# Forecasting environmental migration to the United Kingdom: An exploration using Bayesian models

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## Abstract

Over the next fifty years the potential impact of environmental change on human livelihoods could be considerable, with one possible consequence being increased levels of human mobility. This paper explores how uncertainty about the level of immigration to the United Kingdom as a consequence of environmental factors elsewhere may be forecast using a methodology involving Bayesian models. The conceptual understanding of forecasting is advanced in three ways. First, the analysis is believed to be the first time that the Bayesian modelling approach has been attempted in relation to environmental mobility. Second, the paper considers the expediency of this approach by comparing the responses to a Delphi survey with conventional expectations about environmental mobility in the research literature. Finally, the values and assumptions of the expert evidence provided in the Delphi survey are interrogated to illustrate the limited set of conditions under which forecasts of environmental mobility, as set out in this paper, are likely to hold.

**Keywords:** Bayesian forecasting, Delphi survey, Environmental mobility, Climate change.

## Introduction

It is possible that environmental change will impact significantly on the distribution of world population over the next fifty years (House of Commons, 2008). Increased levels of human mobility may be one possible response to climate change (Black et al., 2011a; Pecoud and Geiger, 2011), but there is huge uncertainty about how many people will move and where they will move to. Recent research (Piguet et al., 2011; Government Office for Science (GOS), 2011) contradicts earlier assertions that climate change will produce mass environmental migration (Myers, 1993, Stern 2007). These perspectives suggest that where environmental movement occurs, it will be focused mainly in the poorer nations of the world, and that regions such as north-west Europe will receive few migrants compared with the scale of environmentally-driven short distance moves that will take place in Asia and Africa (Black et al., 2011b; de Haas, 2011).

The research reported in this paper seeks, for the first time, to evaluate the plausibility of forecasts of the scale of environmental mobility to a specific destination. The analysis combines expert opinion with time-series datasets to produce a Bayesian forecast of so-called 'environmental migration' up to 2060. It is argued that more important than the empirical dimensions of the forecast, is the approach taken by the research team. This suggests first, that there can be value in seeking expert opinion in areas where other evidence is lacking. Second, it points to the folly of giving too much weight to single ballpark estimates of environmental mobility, and instead underscores the value of examining both the sources of uncertainty in forecasts of this kind and the assumptions of experts in making migration forecasts. Whilst the authors are perfectly aware of the difficulties with conceptualisation and definition of 'environmental migration' (see also GOS, 2011), the current study attempts to reflect the surrounding ambiguities in a formal manner, through the uncertainty of the relevant expert views, estimates and predictions.

It is important to highlight a significant caveat at this point. The authors do not propose that predicting the future *precisely* is possible, especially in the case of such unforeseeable events as climate change and migration ( Orrell, 2007). Conversely, we argue that such predictions are inevitably characterised by very high and irreducible uncertainty. However, even though some aspects of the world are completely unpredictable, some predictions are still needed to aid decision makers and warn them about less probable, yet potentially highly influential outcomes. Our goal here is therefore not to predict the exact numbers, and inevitably miss, but to attempt to describe this uncertainty by using different sources of available information: past trends and expert opinion. The adopted approach derived from Bayesian statistics is ideally suited for such a task due to a coherent description of uncertainty stemming from different sources such as past data, expert judgement and models. As stated by Westfall and Hilbe, it is especially in the context of hardly predictable events, that 'sensible judgmental predictions (perhaps Bayesian?), aided by empirical data, are essential' (2007, 194). This understanding provides the main motivation for the choice of methodology in the current study.

The paper opens with a brief summary of what the research literature suggests about mobility trends in relation to environmental change. There subsequently follows a discussion of the research methodology. The discussion then considers in detail the results of the Bayesian forecast, before turning to evaluate what can be learned from the authors' use of this innovative methodology.

## Expectations of Human Mobility in an Era of Environmental Change

The frequency and severity of extreme environmental events seem set to increase over the next fifty years (GOS, 2011). Although there is a broad consensus of scientific opinion linking the observation of increased environmental hazards to climate change, there is less agreement about what the likely impacts will be on a range of human activities, including human migration (Gemenne, 2011; Piguet et al. 2011; Warner, 2009). Early estimates by environmentalists (Myers, 1993) focused on forecasting the numbers of people who would be displaced because they were living in areas deemed to be at high risk of an identifiable environmental process linked to global warming, such as sea level rise. This literature has been widely reviewed and we do not rehearse the arguments once again here (Black et al., 2011b; Gemenne, 2011).

Recent years have seen a series of attempts to gather evidence on the nature of environmentally-linked mobility (Castles, 2011; Kniveton et al., 2011; Warner et al., 2009). Reviews of this literature show that most environmentally-linked mobility is short distance and internal (within a single country), and that perhaps the greatest risk is human immobility in the face of environmental change (Findlay, 2011). The recent migration systems emphasis in the study of human mobility in an era of environmental change has led to recognition of the complex and entangled nature of migration motivations and to the recommendation that researchers should focus on understanding the role of environmental forces in impacting existing migration regimes, both directly and indirectly (Black et al., 2011a; 2011b), as opposed to making estimates based on the populations of areas at highest risks of rapid environmental change.

The multi-causal perspective is widely recognised by social scientists to come closer to offering a realistic understanding of the drivers of environmental mobility (Black et al. 2001a). However, in problematizing the definition of environmental migration as encompassing more than just those situations in which the environment is the 'dominant' cause of movement, it also makes research more difficult for those seeking a working definition of environmental migration, since it acknowledges that migration cannot be reduced to being an outcome of a simple ‘cause-effect’ relationship. The multi-causal approach also recognises the diversity of mobility responses that can emerge in association with different types of environmental events. Piguet et al. (2011), for example, make the important distinction between temporary moves following an environmental event, short-term displacement and migration, and note the different mobility responses to hazards such as hurricanes and typhoons from those witnessed in relation to slow onset disasters such as drought-linked famines (see also Laczko et al. 2009).

The environmentalist perspective continues to inform much of the contemporary debate on climate change and the implications for human mobility. In looking into the future it tends to uphold the popular perception that many millions of people will leave areas adversely affected by climate change, possibly in favour of more secure lives in the global North. By contrast, recent research on migration regimes affected by environmental change points to high levels of immobility, and challenges the view that environmental change will result in significant international migration flows into many of the wealthier countries (de Hass, 2011; Findlay, 2011). Instead, Black et al. (2011a) and GOS (2011) suggest that migration over the decades ahead may shift more people into those areas that are at greatest environmental risk in the poorer countries of the world, such as low lying large urban areas (Seto, 2011).

The literature reviewed above presents an interesting challenge when applied to the question of immigration to the United Kingdom in an era of environmental change. On the one hand, the environmentalist perspective would lead to concern that over the decades ahead the scale of environmentally-linked immigration would increase substantially and come to account for an ever-greater proportion of new arrivals in the country. On the other hand, the migration regimes’ perspective might point to a rather different future, with attention focussing instead on the pattern of UK’s current migration linkages and the prospects of environmental change in countries close to the UK resulting in population displacement. Remarkably, given the significance of the issue, the research literature offers little evidence to inform these very different views of future environmental mobility to the UK. Most recent environmental mobility research has focussed on other parts of the world (for example, Kniveton et al., 2011) where concerns about the current impact of climate change are perceived to be greater. One possible exception is the recent study by Fielding (2011), but this study is limited to internal mobility and thus cannot answer questions about the effects of climate change on future environmentally-linked immigration to Britain. This leads therefore to the key goals of this paper: a) to offer deeper understanding of the sources and nature of uncertainty surrounding forecasts of environmental migration, b) to explore and learn from the use of an innovative method for forecasting environmental mobility, and c) to evaluate the plausibility of expert views on environmental migration to the UK given the limited nature of the evidence available on the subject.

