & Wüstenhagen, 2017; Sheau-Ting et al., 2019) and for business applications (Adams et al, 2017).

The survey was targeted to potential users of air quality climate services at regional and local scale, as opposed to national and regional scales for workshops. It was distributed to regional and local Climate Centres and Environmental Monitoring Centres by Beijing Climate Centre (BCC) during 24th September to 1st October 2018 through e-mail and WeChat (the dominant social media application in China) targeting 2-4 respondents from each local agency.

As a stated preference method, choice-based conjoint analysis assumes that individuals derive utility from the underlying attributes of a service, and that individuals' preferences are revealed through their stated choices (Lancaster, 1966; Amaya-Amaya, 2008). In this study, there were four alternative hypothetical air quality forecasts within a CBC choice task (i.e., a question in the survey) in addition to

an opt-out alternative (“NONE”) (see Figure 1 for an example choice task). Each alternative is a combination of attributes that represents a hypothetical but credible air quality forecast. An experimental design is used to guide the combination of attribute levels across the forecasts shown to a respondent in a given choice task (Chrzan & Orme, 2000). Respondents are then asked to choose their preferred air quality forecast alternative. Their choices reveal relative preferences for attributes and their values.

Question: among the following four air quality forecasts, which one would you choose?

Type of air pollutant or index	PM2.5	Air Quality Index (AQI)	PM2.5	Ozone
Numerical or descriptive value	Anomaly in numerical (e.g. PM2.5 concentration will be 30% higher than the same time in the past)	Anomaly in numerical (e.g. PM2.5 concentration will be 30% higher than the same time in the past)	Anomaly in description (e.g. PM2.5 concentration will be more severe than the past)	Broader qualitative description on air pollution conducive weather/climate conditions (e.g. Winds are going to be stronger in the next season, which is favourable to the diffusion of air pollutants)
Time-scale	Forecast for the next season	Forecast for the next season	Forecast for the next season	Forecast for the next season
Spatial-scale	Regional	City-level	China	City-level
Reliability of prediction	It is likely that the outcome is reliable (e.g. above 70% probable)	It is more likely than not that the outcome is reliable (e.g. above 50% probable)	It is very likely that the outcome is reliable (e.g. above 80% probable)	It is very likely that the outcome is reliable (e.g. above 80% probable)
	<input type="button" value="select"/>	<input type="button" value="select"/>	<input type="button" value="select"/>	<input type="button" value="select"/>
	NONE: I wouldn't choose any of these.			<input type="button" value="select"/>

Figure 1. An example of a choice task of the Choice-Based Conjoint experiment

The five attributes used in the survey were derived from the workshops—type of air pollution information, type of value (i.e., quantitative, qualitative), time-scale, spatial-scale, reliability of prediction and the corresponding attribute levels are shown in Table 2. A total of 20 CBC choice tasks were answered by each respondent. A study conducted by Johnson and Orme (1996) showed that there is no evidence of increasing random error with increasing number of choice tasks when the number is below 20.

Table 2. Attributes and attribute levels for the Choice-Based Conjoint experiment

Attribute	Level 1	Level 2	Level 3	Level 4	Level 5
1. Type of air pollution or indicator	PM _{2.5}	Ozone	Air Quality Index (AQI)	Air quality index related to weather/climate	
2. Numerical or descriptive value	Absolute numerical in concentration or value for AQI or other indices	Anomaly in numerical value	Qualitative anomaly statement (anomaly in description)	Broader qualitative description	
3. Time-scale	Forecast for the next month	Forecast for the next season	Forecast for the next year	Forecast for the next decade	Air quality projection under a scenario of climate change (longer than 10 years)
4. Spatial-scale	Global	East Asia	China	Regional	City-level
5. Reliability of prediction	It is very likely that the outcome is reliable (e.g. above 80% probable)	It is likely that the outcome is reliable (e.g. above 70% probable)	It is probable that the outcome is reliable (e.g. above 60% probable)	It is more likely than not that the outcome is reliable (e.g. above 50% probable)	

A balanced-overlap randomised design approach was used, i.e., each respondent received a unique survey with randomised combinations of attribute levels and choice sets (Chrzan & Orme, 2000). This design imposed constraints on the balance of attribute levels and attribute level combinations, which allowed for some overlap of attribute levels to occur between alternatives but no alternatives could be identical.

