Mortality Effects of Temperature Changes in the United Kingdom

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Abstract

Temperature changes are known to affect the social and environmental determinants of health in various ways. Consequently, excess in deaths as a result of extreme weather conditions may increase over the next decades by cause of climate change. In this article, the relationship between trends in mortality and trends in temperature change (as a proxy for climate change) is investigated using annual data and for specified (warm and cold) periods during the year in the United Kingdom. A new stochastic mortality model is proposed that extends the good features of the Lee and Carter (1992) model and its recent extensions by including an additional temperature-related factor. The model is shown to provide a better fit and more interpretable forecasts.

Keywords: Longevity; Climate Change (Temperature); Lee-Carter Model; Forecasting

Introduction

It is a remarkable achievement that due to the recent advances in science and technology, humans are living on average longer than ever before. Comparing the life expectancy at the beginning of the 21st century with that at the middle of the 18th century, it can be seen that life expectancy has increased by over 30 years in a period of less than 200 years. This is an impressive achievement if someone also considers that life span increased by 25 years over the previous 10,000 years (Pitacco et al. 2009; Niu and Melenberg 2014). Obviously, as a direct consequence, longevity risk is and will be a key risk in the future for individual governments and financial institutions. Thus, appropriate mortality modeling and accurate mortality forecasting are becoming more and more important.

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The climate, which is always a key parameter in the complexity of the earth's system, and changes in average temperature may impact on life expectancy in various ways. Scientific consensus indicates that climate change is likely to cause a range of direct and indirect effects on human health in developed and developing countries (see for instance, Easterling et al. 2000; Intergovernmental Panel on Climate Change 2014). World Health Organization suggests that between 2030 and 2050, climate change is expected to cause approximately 250,000 additional deaths per year, because of malnutrition, malaria, diarrhea and heat stress (WHO 2014). Researchers across the world have investigated links between mortality and temperature changes comparing different countries, regions or cities with diverse climatic profiles. They have mainly focused on *heat* and *cold* waves, *high* and *low* temperatures or additional deaths during *extreme* weather conditions (for instance, very cold winters, etc.). Results from these studies show that the magnitude of the temperature which is related to deaths varies between countries (Meehl and Tebaldi 2004; McMichael et al. 2006; Analitis et al. 2008; Gasparrini et al. 2015) and population groups. According to Hajat et al. (2007, 2014) findings, the most vulnerable age group is elderly people. In addition, Christidis et al. (2010) suggested that the ability of individuals or cohorts to adapt is a major influence on changing mortality rates. At the same time, absence of adaptation can result in climate being a main contributor to increases in heat- and cold-related mortality in comparison to an intermediate "comfortable" temperature range (Patz et al. 2005; McMichael et al. 2006).

The main goal of this paper is to examine for the very first time according to the authors' knowledge, the relationship between trends in mortality and trends in temperature change (as a proxy of the climate change) that can be observed for annual data and for more specified (warm and cold) periods during the year in the United Kingdom over the period 1974-2011. We explore the relationship between the time dependent factor of the Lee and Carter (1992) model (hereafter referred to as the LC model) k_t^2, and the logarithm of the average temperature for males and females at ages between 20 and 85+. We investigate the long run relationship among time series data using the Johansen cointegration test. Additionally, we check correlation between those factors according to various tests. We use also Pearson's correlation coefficient to analyze behavior between age specific mortality rates, and average temperatures. Our investigation suggests there is a long-run relationship between mortality index, and average temperature changes as we observe strong negative correlation coefficients. Additionally, similar results are obtained from the analysis for mortality rates (by ages) and average temperature fluctuations.

Based on our findings, we introduce a new stochastic mortality model that includes an additional temperature-related factor to capture temperature inputs. The starting point for our research is the well-known mortality model introduced by Lee and Carter (1992). However, since we would like to include also good features of other existing extensions of LC model, we would also consider Plat's (2009) and O'Hare and Li's (2012) models (hereafter referred to as the P and OL model, respectively). Our proposed model performs better when compared with the above mortality models and gives very good forecasting results.

Literature Review

Mortality modeling and, in particular the accurate forecasting of mortality rates has a very long history. Probably the first person who considered a scientific approach to mortality data was Edmund Halley (1693). Early mortality tables were deterministic and static in nature and did not take account of potential future improvements in mortality rates over time. We can observe two main approaches in modeling mortality rates over time; *extrapolative* and *explanation*. However, in the literature we find that the vast majority of mortality forecasting methods are extrapolative. They make use of the observable patterns and trends over time, and forecast these into the future. The second approach (i.e. explanation) takes into account relationships between mortality and medical diseases or risk factors. They rely on medical knowledge, information on behavioral or environmental factors (for example, the dependence of lung cancer on tobacco smoking), and use structural, or epidemiological models of mortality from certain causes of death where the key exogenous variables are known and can be measured. We can also find one more forecasting method in the literature based on subjective expectation (Booth and Tickle 2008). This approach is one adopted by experts in the field, for example, actuaries. Each of the methods has advantages and disadvantages and it is difficult to say which one is better. What is more, comparison of outcomes from different approaches is hampered by differences in the explicit assumptions, for example the choice of the length of the historical period. In this article, we combine extrapolation and explanation by considering well known models and improving them by adding the new temperature related factor.

Extrapolative Mortality Modeling

Extrapolative approaches to modeling mortality using time series to extrapolate the time trend based on historic mortality experience began in the early 1990s. The first and most well-known mortality model was proposed by Lee and Carter (1992), which models the period trend using a one factor stochastic model. Their model attempts to explain mortality trends in a stochastic framework by fitting the past mortality data and modeling the time trend as a stochastic process. The model postulated by Lee and Carter (1992) is given by:

$$\ln(m_{xt}) = b_x^1 + b_x^2 k_t^2 + \varepsilon_{xt}, \quad (1)$$

where m_{xt} is the central mortality rate, calculated as the ratio between the number of people aged x who died in a year t, and the exposure to death for age x in year t. Factor b_x^1 ensures that the basic shape of the mortality curve over ages is in line with historical observations. The parameter k_t^2 often labeled as *mortality* index, represents changes in mortality between ages reflecting the historical observations that improvement rates can differ for different age classes independent of time average age specific. Factor b_x^2 is a pattern of deviations from the age of profile as the k_t^2 varies (this explains how rapidly/slowly mortality rates decline in response to k_t^2) and ε_{xt} is the error term at age x and time t, usually defined as independent and identically distributed random variable following a normal (Poisson) distribution.

LC model's popularity when compared with other mortality models is mainly due to its simplicity. It received several extensions including Booth et al. (2002), Brouhns et al. (2002), Renshaw and Haberman (2003a, 2003b, 2006), Currie (2006), Cairns et al. (2006), Plat (2009), O'Hare and Li (2012) and many others.