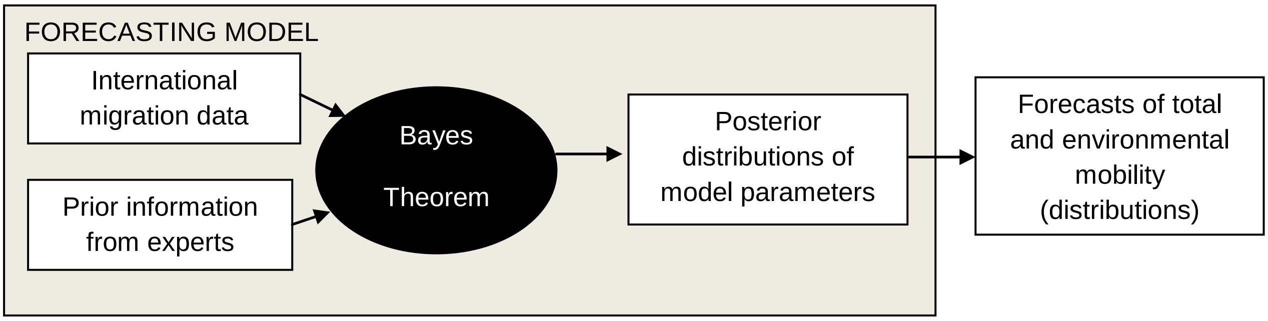
## Research Methodology

The key feature of the researchers' methodology is bringing together expert knowledge and historical data series to generate estimates of future gross immigration, and environmentally-related migration, as well as measures of uncertainty associated with these forecasts. The methodology used a variant of the Delphi survey of experts, embedded within the Bayesian statistical modelling framework.

Bayesian statistics, dating back to the seminal work of Rev. Thomas Bayes on his famous theorem (Bayes, 1763), is characterised by a joint treatment of all quantities of interest in a statistical model as random variables. In particular, Bayesian statistics naturally incorporate the analysis of uncertainty surrounding the estimates or forecasts, described in terms of probability distributions. One of the key attributes specific for the Bayesian inference is the presence of *prior distributions* of the parameters of the underlying model. These distributions can be subjective – for example based on the elicited expert judgement – or, conversely, hardly informative, if no reliable expertise is available. Importantly, all Bayesian inference is based on a subjective definition of probability, treated as a measure of belief, which is better suited for the *epistemic* uncertainty describing non-repeatable events (O'Hagan et al., 2006).

The Bayesian inferential and forecasting mechanism, summarised in Figure 1, consists in updating the prior information in the light of new evidence, which becomes available from the data. By the means of the Bayes theorem, the prior distributions are combined with the data, to produce *posterior distributions* of the parameters. These can be in turn used, together with the historical data series, to produce forecasts – extrapolations of the past into the future. For more detailed exposition of Bayesian statistics, see Bernardo (2003).

Figure 1: The Bayesian approach to forecasting environmental mobility and assessing the uncertainty associated with the forecasts




*Bayesian modelling*

The Bayesian approach has two main advantages over conventional approaches to migration forecasting (Bijak, 2010). First, in using probability distributions to handle uncertainties attached to the predictions, the forecasts go beyond the normal presentation of a single number predicted for each year and instead create a probability fan which indicates the degree of uncertainty around the central trajectory (Abel et al., 2010). Second, Bayesian models have the capacity to allow for expert opinions to be built into projections in the form of prior distributions (see Bernardo, 2003). To this end, the most important aspects of the Delphi questionnaire used in this study were the questions relating to future volumes of immigration, and to immigration related to environmental change, as well as the respondents' subjective confidence in the accuracy of their answers.

In the remainder of this section, the autoregressive time series models and notation used to forecast future immigration to the UK are specified. This is followed with an outline of the model selection procedure. A range of multivariate models were also explored in the original research (see Abel et al., 2011 for detailed description of the autoregressive models), but as they yielded forecasts with too wide uncertainty estimates to be useful, they are not reported in this paper for the sake of clarity of the presentation.

Data series on the total annual immigration to the UK was available from the ONS (Office for National Statistics) from 1975 onwards. In order to model total immigration to the UK we performed two transformations on the data. First we took the logarithm of the observed immigration counts in order to constrain the forecasted values to be non-negative. Second, we differenced the series of the logarithm of observed immigration count to ensure that the mean of the series was stationary. The later of these transformations are standard procedure when fitting time series analysis models with non-stationary means (see for example Chatfield, 2003), as was the case with the original data.

We considered a set of autoregressive (AR) time series models based on the $k$-year history of immigration, AR($k$), defined as:

$$m_t = \mu + \sum_{i=1}^{k} [\phi_i \cdot (m_{t-i} - \mu)] + \varepsilon_t, \quad t < 2010$$
$$m_t = \nu + \sum_{i=1}^{k} [\phi_i \cdot (m_{t-i} - \nu)] + \varepsilon_t, \quad t \geq 2010$$

where $m_t$ refers to the transformed immigration in year t. The $\mu$ and $\nu$ denote the mean level of $m_t$ from the observed data series and forecasted future data series respectively. The inclusion of the $\nu$ parameter allows for a possibility of a structural change in the future $m_t$, whilst future levels of autoregression are assumed to remain the same as their past levels. If no structural change is anticipated by the expert, the $\nu$ parameter will have the same estimated distribution as $\mu$. This approach takes into account more information from the past trends than purely expert-based probabilistic projections (e.g. Lutz et al. 2004). The parameters $\phi_i$ for $i$ = 1, ... , $k$, refer to the ensemble of autoregression coefficients of $m_t$, related to its past history up to $k$ periods (years) before. Finally, the $\varepsilon_t$ parameter denotes an error term, conventionally assumed to follow a univariate Normal distribution with mean 0 and variance $\sigma^2$, $\varepsilon_t \sim N(0, \sigma^2)$. Preliminary inspection of the series suggested that the assumption about the normality of the error terms seems to be appropriate. There was no indication that the variance is unstable over time or that a distribution other than the normal should be considered in the analysis.

The value of $k$ was set to range from zero to 8, providing nine models, from the Independent Normal (IN) model, equivalent to AR(0), through AR(1), etc. to AR(8). In each model, the prior distribution of $\mu$ and $\phi_i$ parameters came from a Normal distribution N(0,1). Standard deviation of the error term ($\sigma$) was assumed to follow a Normal distribution N(0,100), truncated at zero to ensure the positivity of the values of $\sigma$. The prior distribution of $\nu$ was constructed as a mixture distribution based on the forecasts drawn from expert-based trajectories obtained from the Delphi survey, as described in the next section. A fully expert-based approach was also applied to obtain the environmental migration flow in 2010 and future years, expressed as a percentage of total immigration (as also discussed in the next section). This was necessary in the absence of any systematic time-series dataset on environmental immigration to the UK.