The analysis of choices is based on random utility theory (RUT) (McFadden, 1973). Participants in CBC experiments are assumed to be rational decision makers that seek to maximize innate, stable preferences to reach the maximum benefit (utility). The latent utility of an alternative of a choice task perceived by a respondent is composed of two parts: a systematic (explainable) component, and a random component (error term) representing unmeasured variation in preference (*Eq. (B.1); the index B refers to Appendix B*). The “NONE” option was ignored during the estimation of the utilities (i.e., any choice tasks where NONE has been chosen are skipped in the analysis). The frequency of choosing the NONE option is reported in Section 3.2.

The observed utility of an air quality forecast within a CBC choice task is determined by a linear function of the utility of the five attributes (*Eq. (B.2)*). The generic regression coefficients of attributes across alternatives are estimated and interpreted as utilities. Based on the assumption of RUT, a

respondent will choose an alternative if and only if the utility of the alternative exceeds the utility of other alternatives in the choice task.

Utilities are estimated by fitting a conditional logit model (CLM) (Eq. (B.3)) with the maximum likelihood method (Eq. (B.4)) (McFadden, 1973; Allison, 1999; Amaya-Amaya, 2008; Hauber et al., 2016). Appendix B provides details on the statistical approach underpinning the conditional logit analysis. A log-likelihood test (Eq. (B.5)) is used to test the significance of the model against a model that assumes all regression coefficients are zero (i.e., null model), thus implying that each alternative in a choice task has the same probability of being chosen (i.e., random choice). The significance level is set as 0.05.

A statistic for the relative importance of an attribute is also calculated. The relative importance of an attribute is equal to the range of the utility (i.e., maximum utility minus minimum utility) of an attribute divided by the sum of the utility range of all attributes, then scaled to 100% (Sawtooth, 2017). Therefore, attributes with a wider utility range have a higher relative importance, indicating the importance of an attribute relative to other attributes. The survey results are presented in sections 3.2 and 3.3.

3. Results

The workshop discussions (Box One) enabled us to obtain qualitative information on user needs in air quality climate services (Section 3.1) and the survey results provide further quantitative validation within a wider audience of regional and local level users (Section 3.2).

3.1. Categories of needs for AQCS

Analysis of the dialogue in the workshops (Section 2.1) allowed a simple categorisation between different levels of needs.

- *Preference for*—the information is not strictly required to provide current services but, as understanding and technique develops in the future, it may improve the quality of the work; it may also provide useful contextual information today.
- *Need*—the information would improve the provision of existing and emerging services.
- *Strong need*—the information would greatly improve the provision of existing and emerging services.

The workshops allowed us to distinguish between the types of information requested by agencies and, in some cases, on what time-scale and with what level of certainty in order to be of use, as shown in Figure 2. User needs were categorised into the three levels qualitatively by one investigator based on the workshop notes which were also cross-checked with workshop recordings. A consensus about the categorisation was reached among all four investigators, which showed the inter-investigator reliability of the result. The workshop identified a number of themes: spatial-scale, time-scale, type of air pollutant information and uncertainty communication that informed the survey (Section 3.2). We found that user needs vary at different locations, therefore we distinguish between user needs in Figure 2 by using different shades and outlines of the rectangle. The workshops identified that the strongest need is for short term forecasts for early warning of severe air pollution events in Beijing and Hebei, and for monthly to seasonal (winter) forecasts for PM_{2.5} concentrations and for haze events in Shanghai. The full workshop results (Figure 2) are discussed in detail alongside the survey results in Section 3.3, focussing on the key themes outlined above.