Renshaw and Haberman (2006) proposed a model which incorporated the cohort effect. This model provides a significantly better fit to the historical data for countries where the cohort effect is observed in the past. However, it suffers from a lack of robustness and the correlation structure is still trivial.

Cairns et al. (2006) observed by using data from England and Wales, and United States that the fitted cohort effect appears to have a trend in the year of birth. This suggests that the cohort effect compensates the lack of a second age-period effect as it tries to capture the cohort effect from the data. What is more, they introduced a new model with age period effect.

Finally, Cairns et al. (2011) proposed criteria against which a model can be assessed, and they presented a detailed analysis and comparisons for the main six stochastic mortality models.

Plat (2009) proposed a model that incorporates cohort and age-period effects and the model specification is given by:

$$\ln(m_{xt}) = b_x^1 + k_t^2 + (\bar{x} - x)\,k_t^3 + (\bar{x} - x)^+ k_t^4 + \gamma_{t-x}^3 + \varepsilon_{xt}\,, \tag{2}$$

where k_t^3 factor allows changes in mortality to vary between ages reflecting the historical observation that improvement rates can differ for different age classes, k_t^4 models the effects specific to the lower age only, γ_{t-x}^3 models the cohort effect, $(\bar{x} - x)^+ = \max(\bar{x} - x, 0)$, and $\bar{x}$ is the average of the ages considered. This model provides significantly better results again and implies that experience at the younger ages is important to be considered when modeling the mortality experience of a population.

Finally, O'Hare and Li (2012) considered an adaptation of the P model over a wider age range as:

$$\ln(m_{xt}) = b_x^1 + k_t^2 + (\bar{x} - x)\,k_t^3 + \left((\bar{x} - x)^+ + \left[(\bar{x} - x)^+\right]^2\right)k_t^4 + \gamma_{t-x}^3 + \varepsilon_{xt}\,. \tag{3}$$

Their model captures the non-linear profile of mortality at lower ages. It provides also a better fit for the range of countries and what is important does not lose any of the benefits of the previous stochastic models.

Despite the diversity of models, none of them explains what underlies the historical trends or whether these trends will continue. Recently, some authors have tried to show the relationship between exogenous factors like macroeconomic fluctuations (e.g. GDP, unemployment as the proxy) and mortality rates; see Tapia Granados 2008; Hanewald 2011; Niu and Melenberg 2014. Although it is not an easy task to identify all the relevant variables involved in climate change and to comprehend their mechanisms, in the following section, we discuss the relationship between trends in mortality and one of the potential factors: temperature change (as a proxy of the climate change).

Climate change and Mortality rates

Climate change is often described as one of the greatest challenge faced by humanity, with a potentially severe adverse impact on the environment and global population. In this paper, we associate climate change with changes in the weather as a main indicator. Fluctuations in weather conditions are usually described in terms of the mean and variability of temperature, rains and winds over a long period of time (from months to millions of years). What is more, it is generally accepted that those changes can cause direct and indirect effects on human health and wellbeing (see for instance, Intergovernmental Panel on Climate Change 2014). However, there is no single instrument measuring climate changes. Among a number of potential factors, we focus on the role of average temperature as a proxy of climate change. We chose this factor, as there are many studies in temperature extreme events such as heatwaves and temperature fluctuations which are one of the main climatic indicator that can impact on additional deaths (Easterling et al. 2000; Meehl, G.A. & Tebaldi 2004; Schär et al. 2004; Patz et al. 2005; McMichael et al. 2006; Gosling et al. 2009). Patz et al. (2005) underline that climate related mortality is dominated by the difference between temperature extremes and the average temperature. Moreover, according to projections of future climate, increases in extremes in relation to mean temperatures may occur particularly in the mid-latitudes.

Temperature Changes and Mortality Rates

During the twentieth century, several demographic studies of mortality in the United Kingdom showed an association between cold and warm temperatures and deaths (McKee 1989; Curwen 1991; Laake and Sverre 1996; Gemmell et al. 2000; Hajat et. al. 2014; Dell et al. 2014; Vardoulakis et al. 2014; Gasparrini et al. 2015). According to their findings, thousands of preventable deaths occur annually from cold or warm weather, and particularly so during extreme events such as the 2003 heatwave when approximately 2000 excess deaths occurred in England and Wales (Hajat et al. 2014). However, most of the previous studies suggest that cold temperatures rather than warm ones, are the main reason (Analitis et al. 2008; Gasparrini et al. 2015). According to results published by Gemmell et al. (2000), in the United Kingdom there is around 30% difference between summer and winter mortality rates. What is more, this difference is greater than for any other European country on similar latitude (Curwen 1991). Furthermore, elderly are most at risk, which means it is a significant problem as we observe population ageing. Predictions for the United Kingdom presented by Hajat et al. (2014) give meaningful impression how big the problem is. According to them, without any adaptation, the number of heat-related deaths will increase by 66% in the 2020s, 257% by the 2050s and 535% by the 2080s. While, cold weather-related deaths will increase by 3% in the 2020s, then decrease by 2% in the 2050s and by 12% in the 2080s.

Mortality and Temperature Changes

Data from United Kingdom

Our analysis is based on grouped monthly data. Monthly deaths and mid-year estimated population data between 1974 and 2011 divided by sex and age for the same period of time for England and Wales are provided by the *Office for National Statistics*, for Scotland by *General Register Office for Scotland*, and for Northern Ireland by *Northern Ireland Statistics and Research Agency*. In order to have monthly data about population we approximate monthly data from annual data using linear interpolation. Information about the mean monthly temperatures in England and Wales, Scotland, and Northern Ireland between 1950 and 2011 is provided by the Met Office. As we have already discussed in the previous subsection, many studies show the difference between mortality and season during the year, so we divide the calendar year in two parts, i.e., one which is related to *warm* and the other to *cold* months. By the warm months, we have in mind months from *May* till *September*. We choose these months based on temperatures being either above or below the average annual temperature.

Fig. 1 (a) shows the average temperatures in the United Kingdom for annual data and in two selected period: cold and warm months over the period 1974-2011 with additional linear trend line for the next 10 years. Of course, temperature fluctuations are not strictly linear and the presented period of time is quite short, however an increase in average temperatures is observed.

[Insert Figure 1 about here]

Mortality rates for males (see Fig. 1 (b)) shows a decreasing trend over the considerable period of time. This gives an indication there may be a *negative* correlation between temperature, and mortality. In addition, we observe that greater part of annual mortality comes from those cold months. This observation strengthens our belief that it is important to separate the analysis for cold and warm months and suggests the need for more advanced investigation for cold month.

Trends in the Lee-Carter Mortality Index and the Average Temperature Fluctuations

Following the suggestion of examining the relationship between the mortality index from the LC model, and macroeconomic fluctuations (see Tapia Granados 2008; Hanewald 2011; Niu and Melenberg 2014), we start our investigation by checking if there is a relationship between logarithm of average temperatures and the mortality index k_t^2. We estimate the necessary parameters according to the LC model under settings proposed by authors for each gender and set of data. Many studies present that mortality index k_t^2 has a decreasing trend, while average temperature is increasing.