As we had no convincing argument about which one of our nine models served as the correct basis to forecast immigration from, we used a Bayesian model averaging procedure to incorporate uncertainty about model selection. Readers are referred to Raftery et al. (1995) for a full review of Bayesian model averaging in a social science context. What follows is a brief review of our procedure. In computing the posterior probabilities of particular models given the data, the *bridge sampler* algorithm was applied (Meng and Wong, 1996). This algorithm allowed us to calculate the posterior weight of each model, given their goodness of fit with the empirical data and the prior distributions, in comparison to all the other models considered. As with the estimation of parameters in a Bayesian framework, the models themselves require to be assigned prior probabilities. In our case, the nine models were assumed a priori to be equi-probable, i.e. the prior probability of each model was set to equal 11.1% (i.e. 1/9). Consequently, our model averaging procedure would favour simpler models. This is a natural consequence of Bayesian analysis, whereby models with fewer adjustable parameters automatically have an enhanced posterior probability and hence are better equipped to predict new values than those of more complicated models that can potentially over-fit the data. ).

*Elicitation of Expert Opinion*

In order to construct the prior distributions for the forecasting model, expert information on environmental mobility was obtained through a variant of a two-round Delphi survey, sometimes also referred to as a Nominal Group Technique (O'Hagan et al., 2006: 189). The survey results produced information that has shaped the model parameters. Expert views may be gathered in a variety of ways (O'Hagan, 2011), but one well-established approach in situations involving long-range forecasts of uncertain futures has been the Delphi survey method (Hill and Fowles, 1975; Linstone and Turoff, 1975). This perspective involves asking experts their views on a particular topic (Round 1), and then bringing them together as a panel (Round 2) to explore the reasons why they gave the answers that they did and then to provide them with an opportunity to amend their responses in the light of the opinions of the other experts. This is a recognised approach to handling uncertainty in a forecasting context (Schmidt, 1997) and has been previously used in migration modelling (Bijak and Wiśniowski, 2010). Nonetheless, as has been highlighted by the literature on elicitation, obtaining information about uncertainty is universally difficult (Szreder and Osiewalski, 1992; Kadane and Wolfson, 1998; O'Hagan et al., 2006; Dey and Liu, 2007; O'Hagan, 2011) and so far no completely satisfactory solution has been developed.

Ideally, the prior distributions should be independent from the data underlying estimation and prediction. However, in reality this is not always possible for expert-based priors, since, arguably, the expert knowledge and judgement is inevitably influenced by these very data. In our implementation, we have thus ensured that the priors and data are independent *by construction*, but not necessarily with respect to all background information used by the experts. Still, we do not think that this is a major concern, since the majority of the elicited quantities relate to *future* migration flows and, as such, constitute examples of predominantly epistemic uncertainty, driven by our necessarily imperfect knowledge about the future.

In this instance the views of 27 experts with heterogeneous backgrounds, which itself is a desirable feature of a Delphi exercise, were canvassed. Eleven of the experts were prominent demographers (migration and demographic specialists) and sixteen were stakeholders who had participated in the UK Government Office for Science Foresight Project (2011) on *Migration and Global Environmental Change*. The stakeholders were mostly senior members of relevant UK government departments and international inter-governmental organisations. As with any analysis of expert opinion, the outcome can be considered only as good as the expertise of those consulted, but the authors of this paper are satisfied that they included in their research design some of the people that would be regarded as best qualified to comment on environmental mobility to the UK.

Notwithstanding the above, it is equally true that the outcome of an expert elicitation is fundamentally premised on the definitions used for the key terms under consideration. In this study the most important terms were ‘environmental change’ and ‘migration’. Since, as noted in the previous paragraph, the majority of participants were stakeholders in the Government Office for Science (GOS) Foresight Panel, it seemed to the authors that the research team should use the same definitions as those reported in the Foresight Panel report.

The conceptual framework of the GOS (2011, 12) recognised that very considerable migration flows already exist and that there are at least five main drivers (economic, social, demographic, political and environmental). Environmental change is reshaping mobility not only directly through exposing more people to environmental hazards and through changes to ecosystem services, but also indirectly through the ways in which environmental change impacts. Examples include livelihoods and people’s employment opportunities (Black et al., 2011). The GOS (2011) therefore stresses that migration is a multi-casual phenomenon and that environmental change will not only have a direct impact on mobility through population displacement (for example in response to sea-level rise) but also indirectly through amplifying (or sometimes dampening) existing migration flows that may be seen as primarily being driven by other forces. To quote the GOS report, ‘a multitude of drivers and motivations are likely to underlie migration, some of which may be influenced by climate change and some of which may not' (GOS, 2011, 151).

We now move from discussing the definitions accepted by the researchers to the more tricky issue of the definitions adopted by the expert panel. It was decided for the reasons alluded to in the literature review, relating to the difference between environmentalists and migration experts, to leave the definition of environmental migration open in Round 1 of the Delphi and to only encourage debate on the topic during Round 2. Our reason for this was that we wished to capture through the Delphi process a better understanding of the experts' differing conceptions of the role of environmental change in migration. The methodology therefore intentionally sought, for the philosophical reasons outlined in the literature review, to provide an opportunity for key definitions to be discussed by the members of the expert panel.

The issue of definitions was much debated by the experts on the panel and time was devoted to the issue in Round 2 of the survey to allow convergence of views. In the results reported later in this paper there was some evidence of a narrowing of the range of statistical estimates produced by the experts, but unfortunately it is impossible to know whether this reflected a move towards greater consensus about the scale of environmental migration or whether it followed from the researchers introduction in Round 2 of the GOS (2011) definitions of the term. The understanding of what constitutes migration influenced by environmental change, that the researchers proposed to the expert group, was therefore that element of migration systems that can be thought of as being driven either directly or indirectly by environmental change. Critics will argue that any attempt to define what proportion of movers make a decision based on environmental change is not scientifically credible (GOS, 2011, 151), while we would maintain that the same argument could be made of any category of migrants (e.g. labour migrants, international students, marriage migrants, political refugees). All migration is multi-causal, yet because governments create visa categories in relation to other migration 'labels' there is a tendency to accept their existence even although most academics recognise that explanation of mobility cannot be reduced to a single force. The absence in state immigration law of an environmental migration category (even although some have argued vociferously for the recognition of 'environmental refugees') in no way reduces the significance of environmental change as a direct and indirect driver of migration. Hence, for the purposes of the expert evidence on which the remainder of this paper is based, it was agreed that environmental migrants would be defined as those people who moved to the UK either directly or indirectly because of environmental change.

In practical terms, Round 1 involved survey respondents independently completing a questionnaire on current and future environmental migration trends to the UK (see Findlay et al., 2012 for the questions asked and a detailed description and discussion of the variance of the experts' responses). From the point of view of forecasting, two groups of questions were most relevant. The first comprised questions aimed at eliciting target distributions of total immigration, as well as of the shares of environmental migration, for 2030 and 2060. Additionally, a further question dealt with the share of environmental migration in 2010, since currently no relevant data are available. This question also allowed us to reflect the ambiguity surrounding the very concept and definition of 'environmental migration' in the base year of our forecasts. The second group of questions dealt with the impact of particular demographic and economic covariates.