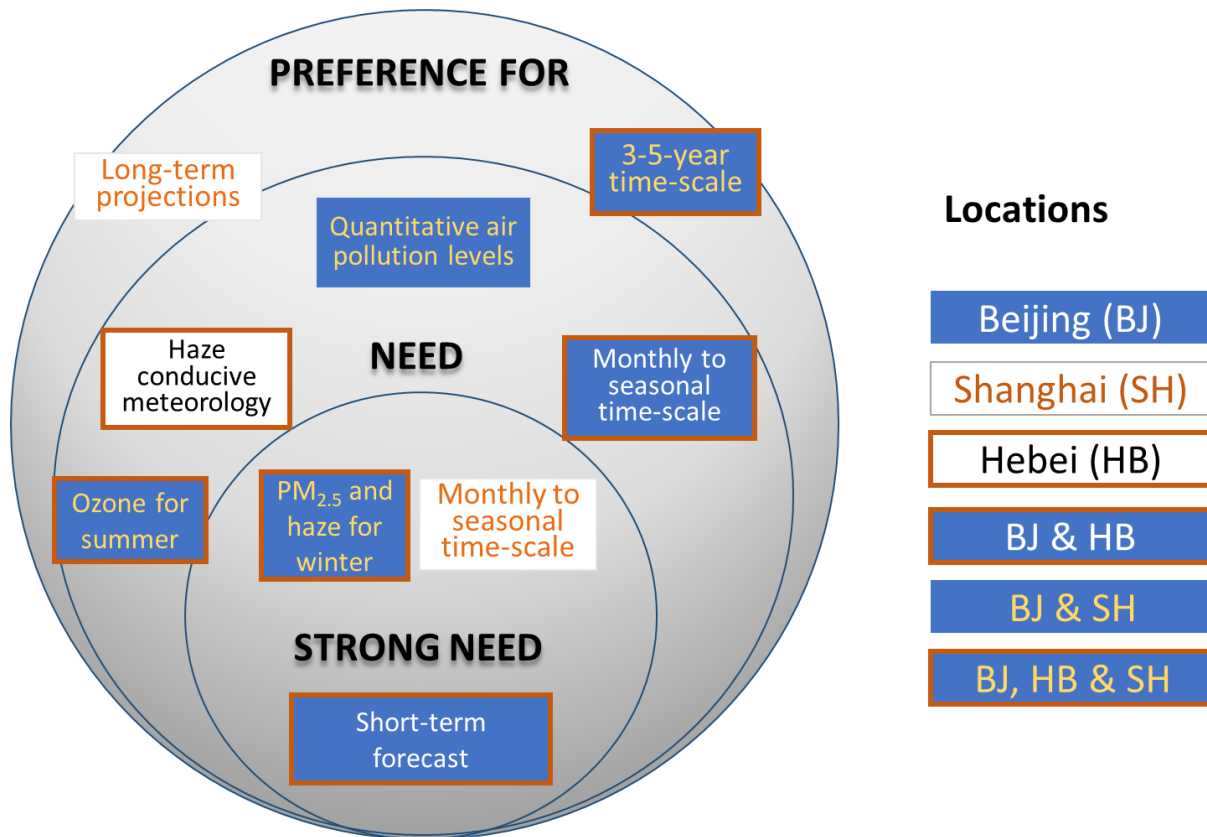


Figure 2. Illustrations of decision-maker needs on air quality climate services – workshop results. The degree of needs changes from high to low from inner to outer circles. The different shades and outlines of rectangles and font colours represent needs expressed by agencies in different locations (see Table 1 for the list of stakeholders). The overlay of shades represents needs expressed by more than one location.

3.2. Relative importance of air quality forecast attributes

112 respondents completed the survey. Respondents were from East China (44%), West China (29%), North China (14%) and South China (13%). 52% of respondents are female, 44% male and 4% preferred not to say. Therefore, survey respondents are fairly evenly distributed across region and gender. Based on a rule of thumb, the minimum sample size given 20 choice tasks and 4 alternatives in each task is $n=31$ (Orme, 2019a). This is considerably smaller than the survey sample size ($n=112$), but a regional level breakdown is not advised given the small sample size for some of the regions.