We analyze the trend behavior of the Lee-Carter mortality index k_t^2 and logarithm of average temperature fluctuations for annual, cold and warm months' data l_t. Firstly, we apply the well-known Phillips and Perron test (1988). Results for male and female are similar (see Panel A of Table 1), in both cases there is no evidence to reject the null hypothesis of non-stationarity series at the 1% significance level. For logarithm of the average temperature, we can reject the null of non-stationarity at the significance level of 1% (except cold months: 5%).

Additionally, we perform the Kwiatkowski-Phillips-Schmidt-Shin test (KPSS) developed by Kwiatkowski et al. (1992) with the null hypothesis that an observable time series is stationary around a deterministic trend. As we can see in Panel B of Table 1, the null of stationarity for k_t^2 (male and female) is rejected at the 1% significance level. For logarithm of the average temperature we can reject the null hypothesis at the 5% and 10% significance level for annual, cold and warm months, respectively.

Long Run Relationship among Lee-Carter Mortality Index and Logarithm of Average Temperature Fluctuations

A common strategy to study the long run relationship among time series data is cointegration analysis. Panel C of Table 1 shows the results based on the Johansen (1988) cointegration test. The null of no cointegration ($r = 0$) is rejected in all cases (for male and female) at a significance level of 1% but the null of one cointegration vector ($r \leq 1$) cannot be rejected in most cases at a significance level of 5%, for male (annual and warm months) cannot be rejected at a significance level of 1%.

[Insert Table 1 about here]

Correlations between the Lee-Carter Mortality Index and Average Temperature Fluctuations

Tapia Granados (2008), and Hanewald (2011) used correlations to study the relationship between macroeconomics fluctuations, and changes in mortality rates in various countries. Similarly, we study the correlation between temperature fluctuations and changes in the Lee-Carter mortality index k_t^2. We test the association between paired samples using Pearson's[1] product moment correlation coefficient, Kendall's[2] τ and Spearman's[3] ρ and test the hypothesis that a particular correlation coefficient is equal to zero (at the significance level of 1%).

[Insert Table 2 about here]

Table 2 gives correlations results for males and females. In all cases, we observe significant negative correlations. For males as well as for females, we can see much stronger correlations for annual and cold months' data than for warm months. Moreover, we can also observe quite similar values for the data of annual and cold months for the Pearson's coefficient, and slightly stronger for cold months according to Kendall and Spearman's definition. Values for both sexes are very similar, however the level of similarity depends on the definition that is considered. For males, the strongest correlation is observed for the Pearson's definition (reaching -0.49, -0.49, and -0.26 for annual, cold, and warm data, respectively). The lowest values are derived for the Kendall correlation coefficient (-0.32, -0.37, and -0.14 for annual, cold, and warm data, respectively).

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[1]Pearson's correlation coefficient is the covariance of the two variables divided by the product of their standard deviations. The form of the definition involves a "product moment", that is, the mean (the first moment about the origin) of the product of the mean-adjusted random variables; hence the modifier product-moment in the name.

[2]It is a measure of rank correlation: the similarity of the orderings of the data when ranked by each of the quantities.

[3]Spearman's rank correlation coefficient is a nonparametric measure of statistical dependence between two variables. It assesses how well the relationship between two variables can be described using a monotonic function.

Correlations between the Mortality Rates (by Ages) and Average Temperature Fluctuations

In addition to examining the relation between the Lee-Carter mortality index and temperature, we also analyze Pearson's correlation coefficient between the mortality rates and average temperatures for every age. Fig. 2 (a) – (b) present results for males and females, respectively. In the case of females, the correlation coefficients are negative for almost all ages. Results for males can be divided in two age range below 38 years with positive correlation coefficient, and above 38 with a negative correlation coefficient. Behavior of correlation curves is similar for annual and cold months' data (both for males and females). Additionally, correlation coefficients for those dataset are much stronger than for warm months. Another interesting observation that confirms previous studies is that both for males and females, correlations results for elderly ages are much stronger than for younger group (see for example Christidis et al. 2010; Hajat et al. 2007, 2014). Moreover, we can notice that behavior of correlation curves for ages above 50 is much more stable and reaches around -0.50 for annual and cold month's data (between -0.2 and -0.3 though, for warm month's data). These results suggest that the relationship between temperature changes and mortality could be very significant during fitting and forecasting process, and further, indicate how important this factor could be in accurate mortality modeling for elderly ages.

In accordance to the authors' knowledge none of the existing models includes a factor related to temperature. Most models include cover cohort effect, different version of age affect (linear, quadratic), but there are no models including a relationship between temperature and mortality. To meet this absence in the next section we propose a model that includes this relationship. We take advantage of the existing knowledge to receive a stochastic model as good as it is possible. The proposed new model in its form incorporate Lee and Carter (1992), Renshaw and Haberman (2003a, 2003b, 2006), Cairns et al. (2006), Plat (2009), O'Hare and Li (2012) ideas with additional temperature related factors.

[Insert Figure 2 about here]

Proposed New Model

Taking previous analysis into consideration, we propose a model for the central mortality rate m_{xt} with a factor c_x that corresponds to relationship between mortality and temperature fluctuations as follow:

$$\ln(m_{xt}) = b_x^1 + k_t^2 + (\bar{x} - x)\, k_t^3 + (\bar{x} - x)^+ k_t^4 + \left([a - x]^+ + c_x[x - a]^+\right)^2 k_t^5 + \gamma_{t-x}^5 + \varepsilon_{xt}. \qquad (4)$$

This model includes a few more parameters in comparison to the LC model. However, the good aspects of their model are maintained and furthermore, it gives some new good features for better performance. Factors b_x^1 and k_t^2 are similar to the original LC model, factor k_t^3 allows changes in mortality to vary between ages reflecting the historical observation that improvement rates can differ for different age classes, k_t^4 models the effects specific to the lower age only, γ_{t-x}^5 models the cohort effect, $(\bar{x} - x)^+ = \max(\bar{x} - x, 0)$, $\bar{x}$ is the average of the ages considered, and ε_{xt} as the error term at age x and time t .

The proposed model follows O'Hare and Li (2012) approach, which captures the nonlinear features of mortality at younger ages for mature ages. However, we add a new factor c_x (for ages after a) which includes fluctuation of the temperature in the nonlinear approach for elderly ages (as this group is particularly exposed on changes of the temperature). This additional factor is appearing as a consequence of Pearson's correlation coefficient between temperatures and mortality rates. In case of the United Kingdom, we assume that a is equal to 50. It is a direct consequence of the analysis of the Pearson's correlation coefficients (presented in Fig. 2) as well as using findings from several other authors (e.g. Christidis et. al 2010).