In Round 2 the aggregated results were presented to the same panel of experts at a specially convened meeting held in London in March 2011. An important part of the research process involved considering what types of moves might qualify as being linked to environmental change. Audio recordings were taken during the meeting and some quotations from these discussions are included later in this paper to provide an understanding of the reasoning behind the choices made by the experts in their predictions. The second round of the Delphi survey provided participants the opportunity to discuss their responses and then either affirm or change their initial estimates.

The elicited respondents' target values of immigration to the UK after the second round were transformed onto the same scale as the response variable, $m_t$, defined in the model in the previous section. These were then treated as means of a mixture of normal prior distributions for the $\nu$ parameter, where all the respondents were given equal weight. The elicitation of uncertainty surrounding the quantities was based on a numerical Likert-type 100-point scale. Earlier studies (e.g. Olson and Budescu, 1997) indicate that numerical scales are appropriate not only for repeatable events (*aleatory* uncertainty), but also for other elicitation problems where the quantities can be precisely defined in measurable terms. Different Likert scales have been used for that purpose in a range of studies, mainly for the reason of their relative simplicity (e.g. Hurd and McGarry, 2002; Bijak and Wiśniowski, 2010; Cox et al., 2012).

In order to express the respondents confidence values as individual variances to be used as a mixture of prior distributions for the $\nu$ parameter we first calculated an overall variance term. For example, for $t$ = 2030,

$$\sigma_c^2 = \sum_{j=1}^{n} \frac{c_j \left(m_{2030} - \overline{m}_{2030}\right)^2}{n}$$

where $c_j$ is the $j$-th individual's confidence on the 1 to 100 Likert scale for their response concerning the 2030 migration levels, $n$ is the number of respondents and $\overline{m}_{2030}$ is the average (transformed) migration level in 2030, for all of the respondents. A respondent-specific variance term for the mixture of normal prior distributions of the $\nu$ parameter was then calculated by dividing the reported confidence values by the overall variance.

Respondent-specific values for the shares of environmental migrants in 2010, 2030 and 2060 (and the associated confidence in the point estimates) were used to derive posterior predictive distributions from the forecast of total immigration. These were obtained by assuming that the percentage of environmental migrants came from a time specific Beta distribution, allowing only values from the range between 0 and 1. Individual means and variances, calculated in a similar fashion to total immigration described above, were used to derive method-of-moments estimates, obtained by matching the empirical mean and variance with their analytical forms, depending on the parameters, and thus to estimate individual Beta distributions. As with the prior distributions for the total immigration, the individual distributions for shares were sampled from with equal weight, to provide a mixture representative of all the survey respondents. Additionally, for each of the interim periods (2011–2029 and 2031–2059) the distributions of environmental migration, as a percentage of total immigration suggested by the experts, were linearly interpolated.

It has to be stressed that the 100-point Likert-type confidence scale was intended to provide a subjective measure of uncertainty surrounding future migration levels. As such, these questions were not aimed at eliciting confidence intervals. Given the heterogeneity of the expert panel, we could not assume that a question requiring statistical background would be understood consistently by all the respondents. Instead, a subjective score with a wide range of options (1 to 100) was intended to allow the experts more flexibility and scope for manoeuvre between both Delphi rounds.

During the second round of the Delphi some respondents raised issues with the use of the Likert scale, and the placing of their level of uncertainty, especially in the middle of the range. These concerns are legitimate. However, obtaining information about uncertainty is universally difficult and no recognised means of addressing this issue has yet been developed. Alternative approaches, such as the ones based on quantiles (O'Hagan et al. 2006), would require more statistical training on the part of the respondents. On the other hand, during the second round of the Delphi survey, when faced with all responses from the first round, the participants were able to move towards a shared understanding of the scale and the underlying concept of subjective uncertainty. In some cases respondents may have also adjusted their uncertainty in light of discussions.

In general, the aim of choosing a point scale subjective measure of uncertainty was thus to obtain a shared understanding of its meaning by the second round of the Delphi survey, despite differences in the methodological background of the experts. Hence, the second round responses to questions on uncertainty reflect subjective views of individual respondents relative to the whole expert panel. It is worth stressing that Bayesian forecasts are characterised by inevitably subjective elements, since they are conditional on expert opinion as well as the past history obtained from the data series.

*Discussion*

As researchers, we have been critically reflexive about our methods. An obvious issue with the presented methodology is that, despite being considered leading experts in their field, the participants in our panel survey nevertheless had imperfect knowledge and openly admitted the limitations of their expertise in relation to forecasting environmental mobility. Thus, their input, upon which the model parameters are based, is inherently subjective, and the resulting forecasts therefore remain only as good as the experts' knowledge allows. Most of the participants, and we as authors, would argue that expert knowledge on the topic remains of great value and that it is better to build forecasts that includes the insights of demographic and environmental experts, rather than relying either on mechanistic models, or indeed on uninformed guesstimates of environmental mobility made by commentators with no understanding of migration processes.

A second issue is that of how definitions should be treated in a Delphi survey. Our approach, as discussed above, was to start Round 1 of the Delphi without giving a definition of ‘environmental migrants’ to the experts for the methodological reason that we were interested in eliciting different views. At Round 2 discussion between experts of their different views and explicit introduction to the experts of the Government Office of Science (2011) definition may have introduced a shift in the experts’ statistical responses that confound two sources of uncertainty – first a possible convergence between experts on the definitional issue and second a change in the opinion of the experts about their level of uncertainty on environmental migration associated with debating their views with others. Clearly, a better experimental design would not confound these two sources of uncertainty.

Another issue on which we have reflected is how best to interpret experts’ answers to the survey: it is possible that respondents interpreted the 0-100 per cent confidence scale in different ways and that this may have impacted on the findings. Finally, the limited availability of appropriate time-series data on past migration trends and the complete absence of any data on environmental migration limit the analysis. This partly explains why official migration forecasts ignore environmental mobility. We would argue that our methods provide a means to provide informed forecasts that include the important topic of how climate change may contribute to future population mobility to specific destination countries.

Despite our self-critical reflections on these methodological matters, we would argue that this paper offers a useful advance to all those wishing to consider the future scale and distribution of environmentally-linked population movements. The paper offers a first attempt at producing quantifiable estimates of environmental mobility towards the UK. More importantly, the methods discussed define the uncertainty levels associated with the forecasts and we would argue that understanding the sources of this uncertainty is itself useful to decision makers.

As to the applications of probabilistic forecasts to actual policy problems, literature on demographic forecasting provides some guidance in this respect, drawing on statistical decision theory (Alho and Spencer, 2005; Bijak, 2010). The basic premise is that the realisation of various future outcomes might imply losses of different magnitude, incurred due to the inevitable lack of perfect insight into the future. For example, underestimation of future migration may result in extra costs to accommodate additional migrants. On the other hand, overestimation of future migration can lead to losses in efficient allocation of resources. If such a decision setting can be even approximately known to the decision maker, then statistical decision theory provides guidance on how to make planning decisions which minimise the expected loss under given probabilities of future events.

A description of such potential losses, implying a particular solution to the decision problem (if it exists), is specific to a given decision setting. For example, if the loss increases linearly with the actual prediction error, the optimal decision strategies are based on appropriate quantiles from the predictive distributions. In particular, when underestimation of future migration is expected to be x times as costly as its overestimation by the same magnitude, statistical decision theory would point the decision-maker to the less costly quantile of rank x/(x+1) of the distribution. Conversely, if overestimation is x times more costly, the solution is the 1/(x+1)-th quantile (Alho and Spencer, 2005; Bijak, 2010). In this way, in order to better (and more prudently) prepare for the unexpected, the policy and planning decisions require taking into account the impacts of possible outcomes, as well as their probabilities. In the next section, we present one element of this puzzle – the predicted probabilities of future migration flows, the other one (impacts) remaining beyond the scope of the current study.