The “NONE” option was chosen on average 1.4 times per person. There is no indication that the frequency of choosing the “NONE” option differs between the first 10 choice tasks and the last 10 choices tasks. The log-likelihood test statistic for model fit is 488, which compared to a critical value of 287 (17 df) at a 5% significance level suggesting that the model provides a significant fit to the data.

Figure 3 shows the relative importance of the five attributes (Table 2). Among the five attributes, spatial-scale is the most important, followed by reliability of prediction and time-scale which are of similar importance. The type of air pollutant is less important, with the type of value (numerical or descriptive) having the least importance.

Relative importance of air pollution forecast attributes

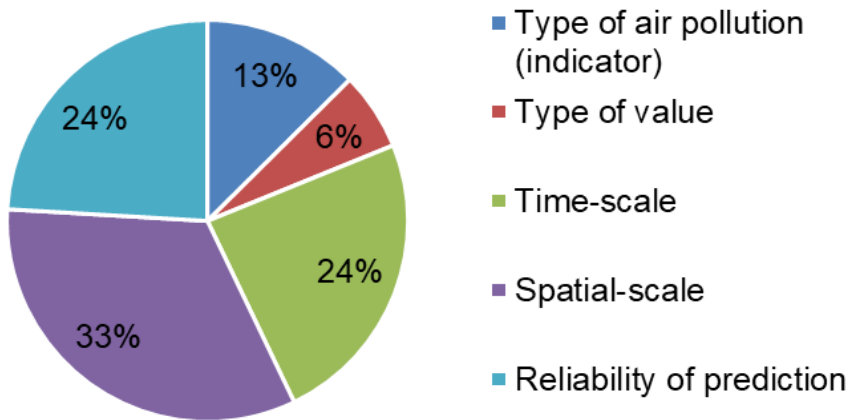


Figure 3. The relative importance for five attributes of air quality climate forecasts.

The utility estimates for attribute levels with error bars (95% confidence interval) are shown in Figure 4, whereby the estimates of attribute levels are centred around zero for each attribute, which means the sum of their utilities are zero. Hence, the values represent relative rather than absolute preferences: negative values only mean that they have relatively less utility than the mean across all attribute levels. Two attribute levels are identified as significantly different when there is no overlap between the confidence intervals. For example, the utility of monthly time-scale is significantly higher than other time-scales (Figure 4), which suggests that decision-makers have higher needs for air quality forecasts at the monthly time-scale compared to other longer time-scales. The utilities are discussed in detail by themes (attributes) in Section 3.3. Please see Appendix C for the original value of the utilities and standard errors.