Estimation and Quality of Fitting

The proposed new model has six stochastic factors and follows many others authors, see for example Lee and Carter (1992), Renshaw and Haberman (2003a, 2003b, 2006), Cairns et al. (2006), Plat (2009), O'Hare and Li (2012). It assumes that number of deaths is modelled as follows:

$$D_{xt} \sim Poisson(E_{xt} m_{xt}).$$

The parameters are estimated by maximizing the log-likelihood function, where the log-likelihood function is given by:

$$L(\varphi; D, E) = \sum_{xt} \{D_{xt} \ln[E_{xt} m_{xt}(\varphi)] - E_{xt} m_{xt}(\varphi) - \ln(D_{xt}!)\}. \tag{5}$$

To calculate the estimated values of the parameters that we are looking for we used the R-code of the software package "*Lifemetrics*"[4] (this package gives the opportunity to make a good comparison between our proposed model and existing models). The procedure to fit the model leads to time series of estimations of k_t^2, k_t^3, k_t^4, k_t^5, k_t^6 and γ_{t-x}^3. After fitting the model, we take the fitted values for the time series and fit suitable ARIMA-processes. For this purpose, we use auto.arima function from the *R* package "forecast", which returns best ARIMA model according to either *Akaike Information Criterion* (AIC)[5] or *Bayesian Information Criterion* (BIC) value. The function conducts a search over possible models within the order constraints provided.

In the Fig. 3 (a) – (d), we can see the estimated values of k_t^2, k_t^3, k_t^4, k_t^5 for males from the United Kingdom for annual data, and cold and warm months. General shape for those factors is the same for annual, cold and warm months' data. Factor k_t^2 shows a linear decreasing trend which is consistent with expectations for this parameter (see Fig. 3(a)). Additionally, there are noticeable longer values for warm month's results. Behavior of k_t^3 differs a bit between annual, warm month's data and cold months. However, in all cases the values are negative with some more fluctuations for warm month's dataset (see Fig. 3 (b)). The bahaviour of factors k_t^4, k_t^5 is exactly opposite. For k_t^4 during the first 20 years of the period of time under consideration a noticeable decreasing trend is observed (increasing for k_t^5). After this time the trend changes to increasing (decreasing for k_t^5), see Fig. (c) - (d)). What is more, for the last ten years new trend is strictly linear.

[Insert Figure 3 about here]

[4] "Lifemetrics" is an open source toolkit for measuring and managing longevity and mortality risk, designed by J.P. Morgan, see http://www.lifemetrics.com and http://www.r-project.org/.
[5] Where AIC=2k-2ln(L), L is the maximized value of the likelihood function for the model; k is the number of estimated parameters in the model.

The goodness of fitting of the proposed model and all the other models, we compare using three measures: *Mean Absolute Percent Error* (MAPE), *Mean Absolute Deviation* (MAD) and very popular criterion that takes into account the balance between parsimony and goodness of fit of the model *Bayesian Information Criterion* (BIC).

Mean Absolute Percent Error and Mean Absolute Deviation measure in our case are defined as:

$$\text{MAPE} = \frac{1}{NM}\sum_{x,t}\frac{\left\|\hat{m}_{x,t} - m_{x,t}\right\|}{m_{x,t}},$$

and

$$\text{MAD} = \sum_{x,t}\frac{\left|\hat{m}_{x,t} - m_{x,t}\right|^2}{NM},$$

where we have N (N=33) time dimensions and M (M=66) age dimensions. While for the Bayesian Information Criterion, we follow the definition proposed by Cairns et al. (2006)

$$\text{BIC} = L(\varphi) - \frac{1}{2}K\ln(P),$$

where $L(\varphi)$ is the log-likelihood of the estimated parameter φ, P is the number of observations and K is the number of parameters being estimated.

Table 3 presents the results for MAPE, MAD and BIC for males. In comparison particularly to the LC model, the proposed model has much more parameters so in terms of MAPE and MAD, better fitting results are observed and indeed in all cases the proposed model is superior, i.e., the errors for the proposed model are lower comparing with the LC model (3.20% and 3.97% for MAPE, and 0.00048 and 0.00056 for MAD, respectively for annual data). What is more, for other models that were considered during the study we observe better fitting results as well, for example, we can see significant improvement comparing with O'Hare and Li model, i.e., 44%, 34%, and 28% for annual, cold and warm months, respectively.

The best improvement in fit, as was expected, is observed for the annual and cold months' data. Furthermore, the results based on the BIC are very good as well. According to this measure, for annual data, the proposed model improves LC model by over 8% (7.52% and 0.35% for cold and warm months, respectively), and by over 12% the O'Hare and Li model

(8.66% and 4.60% for cold and warm data, respectively). Similar results can be observed for the females' dataset.

Generally speaking, the fitting results show that the proposed new model produces good quality estimations for the mortality rates both for males and females.

[Insert Table 3 about here]

Robustness Checks

Robustness is a very important feature of a good model. In this subsection, we investigate the robustness of the correlation between mortality rates by age and temperature changes over the time. As a further step, we analyze the robustness of the results for the proposed model. Fig. 4 plot separates Pearson's correlation coefficient for males over various period of time; 23 years, 28 years, 33 years, and 38 years for annual, warm months and cold months' dataset. Over all of the chosen periods of time we observe similar trends in the results with noticeable negatives values. Very similar behavior is visible for females. However, we can see some differences between the results for warm months and the rest of datasets. The differences between correlation curves for warm dataset over the periods of time considered are very small with the biggest difference between the values during the years 23 and 33 to be around 0.03. For annual and cold months those differences are bigger, for instance, they can reach 0.05, but even in the worst case, correlation coefficients are significant. In other words, reducing the number of observations for annual and cold months' data decreases values of correlations nonetheless the general shape remains.

[Insert Figure 4 about here]

During the fitting process, data set were used for years between 1974 and 2006, and for age range 20-85+ (we left 5 years of our data set to have opportunity to compare estimated forecasting results with mortality rates). As a next step, we reduce the sample period of 1974-2006 to 1974-1996 and estimate necessary parameters according the LC model and proposed model to compare fitting results. Also in this shorter period of time fitting results for the proposed model are superior to others under consideration.

Forecasting Using the New Model

Having a model that shows a good-fitting performance, a natural consequence is forecasting future mortality rates and this is the last step in the paper. During the estimation of the stochastic factors of the proposed model we sought appropriate ARIMA time series processes for the extracted time series. At this stage we make forecast of the stochastic parameters using *forecast.Arima* function from *R* package "forecast". In order to have good comparison, we forecast stochastic parameters for the LC model as a reference model using the same methodology for the next 20 years. As the data set used in this study differs to those in original papers, parameters estimated in the ARIMA processes are different. For example, during the estimation procedure for k_t^2, Lee and Carter (1992) uses ARIMA(0,1,0) process for the U.S. males data, while Renshaw and Haberman (2003a, 2003b) in their studies for males from England and Wales have chosen ARIMA(1,1,0). Here, for instance, we find that for cold months the best ARIMA process is ARIMA(1,1,0), while for the warm months ARIMA(0,2,1).