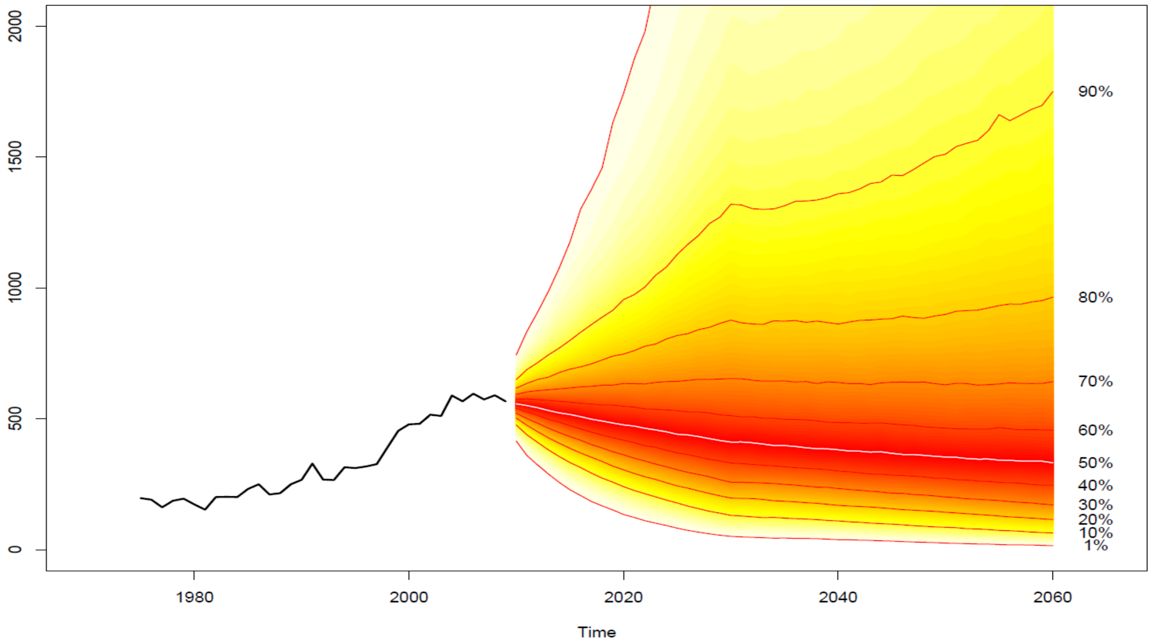
## Forecasts of Environmental Migration

By applying the methodology outlined above, univariate forecasts of total and environmental migration to the UK, based on autoregressive models, were obtained. The forecasts of the total immigration are weighted averages of predictions yielded by particular models, from IN and AR(1) up to AR(8). The weights used were the posterior probabilities of particular models, obtained from the bridge sampler algorithm of Meng and Wong (1996). In this example, the averaged model was 58.5% influenced by the Independent Normal ('AR(0)') model, 21.3% by AR(2), and 16.1% by AR(1), with a trace impact of AR(3) and AR(4). Noteworthy, other goodness-of-fit criteria also pointed to models with high posterior probability: the Akaike Information Criterion (AIC) pointed to AR(2), while the Bayesian Information Criterion (BIC) to AR(1).

In order to derive forecasts of environmental migration, the expert-based predicted distributions of relevant shares were juxtaposed with the results for the overall immigration. The resulting forecasts of total and environmental immigration to the UK are illustrated respectively in Figures 2 and 3.

The medial predictions, indicating that for 50% of the time higher values can be expected, and lower values for the remaining 50%, suggest an ever-slower-declining trend of total migration, and a long-term stability of environmental migration. Hence, in the median trajectory, overall immigration is expected to decline from the recent levels of 567,000 in 2009, to 411,000 in 2030, and then to 332,000 in 2060. At the same time, the median trajectory of the volume of environmental migration is expected first to increase slightly from the expert-based estimate of 19,600 thousand in 2010, to 26,800 in 2030, and then decline to 24,900 by 2060. With respect to environmental migration, Figure 3 clearly shows a change in slope around 2030, resulting from the values having to conform both to overall migration totals, as well as to the shares of environmental migration envisaged for 2030 by the experts. The values are the result of the history of migration and its impact on the forecasts through the parameters of the forecasting model. In addition, respondent's answers for the mean levels are weighted by their associated uncertainty levels in the prior distributions.

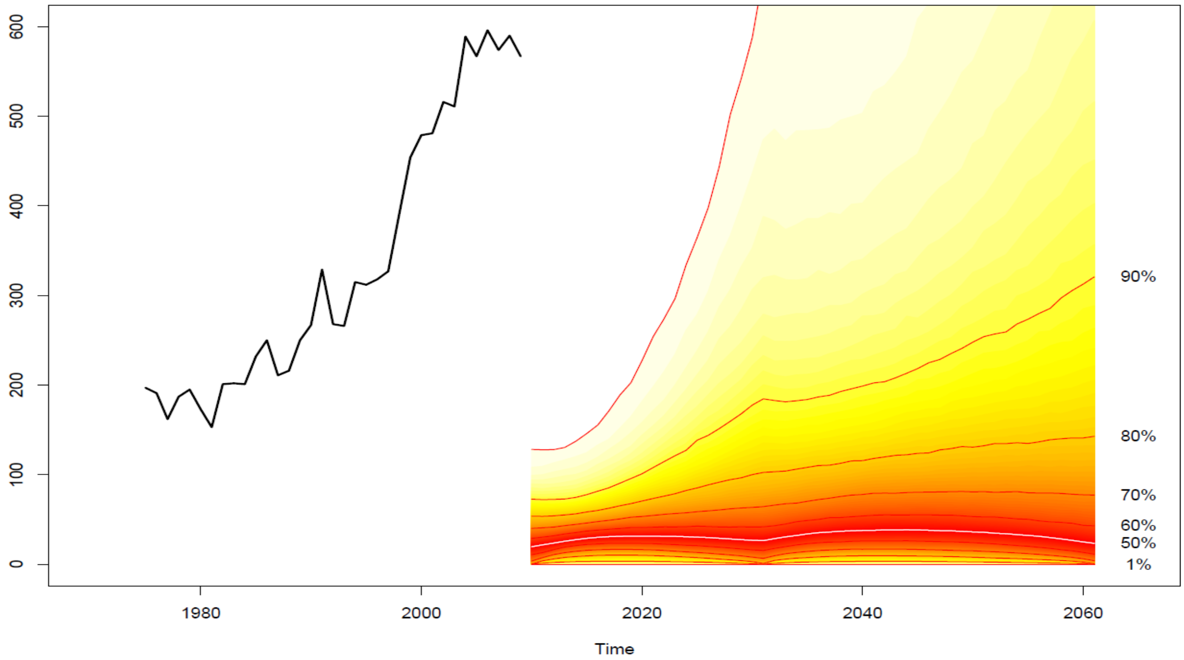
Figure 2: Forecasts of total immigration to the UK, averaged univariate models (in thousands)




Note: White line on the forecast fan denotes the median forecast of total immigration to the UK.