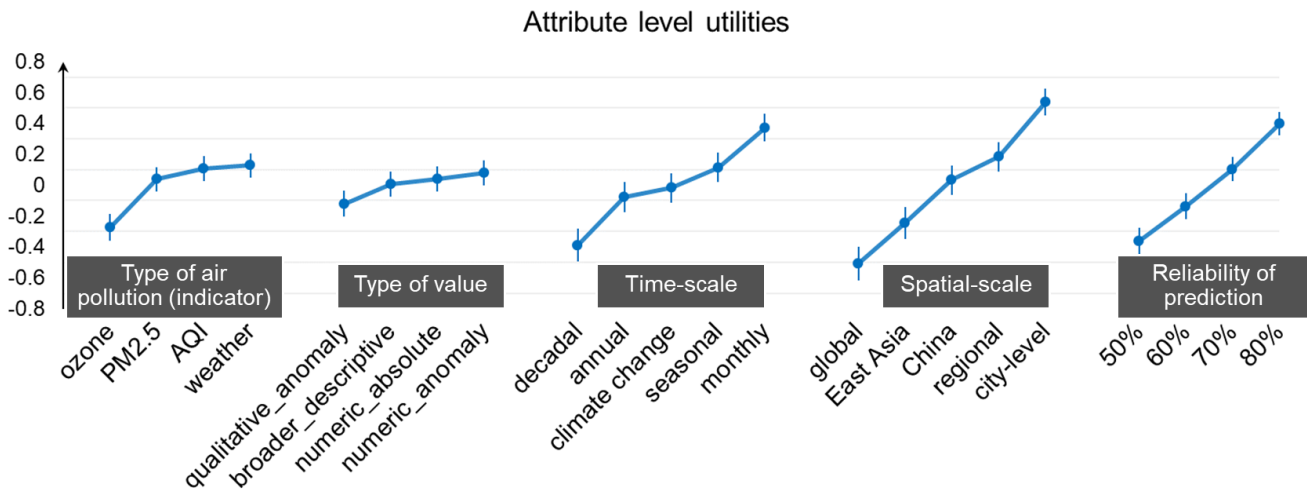


Figure 4. Utilities of attribute levels. Error bars denote 95% confidence interval.

3.3. Decision-makers' needs on air quality climate services

In this section, needs on air quality climate information by potential users as elucidated from the workshops and the online survey together are discussed in detail focusing on the themes or attributes of spatial-scale, time-scale, type of air pollutant information and uncertainty.

3.3.1. Spatial-scale

The workshop participants from the ACEE and the CRAES who support the Ministry for Ecology and Environment (MEE), expressed their needs for both national-scale information, regional and local information to support policies at these different levels.

The survey results from decision-makers and stakeholders at regional (refers to provincial and regional administration level, see Appendix I) and local (refers to prefectural and county-level) Climate Centres and Environmental Monitoring Centres show that spatial-scale has the largest relative importance (33%; Figure 3) among all attributes. Smaller spatial-scales have significantly larger utilities than larger scales hence the user is typically more interested in air quality climate services at the city/megacity-level as compared to national and global level (Figure 4). The ranking of the utility of different spatial-scales (from high to low) is: city-level, regional, China, East Asia and global.

It is important to note that the survey results reflect stakeholder needs at regional and local scales, since the survey was distributed to regional and local Climate Centres and Environmental Monitoring Centres (Section 2.2). This is in contrast to some workshop results gained from participants who are in national institutions hence reflect national level needs. Whilst both workshop and survey results highlight the need for city-level services, the national level is important for agencies that directly report to and inform the MEE.

3.3.2. Time-scale

The results of the workshop (Figure 2) show that user needs with respect to different time-scales vary by location. In Beijing and Hebei, there is a *strong need* for short-term air quality forecasts (i.e., daily to weekly), which could support decision-makers in providing an early warning for severe haze episodes and to take contingent emission reduction actions. This is followed by a *need* for monthly to seasonal air quality forecasts, with winter as the main season of interest. There are two main uses of monthly to seasonal air quality forecasts: a) decision-makers could set up air quality targets, especially for winter haze pollution, that take the influence of the meteorology into account. If the meteorology is favourable toward the dispersion of air pollution and hence good air quality, either a stricter air quality goal can be set up or emission controls can be relaxed to some extent, and vice versa; b) air quality forecasts one month or one season ahead enable local environmental bureaus to have sufficient time for compiling emission-related countermeasures to decrease the air pollution level and meet air quality targets, hence minimising the impacts on industrial activities and ordinary daily life of the public caused by short-term mandatory emission reduction actions, such as traffic restrictions. Therefore, monthly to seasonal air quality forecasts could potentially support the annual planning for the Autumn and Winter Air Pollution Comprehensive Control Action Plan in Beijing, Tianjin and Hebei and surrounding areas led by the MEE (2019).