To compare goodness of forecasting results we use MAPE. Table 4 presents the out-of-sample MAPE results for males and females. Results are very good, using forecasting period of 2007- 2011. The forecast period is very short (only 5 years) so as an additional robustness check we consider longer forecasting period. To have longer forecasting period we use 23 years dataset (from 1974 to 1996) to calculate factors from the models, and then forecast mortality rates from 1997 to 2011 (so 15 years). Panel A of the Table 4 shows results for 5 years period forecasts, while Panel B shows 15 years forecasts. As it can be seen the proposed model gives better performance than the Lee and Carter model for both periods and for both sexes. However, it is noticeable that better results appear for shorter forecasting period of time. There is observed impressive improvement for males. For example, for annual data, MAPE performance moves from 12.13% for the LC model to 4.49% for the proposed model (and particularly, from 12.05% to 6.06%, and from 12.25% to 7.37%, for cold and warm months, respectively). While, for female the most significant betterment is observed for cold months' data (from 15.36% for the LC model to 8.96% for the proposed model).

From panel B of the Table 4, we observe that the forecasting results for longer periods of time generate much bigger errors for both models and sexes. However, the proposed model fits better in comparison to LC model with the best improvement for annual data for males (15.67% in comparison to 18.37% for LC model), and females (9.82% in comparison to

11.07%). For females, slightly better results are observed for cold months (11.88% for LC model and 7.13% for the proposed model).

[Insert Table 4 about here]

At the end of this section, we present estimation examples for 50 years old males. Fig. 5 illustrates mortality rates for males at age – 50 from 1974-2006 followed by forecasting results 2007 – 2026 from the proposed model. Additionally, we construct the forecast intervals (5% and 95% quartiles).

[Insert Figure 5 about here]

Conclusion

Many demographic studies show that there is a significant relationship between temperature change and mortality around the World. In our study, we focus on the relationship between trends in mortality and temperature fluctuations in the United Kingdom. First, we investigate the relationship and correlation between latent mortality index k_t^2 in the LC model and logarithm of average temperature. Second, we examine correlation between mortality rates by age and average temperature (for annual, cold and warm months' data). We note strong negative correlation between temperature and mortality for all ages. What is more, correlation for older ages is much stronger, especially for cold months.

Taking advantage of the previous extensions of the LC model and outcomes from our investigation we propose a new model and show that this model, which takes into account the impact of the fluctuation of temperature on mortality rates, performs very well. The new model extends to OL model to include a temperature related factor.

Furthermore, in terms of MAPE, MAD and BIC measures, the proposed model has a significantly better fitting performance in comparison to LC, P and OL models both for female and male sexes. We also demonstrate that the proposed model can be used to produce good quality forecasts of mortality rates. For instance, in terms of the MAPE measure, we receive a very good improvement in comparison to the LC model as a reference model for shorter and longer forecasting period of time.

Having a very good model, further research should be considered to explore other fitting and forecasting method such as the fully integrated and dynamic Bayesian approach presented by Wisniowski et al. (2015), or the functional models developed by Hyndman and Booth (2008). Of course, we cannot forget that this model includes the impact of the temperature changes. More and more arguments appear suggesting that the future direction of temperature fluctuations might change in a more severe way. Very recently, in 2015, during The Royal Astronomical Society National Astronomy Meeting, Prof. Zharkova suggested that new research shows Earth could be heading for a new ice age, maybe as soon as the 2030s (Shepherd et al. 2014). Therefore, there is a need to consider the future trends in temperature fluctuations and their impact on future mortality.

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Tables

Table 1. Results of unit root tests and Johansen cointegration test

	Annual	cold months	warm months
Panel A: **Phillips – Perron Test (PP)**			
$k^2_{t,male}$	4.9182	3.5291	3.5101
$k^2_{t,female}$	2.0163	1.6102	0.8879
l_t	-4.021**	-3.1174*	-6.5202**
Panel B: **Kwiatkowski–Phillips–Schmidt–Shin Test (KPSS)**			
$k^2_{t,male}$	0.9205**	0.9199**	0.9197**
$k^2_{t,female}$	0.9294**	0.9259**	0.9314**
l_t	0.4993*	0.4187†	0.3419†
Panel C: **Johansen cointegration test statistic**			
Males			
$r \leq 1$	9.79	4.43	8.98
$r = 0$	23.16	23.77	21.77
Female			
$r \leq 1$	2.40	1.16	0.80
$r = 0$	20.87	23.54	24.69

Notes: †p < .10; *p < .05, **p < .01, Critical values for the null of $r = 0$ are 12.91 for $p < 0.10$, 14.9 for $p < 0.05$, and 19.19 for $p < 0.01$. Critical values for null of $r \leq 1$ are 6.5 for $p < 0.10$, 8.18 for $p < 0.05$, and 11.65 for $p < 0.01$.

Table 2. Correlations between k_t^2 and average temperature

	annual	cold months	warm months
Males			
Pearson	-0.49	-0.49	-0.26
Kendall	-0.32	-0.37	-0.14
Spearman	-0.41	-0.50	-0.21
Female			
Pearson	-0.47	-0.48	-0.27
Kendall	-0.31	-0.38	-0.16
Spearman	-0.42	-0.50	-0.21

Table 3. Results of fit of proposed model and LC model (males)

	Lee and Carter	Plat	O'Hare and Li	**Proposed model**
Panel A: Mean Absolute Percent Error (MAPE)				
Annual	3.97%	4.08%	4.59%	**3.20%**
cold months	4.43%	4.32%	4.78%	**3.56%**
warm months	4.60%	5.05%	5.55%	**4.32%**
Panel B: Mean Absolute Deviation (MAD)				
Annual	0.00056	0.00074	0.00081	**0.00048**
cold months	0.00038	0.00048	0.00052	**0.00037**
warm months	0.00024	0.00032	0.00035	**0.00022**
Panel C: Bayesian Information Criterion (BIC)				
Annual	-15473	-15284	-16100	**-14320**
cold months	-13591	-13310	-13746	**-12569**
warm months	-12267	-12416	-12788	**-12223**

Table 4. Out-of-sample test results for MAPE.

	Males		**Females**	
	Lee and Carter	**Proposed model**	Lee and Carter	**Proposed model**
Panel A: **Between 2007 and 2011**				
Annual	12.13%	**4.49%**	8.72%	**8.49%**
cold months	12.05%	**6.06%**	15.36%	**8.96%**
warm months	12.25%	**7.37%**	9.64%	**6.74%**
Panel B: **Between 1997 and 2011**				
Annual	18.37%	**15.67%**	11.07%	**9.82%**
cold months	12.94%	**12.21%**	11.88%	**7.13%**
warm months	13.27%	**12.37%**	12.07%	**11.76%**

Mean Absolute Percent Error (MAPE) for data between 1974 and 1996.