Source: Data – ONS; Forecasts – own elaboration in OpenBUGS/R.

Figure 3: Forecasts of environmental immigration to the UK, averaged models (in thousands)




Notes: Black line denotes historical total immigration – the same series as in Figure 2 (rescaled).

White line on the forecast fan denotes the median prediction of environmental immigration to the UK.

Source: Data – ONS; Forecasts – own elaboration in OpenBUGS/R.

Figure 3 is innovative in providing for the first time expert-based estimates of the volume of environmental migration to the UK that might occur year on year over the next 50 years. It not only shows the possible levels of environmental mobility, but perhaps more significantly it predicts that a continuous increase in the number of environmental immigrants, as suggested by some environmentalists (e.g. Myers, 1993), is unlikely. Of course, the values shown in the diagram (while being the best estimate available to decision makers) are conditional on past data, the knowledge base of the Delphi panel experts and the univariate models that have been employed to generate this forecast. Nevertheless, by recognising that the expert panel was selected to represent some of best available knowledge on the topic, and that the model has taken into account the panellists' self-defined uncertainty about current and future levels, the forecast provides unique estimates of the possible scale of environmental migration to the UK. This potentially provides an important baseline for policy makers to work with until better estimates may be obtained.

The predictive uncertainty shown in Figure 2 is, as expected, quite high. For example, the 80% intervals[1], related to chances of one in ten that in any particular year the actual total immigration to the UK will be above the given range, and one in ten that it will be below, are estimated to be between 131,100 and 1.32 million immigrants in 2030, and between 64,000 thousand and 1.75 million in 2060. It has to be stressed that these intervals, and in general the probability bounds, refer to particular years, and not to the whole long-term trajectories of such a volatile process as migration.

By definition, the volume of environmental migration must fall below the value of the total. Thus, in 2030 between 0.6 and 177.7 thousand immigrations to the UK could be related – directly or indirectly – to environmental drivers, while in 2060, this range could be between 0.6 and 312.7 thousand. In the short term, the uncertainty assessment seem plausible; however, due to the nature of the processes under study, as well as of the forecasting models, the intervals beyond 2020 or 2030 clearly become too wide, especially at the upper end. From this point of view, the statistical migration forecasts can be useful within the horizon of about ten years (see also Bijak and Wiśniowski, 2010). Beyond that the exploration of possible futures should be ideally complemented by use of other tools, such as scenarios, examples of which are available from the GOS (2011) study. The results of our forecasting exercise presented in the next section should be interpreted with these caveats in mind.

[1] Probabilistic population forecasters tend to prefer 80% predictive intervals over, for example, 95% ones, main arguments being that the former are more robust and less affected by the extremes, and do not unnecessarily amplify the impression of uncertainty (Lutz et al. 2004: 37). Besides, as argued by Bijak (2010: 107), "such intervals can also provide additional warning to the forecast users, as the probability that the process will fall beyond their limits from time to time cannot be neglected."

## Bayesian forecasts in relation to expert views

Based on the Bayesian forecasts obtained from extrapolating immigration data augmented by expert opinion, Figure 3 suggests that environmental immigration to UK will probably not change much over the next 50 years from current levels. It is possible that there may be a very slight rise over the next few decades, but that the trend is unlikely to be one involving ever-increasing numbers. Instead, the median forecast suggests that the total volume of environmental immigration (while hovering between 25,000 and 27,000 people between 2030 and 2060) is not set to expand exponentially as Britain moves forward into an era of significant climate change.

In addition, environmental migration will most likely remain a small percentage of the overall migration inflow into the UK. The median environmental flows in 2030 and 2060 correspond to respectively 6.5% and 7.5% of the median total immigration flow. In addition to these estimates, Figure 3 provides policy makers with the challenge of considering how to respond to unlikely outcomes as well as to the more probable estimates around the median line.

A number of interesting points emerge when the reasons given by the panel members for their views are considered. First, the expert panel anticipated a minor decline in UK immigration by 2030. This expectation revolved around perceptions that the relative attractiveness of the UK as a migrant destination would recede over time and that tighter controls on immigration would be an effective barrier.

> *'My expectation would be that a lot of the future growth poles globally are going to be in the emerging economies and not in OECD economies. And I would also make the assumption that British immigration policy will not allow in so many migrants… so it is not just a simple matter of economics, we'll still see some immigration but I suspect that it will be lower'.*
>
> *(Expert A)*

> *'I focused on how desirable this country will be in 50 years from now and for me it is going to be a less desirable country. Southeast Asia will develop so it will become more attractive but I believe that people will continue to see this country as a desirable place to live in. But you also have to take into consideration the impact of this government and movements in other countries to control migration; so I do not think that immigration to the UK will change that much'.*
>
> *(Expert B)*

These comments indicate that one reason why environmental mobility forecasts for the UK appear stable over time (rather than increasing rapidly): the experts did not predict an increase in overall immigration, of which, by definition, the volume of environmental mobility is only a fraction.

Turning to current levels of environmental mobility, experts contended that there was very little immigration to the UK due to environmental change. Consider the following comment:

> *'I am of the view that we get very few, if any, environmental migrants and that's because I think that migration is overwhelmingly an economic decision or outcome'*
>
> *(Expert C)*

By the end of round two of the Delphi survey it was clear that there was strong agreement amongst the experts on this, and a high degree of confidence was attached to this position (see Findlay et al., 2012 for a detailed discussion of the Delphi survey results).

Looking forward 20 years, the view of the experts was that environmental change would become a more important contributor in proportional terms to immigration to UK than at present, but because overall immigration was falling this did not imply an absolute increase. Even those who felt that there would be an upward trend did not expect it to account for more than 20 per cent of total immigration (80% of responses estimated environmental mobility to be below 20% of the total). Interestingly, those who were most confident in their forecasts were also those most likely to give low estimates of future environmental mobility to the UK.

This view was based on assumptions about how migration systems operate. The case was not that there would be minimal human displacement at a global level arising from environmental hazards, but that those moving for environmental and other reasons would mainly move short distances within the less wealthy countries, and even those moving longer distances would be entrained in migration flows to destinations other than the UK.

> *'What are the things that actually drive people to move from their country or their immediate surroundings to a country that is much further away? If you look at the flooding that happened in X (Asian country) people got displaced and many of them don't want to go back even though that is where they have got a potential livelihood … but their decision is not to migrate to UK unless they already have links here. Their coping strategy is to say, I have family members close by that can provide me with temporary shelter while I get on my feet. …so my point is that migration is there, but it is not to the UK.'*
>
> *(Expert D)*

The same logic suggests that much environmental mobility towards the UK will be European in origin. This is so, first because this is the origin of most current UK immigration and, second, because this is the region within which environmental change might impact on populations who are currently likely to select the UK as a destination (e.g. agricultural workers from other parts of Europe).