Agencies in Shanghai have a *strong need* for monthly to seasonal air quality forecasts (Figure 2). A possible reason why Shanghai agencies have more of a need for monthly to seasonal time-scales, compared to Beijing and Hebei, is that high air pollution events occurred less frequently in Shanghai than in Beijing and Hebei. Hence, decision-makers in Shanghai have less need for a short-term accurate air quality forecast to support severe air pollution early warning as compared to agencies in Beijing and Hebei. For example, seasonal PM_{2.5} concentration averaged for November, December,

January and February from 2016/2017 to 2018/2019 was $72 \mu\text{gm}^{-3}$ in Beijing, $120 \mu\text{gm}^{-3}$ in Shijiazhuang, the capital city of Hebei province, and $46 \mu\text{gm}^{-3}$ in Shanghai (data in December 2016 is missing) (MEE, n.d.). However, increased knowledge of the likelihood of high levels of air pollution episodes due to transport from upwind regions to Shanghai was noted. In addition, there is already an efficient system for 7-day air quality forecasting, but the system for monthly to seasonal air quality forecasting is less developed.

There is also a *preference* for 3-5-year air quality forecasts in both Beijing, Hebei and Shanghai (Figure 2). Air quality forecasts on this time-scale could support the strategic plans such as the 5-Year Plan on National Economic and Social Development Plan, and air pollution plans, such as the Air Pollution Control and Prevention Plan for 2013-2017 and the subsequent Blue Sky Protection Campaign for 2017-2020. SCDCP expressed a *preference* for multi-decadal projections in support of the Healthy China by 2030 Blueprint, which ensures health, including environmental health, becoming an explicit national political priority in China (State Council, 2016; WHO, 2016).

The survey results suggest time-scales and reliability of prediction are jointly the next most important attributes (24%; Figure 3) after spatial-scale. The order of different time-scales in terms of utility from the survey results is (from high to low): monthly, seasonal, climate change-related time-scales, annual, decadal (Figure 4). Because the research focuses on climate-related time-scales, the shortest time-scale included in the survey is monthly. Monthly time-scale has significantly greater utility, and decadal time-scale has much lower utility than other time-scales. The overall trend is that shorter time-scales have larger utilities, however, climate change-related time-scales have higher utility than annual and decadal time-scales (but no significant difference was detected among seasonal, climate change-related and annual time-scales (Figure 4).

The survey and workshop results generally show agreement in terms of elucidating the most needed and important time-scales. Although winter was discussed as the most important season for air pollution and haze at the workshops, the survey suggested monthly forecasts in preference to seasonal. This may be because the survey did not ask about specific seasons. The workshop also revealed greater clarity of the relevant climate-related time-scales.

3.3.3. The type of air pollution (indicator) and value type

In both Beijing, Hebei and Shanghai, agencies at the workshops expressed their *strong need* for information about $\text{PM}_{2.5}$ levels, and/or haze for the coming winter. There is also a *need* for information about ozone pollution in summer as it is perceived as an emerging problem in China (Figure 2). While emission control measures have led to reductions in $\text{PM}_{2.5}$ concentrations, this has not been the case for ozone, partly as it is a secondary pollutant formed in the atmosphere and thus strongly sensitive to meteorological conditions.

Workshop participants in Beijing and Shanghai have a *strong need* for quantitative air pollution concentrations for the next one to several months under the condition that the science is available to generate the forecast with sufficient accuracy. HEEHPWFC expressed a cautious view towards relying upon on the quantitative air pollution forecasts provided by numerical air pollution models as the outputs are perceived to be insufficiently reliable for operational purposes. Instead, information about meteorological conditions that are conducive to the accumulation or dispersion of air pollutants is considered to be more useful by the HEEHPWFC since such data can be incorporated into its own statistical model, which uses neural-network methodologies to correlate the meteorology conditions to the air pollution levels.

The survey results suggest the type of air pollutant or indicator is a less important attribute than spatial-scale, time-scale and reliability of prediction (Figure 3). The utility of air quality forecasts for PM_{2.5} concentrations, the AQI and air quality indices related to weather showed no significant difference (Figure 4). The utility of ozone forecast is significantly lower than PM_{2.5} concentrations, AQI or weather-related AQ indices. This result is in line with the suggestion from the workshop that, while ozone has become increasingly important, the priority for most agencies is still lowering PM_{2.5} levels.