	Males		**Females**	
	Lee and Carter	**Proposed model**	Lee and Carter	**Proposed model**
Annual	3.87%	**2.57%**	3.62%	**2.98%**
cold months	3.58%	**2.98%**	4.38%	**3.66%**
warm months	3.89%	**3.86%**	4.69%	**4.33%**

Figure

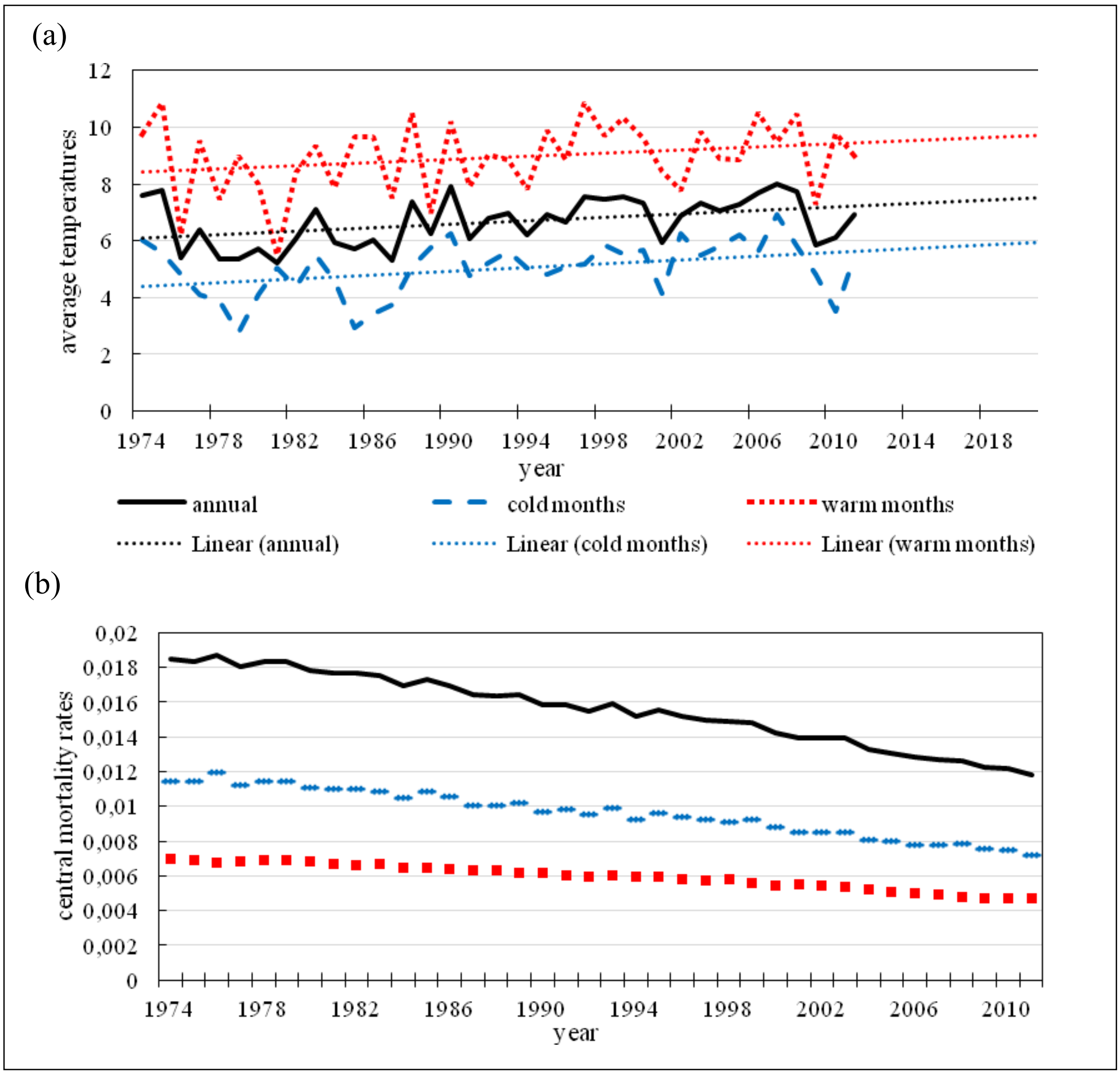

Figure 1. (a) Average temperatures for annual, cold and warm months' data (1974-2011) with linear trend line (with forecast for the next 10 years); (b) Mortality rates for males from the United Kingdom from 1974 to 2011 (annual, cold and warm months data).