> *'By 2060 from my point of view we will have more intra-European migration flows from countries likely to suffer from climate change and they are southern European countries basically because of water scarcity and issues like that. So I mean countries like the UK could be facing immigration flows coming from people that are pushed from southern Europe. That is why I have chosen a higher rank and in my mind that was due to regional migration'.*
>
> *(Expert E)*

## Discussion and Conclusions

The environmental mobility forecasts presented in this paper suggest that environmental immigration to UK will not rise significantly over the next few decades, although it may become a more important share of all UK immigration (Figure 3). The median forecast suggests that the total volume of environmental immigration (while hovering between 25,000 and 27,000 people between 2030 and 2060) is unlikely to expand exponentially. The median environmental flows in 2030 and 2060 correspond to respectively 6.5% and 7.5% of the median total immigration flow. In addition to these estimates, Figure 3 provides policy makers with the challenge of considering how to respond to less likely outcomes, as well as to the more probable estimates around the median line.

The outputs from the Bayesian models reinforce arguments about the general unpredictability of migration when we look into the future, and the shortness of plausible forecast horizons (Bijak, 2010). The originality of the approach outlined in this paper has been to offer an advance in forecasting environmental migration that places uncertainty at the heart of the modelling approach and which combines expert views about generally unknown future levels of environmental mobility with known historical data series about overall immigration levels. Going beyond this, our suggestion is that the value of such an approach has been enhanced rather than reduced by interrogating, using a multi-round Delphi survey, the meanings and assumptions underpinning expert evidence. As such, this paper has been innovative in as far as the Delphi element of the methodology has been used not only in a conventional fashion (i.e. as a means of turning expert views into metrics that were of value for forecasting purposes), but also as a means of eliciting the values and meanings underlying the particular expert knowledge of the panel members, and thus the envelope of plausibility of the metrics.

In one sense the key result of the approach was the identification of a fan of possible environmental forecasts developed from Bayesian statistical modelling. In another sense the more important result is the recognition by the authors of the limitations of this kind of modelling exercise. The authors have argued that it does not undermine the value of their forecasts to conclude that instead of striving for (unrealistic) precision in forecasting a singular level of future environmental mobility, planners and policy makes would be better placed conceding that uncertainty is inevitable and inescapable, and considering novel approaches to immigration estimates. Thus, while the median forecast is of interest, what it tells us mainly is the nature of the assumptions of the expert panel. Of just as great an interest are the probability fans above and below the median forecast line. They offer an opportunity for decision makers to consider the scenarios that might produce other kinds of environmental mobility outcomes. In statistical terms these might be considered to be just as likely as the median outcome, but they deviate more from the assumptions of the experts.

As argued throughout this paper, the aim of the proposed forecasts is not to try to predict the future precisely, which in itself is impossible. As an alternative, we propose a coherent mechanism which would aid the decision-making process by attempting to assess the future uncertainty of the magnitude of migration related to environmental factors. This is related to a change in perspective concerned with assessing the accuracy of predictions: instead of 'how precisely can we predict the future', the question becomes 'how well calibrated are our predicted probabilities'. In the context of general migration forecasts, Bijak (2010) has shown that Bayesian methods can offer more realistic (in this case, wider) estimates of uncertainty ranges than traditional extrapolative methods based on data alone. In this way, the addition of expert knowledge provides extra information and thus reduces vulnerability to unpredicted outcomes. In particular, without expert input, the probability of rare events, located in the tails of the distributions, can be underestimated (idem). In this situation, it is crucial to have heterogeneous views represented amongst the experts, so that the probabilities of various rare, yet potentially very influential events, is not underestimated.

In more general terms, we concur with the general conclusions made by Collins et al. in their review of approaches to climate predictions that 'it is possible to produce quantitative projections of climate change, combining models of varying complexity and observations, expressed in terms of probabilities that measure our current uncertainty in those projections' (2012, 408). Our approach, even though in itself extremely modest, includes many of these features, such as combination of models, and presenting probabilistic outcomes. Even though the complexity of our approach is nowhere near the one of current climate models, we believe that, in the absence of existing relevant theories and explanations, it provides a good first approximation by combining the available sources of information: historical data, where available, and expert opinion.

Looking ahead, it is useful to note that further methodological refinement of this approach could be sought in terms of examining the effect of shifting from a univariate model to more powerful models, including more complex causal mechanisms and a range of different drivers. Other directions for research would be to explore more sophisticated methods for eliciting expert opinions, including more rigorous interrogation of the meanings given by different experts to the term 'environmental mobility'. In particular, the authors acknowledge that two sources of uncertainty were confounded by the experimental design used in the research reported in this paper. Hence, we recommend that the innovative method used in this paper, if repeated in other contexts, adopts a single consistent definition of key terms from Round 1 of a Delphi survey rather than introducing the possibility of a definitional switch at the Round 2 stage. We have sought to be transparent within this paper in explaining the approach we have taken, and we believe that there remains great value in the exploratory methodological work reported here, even although if the work were to be repeated we would change the research design in the fashion indicated earlier.

In terms of other lessons learned from this study, it is clear that further research endeavours should also pay more attention to the elicitation of expert opinion with respect to uncertainty surrounding various quantities. The Likert scale-based approach adopted here was relatively simple, but could potentially conflate two different sources of uncertainty, one related to the interpretation of the scale itself, and the other to the actual differences between the experts. For the future, either quantile-based approaches could be used, subject to appropriate explanation to non-statistical experts, or the scale-based results could be subject to calibration, as suggested by O'Hagan et al. (2006).

Finally, the policy implications of the environmental mobility forecasts provided by this paper deserve thought. As Figure 3 has shown, it is quite likely that future environmental immigration to the UK in 2060 will not be much different from the current median estimate. The paper has argued that this is a highly plausible outcome, but it is one based on the values and assumptions held by the panel of experts. It also sits with the expectations of the small body of evidence-based literature on environmental mobility. Thus, it is an outcome that assumes that overall UK immigration levels will fall as we move into the future, and that the UK will become a less desirable destination not only for migrants in general but for environmental migrants in particular. This line of reasoning leads to two conclusions of relevance to policy makers and planners.

First, plausible as are the assumptions made by the expert panel, policy makers and planners should recognise that there are no immutable laws underpinning the validity of these assumptions. Therefore there is great value in exploring the scenarios that would produce higher levels of overall migration and that might make UK more rather than less attractive to migrants whose mobility has been influenced by environmental factors. Recognition of such circumstances would help in providing an early warning of the contexts within which the UK might become a significant destination for environmental migration flows[2].

Second, if current assumptions hold, the implication is that over the next 50 years environmental mobility will focus on other destination regions. This does not absolve UK policy makers from taking action, but suggests that in place of focussing on UK border control, policy makers might usefully devote attention to international development strategies. As suggested by the recent Government Office for Science (2011) report on *Migration and Global Environmental Change*, it points to the need for international assistance to be directed to developing relevant adaptation strategies for populations in other parts of the world. This is needed on the one hand amongst those populations of the global South living in areas of high vulnerability to climate change, but who because of poverty are immobile and unable to adapt to the impact of these changes on their livelihoods. On the other hand, this would benefit the reception areas of large cities in the global South that have been selected by many millions of people seeking a better livelihood, but who have moved to environmentally-high risk destinations in order to achieve it (Black et al., 2011b). In this context, the authors hope that the current study may help contribute to changing the focus from the developed to developing countries, potentially much more important migration actors in the times of global environmental change.

[2] For example, if an international body such as the UN were to grant legal status and rights to 'environmental refugees' equivalent to that of the current Geneva Convention on political refugees, then current immigration policies in UK and elsewhere would be impacted (although individual states retain a large margin of autonomy in granting the refugee status).