We also explored the need for different types of values through the survey. No significant difference was found among the utilities of absolute numerical value, anomaly in numerical value, qualitative anomaly statement, and broader qualitative description (Figure 4). The type of value is the least important attribute (Figure 3).

3.3.4. Uncertainty

A high level of certainty is required by decision-makers because of the economic and social consequences of the forecast. There is a heavy responsibility for decision-makers to meet the air quality targets, for example, the mayors on provisional, prefectural and county-level are directly responsible for fulfilling their respective air quality targets. Also, if the air quality is forecast to be worse than the expected level, acute emergency actions will be taken by the government such as shutting down factories, which will cause impacts on the economy and would damage the credibility of the agencies and local government if the poor air quality episode does not happen. BJEEB stated that an air quality forecast needs to reach 60%-70% accuracy for it to be perceived as useful by decision-makers (Figure 2).

Two main sources of uncertainty in generating long-term air quality forecasts were expressed by workshop participants. Firstly, the rapid changes in emissions result in uncertainty in emission inventories data, e.g. some factories may shut down permanently or temporarily due to a change in regulations or the volatility of demand which cannot easily be represented in the emission inventory or move in location (as noted by HEEHPWFC and SEMC). Secondly, the inherent uncertainty in the weather data (SEMC), which is used in creating correlations between air pollution and meteorological variables or as input for air pollution modelling with atmospheric chemistry transport models.

Two main ways of indicating model uncertainties were highlighted by the BCC, although uncertainty can be a different concept to different users. One is to compare model results in a multi-model ensemble forecast. For example, elucidate probabilistic estimates of how many model ensemble members predict the temperature in the next season in Beijing to be above or below normal. This does not measure the true probability that the temperature in the next season is going to be above or below normal, but is rather a statistical representation based on ensemble members that may be biased relative to the real situation. Another indicator of uncertainty is reliability, which is a measurement of the accuracy of past model forecasts or “hindcasts”.

The HEEHPWFC uses a fixed range to express uncertainty for the current 3-5-day AQI forecast. The range is usually +/- 15 units and +/- 25 units for severe haze episodes. For example, if the AQI is predicted to be 50 (not severe), the AQI released to the public would be 35-65.

Reliability of prediction is the joint second most important attribute highlighted in the survey (Figure 3). The survey results show that higher reliability levels were preferred compared with lower reliability levels, in alignment with the workshop results (Figure 4).

4. Discussion and conclusions

The Chinese government has been active in implementing strict regulations to improve air quality and prevent the negative health impacts of air pollution, and such activities involve strong interactions between policy-makers and scientists (Huang et al., 2018, Zheng et al. 2018). In order to enhance the science-policy interplay in the provision of air quality climate services, decision-maker needs on air quality climate services in China have been investigated in this study with a mixed-methods approach. Mixed-methods approaches have been widely applied to social, health, management and have been shown to potentially provide deeper understanding (Bergeron, 2016; Bryman, 2016). In this study, qualitative and quantitative information on decision-makers' needs for air quality climate services were compared and combined, so as to better understand the priority and basis of such needs. We reported on the consensus opinions of those whom we engaged with by location (i.e., Beijing, Shanghai and Hebei) for brevity.