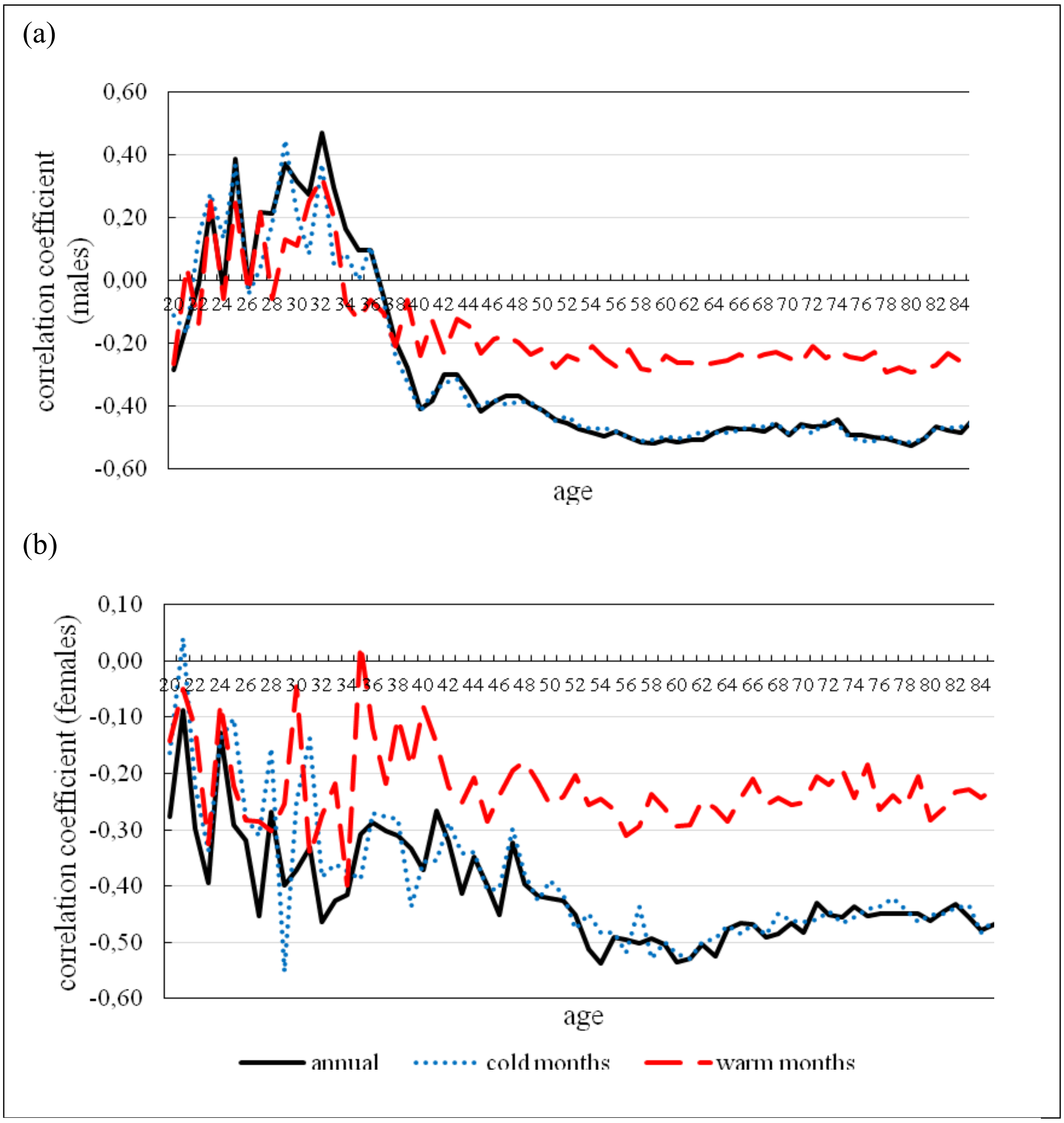

Figure 2. Results of correlation between mortality rates and average temperatures for males (data from 1974 to 2006): (a) males, (b) females.

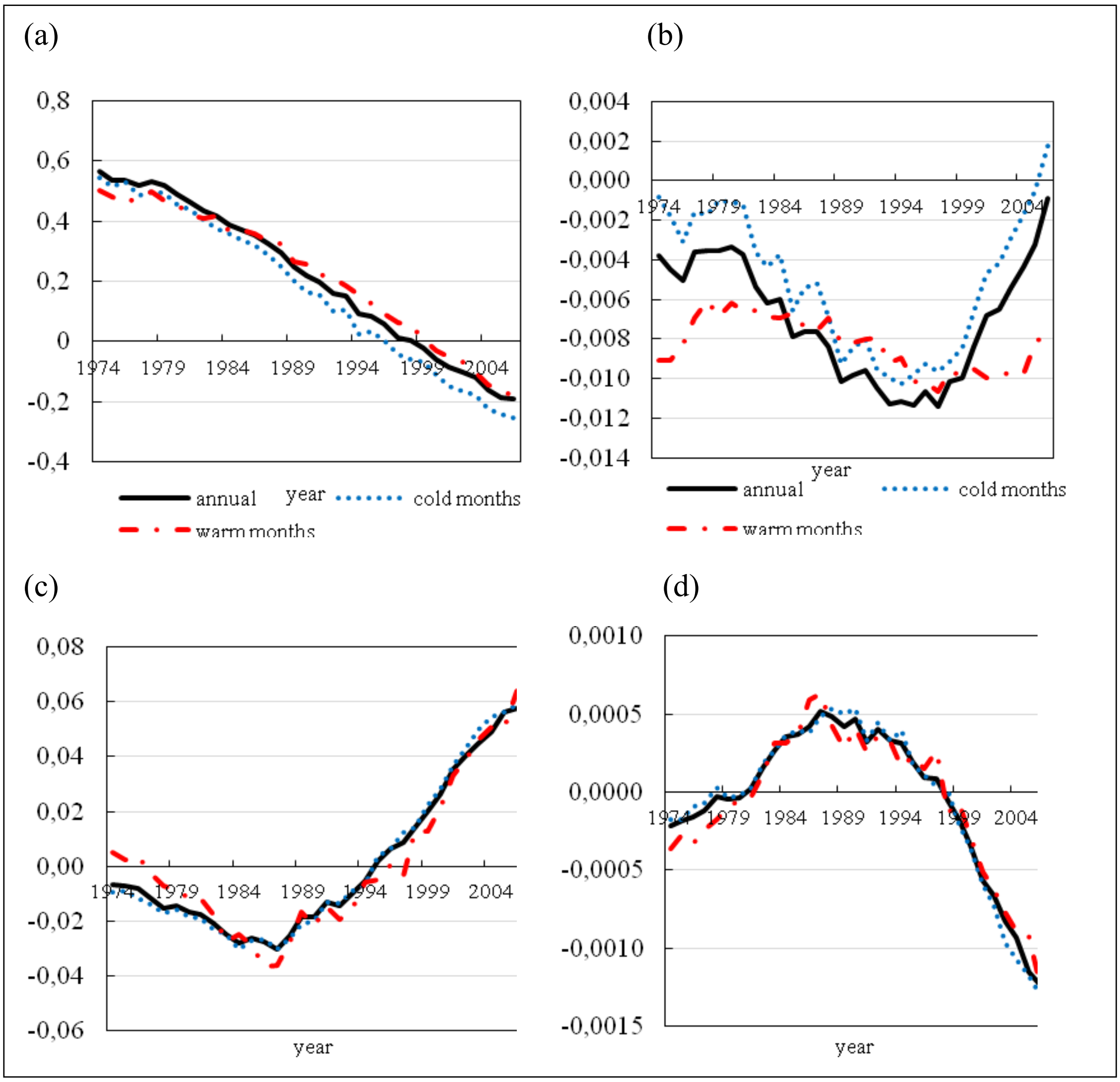

Figure 3. Estimated values of factors based on data for males from the United Kingdom, aged 20-85+ between years 1974 and 2006: (a) k_t^2, (b) k_t^3, (c) k_t^4, (d) k_t^5.