## References

Abel, G,J. Bijak, J. and Raymer, J. 2010 ‘A comparison of official population projections with Bayesian time series forecasts for England and Wales’. *Population Trends*, 141: 95–114.

Abel, G. Bijak, J. Wiśniowski, A. Findlay, A. and McCollum, D. 2011. ‘Migration and Global Environmental Change. MR8: Model specification and results of Bayesian forecast of total and environmental immigration to the United Kingdom, 2010-2060’. Evidence Paper for the Government Office for Science. Global Environmental Migration Project. GOS. London.

Alho, J.M. and Spencer, B.D. 2005. *Statistical Demography and Forecasting*. New York: Springer.

Bayes, T. 1763. ‘An Essay towards solving a Problem in the Doctrine of Chances’. *Philosophical Transactions of the Royal Society*, 53: 370–418.

Bernardo, J.M. 2003 ‘Bayesian Statistics’. In: R. Viertl (ed.), *Probability and Statistics. Encyclopaedia of Life Support Systems (EOLSS): An Integrated Virtual Library*. UNESCO, Oxford; www.eolss.net

Bijak, J. 2010. ‘Forecasting International Migration in Europe: A Bayesian View’. *Springer Series on Demographic Methods and Population Analysis* vol. 24. Springer, Dordrecht.

Bijak, J. and Wiśniowski, A. 2010. ‘Bayesian forecasting of immigration to selected European countries by using expert knowledge’. *Journal of the Royal Statistical Society* 173: 775–796.

Black, R. Adger, N. Arnell, N. Dercon, S. Geddes, A. and Thomas, D. 2011a. ‘The effect of environmental change on human migration’ *Global Environmental Change*, 21S, S31-11.

Black, R. Kniveton, D. and Schmidt-Verkerk, K. (2011b). ‚Migration and climate change: towards an integrated assessment of sensitivity’ *Environment and Planning A* 43: 431–450.

Castles, S. 2011. ‘Concluding comments on the climate change-migration nexus’ In Piguet E, Pecoud A and De Guchteneire P (eds) *Migration and Climate Change*. Cambridge: Cambridge University Press, 415-27.

Chatfield, C. 2003 *The Analysis of Time Series: An Introduction*. Sixth Edition. Chapman and Hall/CRC, Boca Raton.

Collins, M. Chandler, R.E. Cox, P.M., Huthnance, J.M. Rougier, J. and Stephenson, D.B. 2012 ‘Quantifying future climate change’. *Nature Climate Change*, 2(6), 403–409.

Cox, R. Revie, C.W. and Sanchez, J. 2012 ‘The Use of Expert Opinion to Assess the Risk of Emergence or Re-Emergence of Infectious Diseases in Canada Associated with Climate Change’. *PLoS ONE* 7(7): e41590. doi:10.1371/journal.pone.0041590 (as of 18/02/2013).

Dey, D.K. and Liu, J. 2007. ‘A quantitative study of quantile based direct prior elicitation from expert opinion’. *Bayesian Analysis* 2: 137–166.

Fielding, A. 2011 ‘The impacts of environmental change on UK internal migration’ *Global Environmental Change*, 21S, S121-130.

Findlay, A. 2011 ‘Migration destinations in an era of global environmental change’ *Global Environmental Change*, 21S, S50-58.

Findlay, A. McCollum, D. Abel, G. Wiśniowski, A. and Bijak, J. 2012. ‘A Delphi Survey of Immigration to the UK to 2060’. *Centre for Population Change. Working Paper* 28.

Gemenne, F. 2011 ‘Why the numbers do not add up’ *Global Environmental Change*, 21S, S41-49.

Government Office for Science. 2011. *Migration and Global Environmental Change* Foresight Final Project Report, Government Office for Science: London

de Haas, H. 2011. ‘Mediterranean migration futures’ *Global Environmental Change*, 21S, S59-69.

Hill, K. and Fowles, J. 1975. 'The methodological worth of the Delphi forecasting technique'. *Technological Forecasting and Social Change* 7: 193–194.

House of Commons. 2008. *Sustainable Development in a Changing Climate*. Fifth Report of Session 2008–09. London: House of Commons, International Development Committee.

Hurd, M.D. and McGarry, K. 2002. 'The Predictive Validity of Subjective Probabilities of Survival'. *The Economic Journal*, 112 (482): 966–985.

Kadane, J.B. and Wolfson, L.J. 1998. 'Experiences in elicitation'. *Statistician* 47: 3–19.

Kniveton, D. Smith, C. and Wood, S. 2011. 'Agent based model simulations of future changes in migration flows for Burkino Faso'. *Global Environmental Change*, 21, S34-40.

Linstone, H. and Turoff, M. 1975. *The Delphi Method: Techniques and Applications*. Reading, MA: Addison-Wesley Publishing Company.

Lutz, W. Sanderson, W.C. and Scherbov, S. (eds). 2004. *The End of World Population Growth in the 21st Century: New Challenges for Human Capital Formation and Sustainable Development.* London: Earthscan.

Meng, X.L. and Wong, W.H. 1996. 'Simulating Ratios of Normalizing Constants via a Simple Identity'. *Statistica Sinica*, 6, 831-860

Myers, N. 1993. 'Environmental Refugees in a Globally Warmed World'. *BioScience* 43: 752–761.

O'Hagan, A. 2011. 'Probabilistic uncertainty specification: Overview, elaboration techniques and their application to a mechanistic model of carbon flux'. *Environmental Modelling and Software*. 1–14.

O'Hagan, A. Buck, C. E. Daneshkhah, A. Eiser, J. R. Garthwaite, P. H. Jenkinson, D. J. Oakley, J.E. and Rakow, T. 2006. *Uncertain Judgements: Eliciting Experts Probabilities*. New York: Wiley.

Olson, M.J. and Budescu, D.V. 1997 ‘Patterns of Preference for Numerical and Verbal Probabilities’. *Journal of Behavioural Decision Making*, 10 (2): 117–131.

Orrell, D. 2007. *The Future of Everything: The Science of Prediction*. New York: Thunder’s Mouth Press.

Pecoud, A. and Geiger, M. 2011. *The New Politics of Migration Management*. New York: Springer.

Piguet, E. Pecoud, A. and De Guchteneire, P. (eds). 2011. *Migration and Climate Change*. Cambridge: Cambridge University Press

Raftery, A.E. 1995. ‘Bayesian model selection in social research’. *Sociological Methodology*, 25, 111–163.

Schmidt, R.C. 1997. ‘Managing Delphi Surveys Using Nonparametric Statistical Techniques’. *Decision Sciences* 28: 763–774.

Seto, K.C. 2011. ‘Exploring the dynamics of migration to mega-delta cities in Asia and Africa’ *Global Environmental Change*, 21, S94-107

Stern, N. 2007. *The Economics of Climate Change: The Stern Review*. Cambridge: Cambridge University Press.

Szreder, M. and Osiewalski, J. 1992. *Subjective probability distributions in Bayesian estimation of all-excess-demand models*. Discussion Paper in Economics 92-7.University of Leicester, Leicester.

Warner, K. 2009. ‘Global environmental change and migration: governance challenges’. *Global Environmental Change*, 20, 402-13

Westfall, P.H. and Hilbe, J.M. 2007. ‘The Black Swan: Praise and Criticism’. *The American Statistician*, 61(3): 193–194

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