Previous studies have examined aspects of climate services most desirable for users such as regional detail (Golding et al. 2019). Here, we have examined the importance of key attributes of air quality climate services: spatial-scale, time-scale, type of air pollutant information and uncertainty communication. The workshop and the survey results are largely in agreement. Both showed similar preferences for air pollution forecasts for PM_{2.5}, Air Quality Index (AQI) and air quality indices related to weather on monthly to seasonal time-scales. The need for prediction of ozone pollution was significantly lower in the survey than for PM_{2.5} pollution, though stakeholders in Beijing, Hebei and Shanghai noted that ozone pollution is becoming more important. This is in accordance with research findings that ozone pollution is worsening in the Beijing-Tianjin-Hebei and the Yangtze River Delta regions and targeted control of precursors is crucial in controlling ozone pollution (Wang et al., 2017). This is also in agreement with the findings in Zheng et al. (2018) that during 2010-2017, anthropogenic emission of PM_{2.5} decreased, whereas emissions of Volatile Organic Compounds (VOCs), precursors of ozone pollution, increased, indicating a lack of effective control measures on VOCs and ozone. Facing an increase in summer ozone pollution episodes (Li et al., 2020), the MEE (2020) published an action plan on Volatile Organic Compounds Governance in order to control ozone pollution. This is in accord with the findings of this study of an increasing need for ozone pollution forecasts. An interest in long-term air quality projection under climate change was noted by both the workshop participants and the survey respondents. We postulate that a possible reason for climate change-related time-scales gaining larger preference than decadal time-scales in the survey result is that the term "climate change" is a 'hot topic' for both academic and administrative communities (Jiang et al, 2013).

All user agencies highlighted emission inventories as a major source of uncertainty for air pollution modelling as well as inherent uncertainties in weather forecasting. These suggestions are largely consistent with uncertainties identified by scientific studies in the literature. Wang et al. (2018) evaluated the Nested Air Quality Predicting Modelling System (NAQPMS) with observations in five Chinese cities for 2013-2015 and found the uncertainties mainly arose from the input emission inventories, meteorological data and lack of air pollution observations prior to 2013. Uncertainties in emission inventories arise from both the modelling of spatial, vertical and temporal variation of emissions (de Meij et al., 2006) and the quantification of emissions, including source location, emission activity, emission factor (amount of emission per unit activity) and end-of-pipe removal efficiency (Cheng et al. 2019).

When severe air pollution is forecast, a series of contingency measures are implemented to reduce emissions, e.g. certain industries have to reduce their production or shut down (Beijing Government, 2018). Facing potentially severe economic and social consequences of forecast air quality outcomes,

users understandably prefer high levels of confidence in the accuracy of air quality forecasts. Decision-makers lack confidence in the ability of scientists to measure the uncertainty associated with the numerical models and data inputs that are used to produce forecasts. Scientists are exploring a variety of uncertainty measurements to help guide stakeholders such as probability and reliability. We focussed our discussion on the information needs regarding uncertainty as in Section 3.3.4. Although we initially aimed to also explore how policy-makers make decisions when faced with uncertainty, this was not fully discussed in our workshops. However, our findings on the sources and perceptions of uncertainties are of potential use for communicating and making decisions that involve uncertainties.

To conclude, this study investigated the needs for air quality services on climate time-scales in China by environmental agencies tasked with air quality policy and regulation and by users of air pollution information in the health sector, including researchers who provide technical support to such agencies. In general, both qualitative and quantitative evidence from workshops and surveys suggests a strong need for a forecast for PM_{2.5} and haze events in the coming winter of a given year, with an increasing need for ozone forecast for the coming summer. There were different user preferences for air pollution forecasts by numerical models versus results derived from statistical models based on the meteorological conditions influencing the dispersion of air pollution, partly driven by uncertainties in the numerical models, emission inventories and lack of air pollution observations prior to 2013. Both the environment and the health sectors expressed a preference for air quality information under climate change. User perceptions on forecast uncertainties were also discussed. The findings in this paper enhance the understanding of the needs of air pollution decision-makers. The specific user needs in these sectors can inform future research aimed at the improved provision of tailored air quality services to decision-makers.

Acknowledgement

This work is part of the Providing Air Quality Climate Services for China Scoping Study project (contract reference number: P103590), which is funded by the UK-China Research & Innovation Partnership Fund through the Met Office Climate Science for Service Partnership (CSSP) China as part of the Newton Fund. We sincerely thank the workshop participants and survey respondents.

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