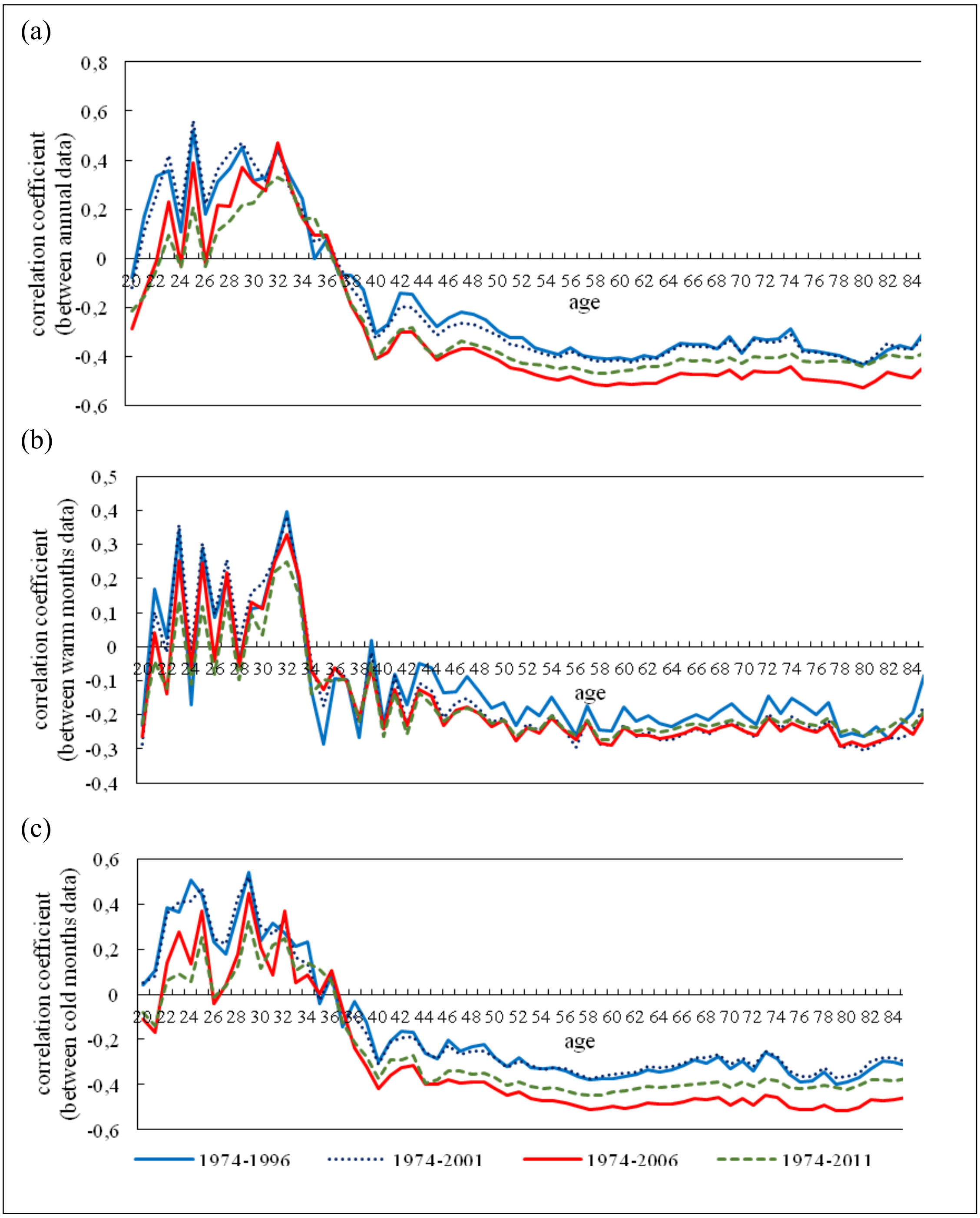

Figure 4. Pearson's correlation coefficient for males from the United Kingdom, aged 20-85+ over various period of time: (a) annual data, (b) warm months, (c) cold months.

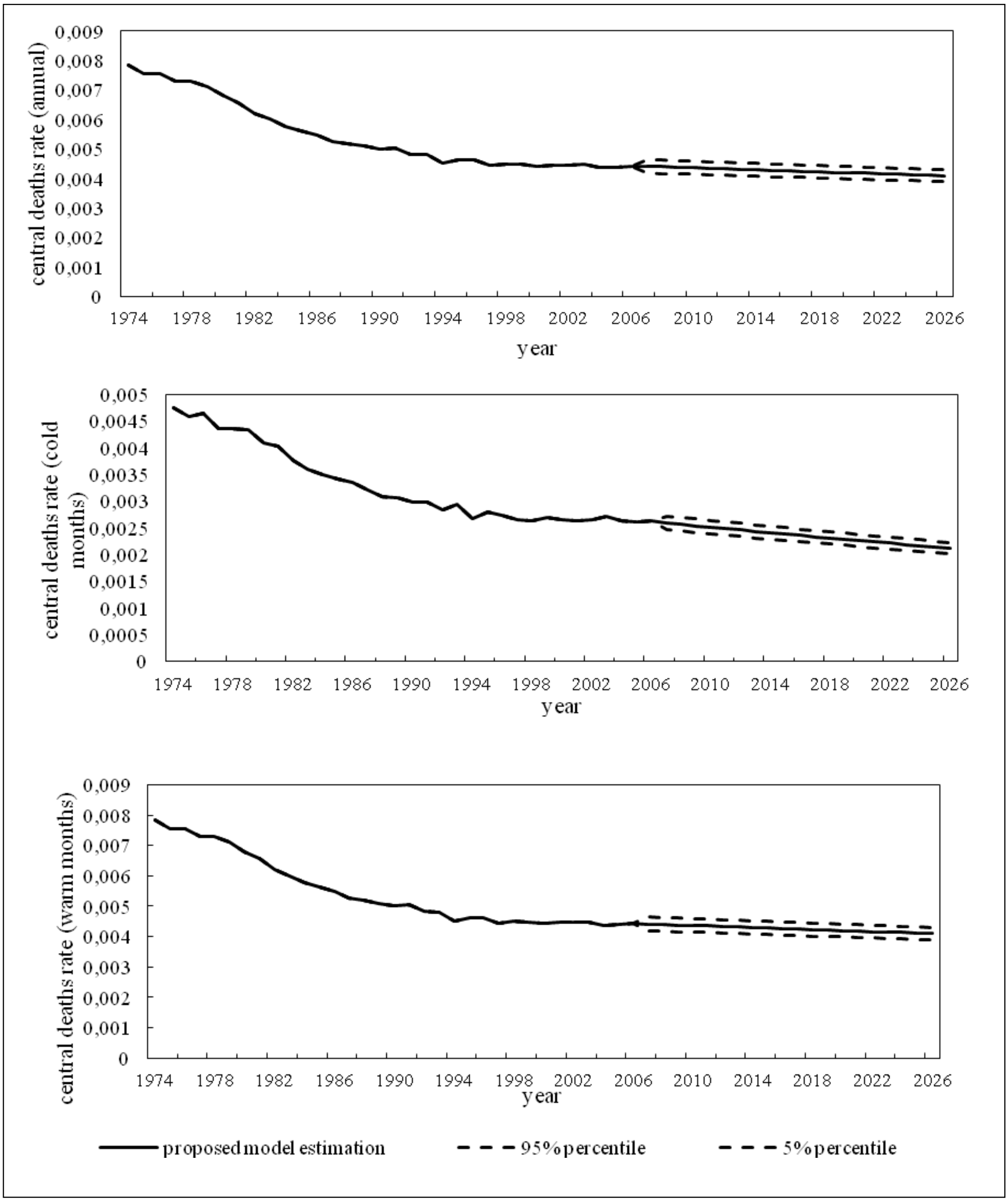

Figure 5. Mortality rates for 50 years old male from the United Kingdom from 1974–2006 followed by forecasting results 2007–2026 (annual, cold and warm months).