Past and projected trends of body mass index and weight status in South Australia: 2003 to 2019

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Abstract

Background: Functional data analysis (FDA) is a forecasting approach that, to date, has not been applied to obesity, and that may provide more accurate forecasting analysis to manage uncertainty in public health. The aim of this paper was to use FDA to provide projections of Body Mass Index (BMI), overweight and obesity in an Australian population through to 2019.

Methods: Data from the South Australian Monitoring and Surveillance System (January 2003 to December 2012, n=51,618 adults) were collected via telephone interview survey. FDA was conducted in four steps: (1) age-gender specific BMIs for each year were smoothed using a weighted regression; (2) the functional principal components decomposition was applied to estimate the basis functions; (3) an exponential smoothing state space model was used for forecasting the coefficient series; (4) forecast coefficients combined with the basis function.

Results: The forecast models suggest that between 2012 and 2019, average BMI will increase from 27.2kg/m^2 to 28.0kg/m^2 in males and 26.4kg/m^2 to 27.6kg/m^2 in females. The prevalence of obesity is forecasted to increase by 6-7 percentage points to 2019 (to 28.7% in males and 29.2% in females).

Conclusions: Projections identify age-gender groups at greatest risk of obesity over time. The novel approach will be useful to facilitate more accurate planning and policy development.

Key words: obesity, body mass index, forecasting, Functional Data Analysis

Introduction

The rapid rise in obesity has been well documented internationally (1-2). For example, the United States has maintained an historical record of the rise in obesity through its National Health and Nutrition Examination Survey (NHANES) series. In the 1960s, the prevalence of overweight and obesity was about 45 precent and has steadily increased to a point where now the latest figures suggest almost three quarters of American adults are overweight or obese (3-4) and 35 percent are obese (5). Population monitoring in other industrialised countries including Australia, France and the UK, has also tracked this rise, albeit at a lower prevalence than the USA (6-8). Australia's monitoring in nationally representative samples has been sporadic, but shows overweight and obesity has increased from 56.3 percent in 1995 to 62.8 percent in 2011-12. As a subset of this, the proportion of Australians who are obese has increased from 18.7 percent to 27.5 percent (9).

Projection analysis undertaken as part of the OECD Economics of Prevention (2009) used national health survey data from 12 countries to estimate overweight and obesity prevalence for 2014 and forward to 2019. Generally, the results suggest stabilization in rates of overweight, but continuing increases in obesity. The Australian projections used data from four national surveys (1989-2005) and the forecasted rates of overweight and obesity were estimated to be about 60 percent in 2014 and 65 percent in 2019 (1). However, recent national health survey data shows Australia has surpassed the 2014 projections and is fast approaching the estimated prevalence for 2019 – almost five years early (9).

Time series forecasting is used as a practical planning tool for governments to help manage future uncertainty, and inform health policy change. It is most useful when it is based on quality data and uses robust statistical methods. Functional data analysis (FDA) is one such approach starting to receive attention in the literature, particularly in terms of its public health and biomedical applications (10-12), but has yet to be applied to obesity. Commonly, time series data are treated as multivariate data because they are given as a discrete time series, and important information about the smooth functional behaviour of generating trend analysis tends to be ignored. FDA has the advantage of generating models that can be described by continuous smooth dynamics. It uses effective data noise reduction through curve smoothing techniques, which then allow for more accurate estimates of parameters for use in the forecasting analysis.

The aim of this paper is to apply FDA to 10 years of population survey data to provide projections of overweight and obesity in South Australia forward to 2019. This outlook will allow comparison with other international projections provided by the OECD Economics of Prevention but will also be a useful time frame to facilitate government planning and policy development. The objectives of this paper are firstly to describe the past trends (2003-2012) and future projections (through to 2019) in body mass index, overweight and obesity prevalence rates in South Australia; and secondly to identify particular age-gender subgroups of the population at higher risk of obesity.

Methods

Sample

Data were collected using the South Australian Monitoring and Surveillance System (SAMSS) from January 2003 to December 2012. The population of South Australia is about one and a half million (in 2011), accounting for 7.5 percent of the total Australian population (13). The SAMSS is a Computer Assisted Telephone Interview survey that monitors self-reported trends in risk factors, disease, and other health service issues. Interviews are conducted on a minimum of 600 randomly selected people each month. All households in South Australia with a telephone connected and the telephone number listed in the Electronic White Pages are eligible for selection. A letter introducing the survey is sent to the selected household and the person with the last birthday within a 12-month period is chosen for interview. Interviews are conducted with people of all ages, using parent-proxies for children under 16 years of age. Up to ten call backs were made to the household to interview the selected persons, with no replacements were made for non-respondents. Interviews were conducted by trained health interviewers. To ensure the SAMSS data is representative, the data were weighted by age, gender and area (metropolitan/rural) of residence to reflect the structure of the South Australian population in the Australian Census and the probability of selection in the household. Weighting was corrected for disproportionality of the sample with respect to the population of interest. This weighting is based on a random selection of households and one person within the household (14). The method is described in more detail elsewhere (14).

From January 2003 to December 2012, 65,557 interviews were conducted with participants from birth through to 102 years of age (participation rate ranged from 60-70 percent). This paper is limited to data collected from 51,618 adults (18 years and over). This represent all adults records in the survey (the expected total of 72,000, that is 600 per month over 10 years (2003-12) includes children). The sample size ranged from 4502 to 5401 people per year, was 50.3 percent female overall, and had a relatively even distribution across the age groups (Supplementary Table 1).

The interview questions of relevance to this paper included self-reported height and weight and personal details such as age and gender (Ethics approval number: HREC 479/11/2014).

Body Mass Index and weight status

BMI was calculated (in kg/m^2) and converted to weight status categories using the World Health Organization cut-offs (15). Data were categorised into three weight status groups: underweight and healthy weight (BMI less than 25kg/m^2), overweight (greater than or equal to 25kg/m^2 and less than 30kg/m^2) and obese (greater than or equal to 30 kg/m^2) (15). Nine extreme BMI values (less than 13kg/m^2 or greater than 97kg/m^2) were excluded from the analysis based on cut-offs provided by the Australian Bureau of Statistics, consistent with those used in the recent National Health Survey (16) and personal communication.

The BMI data were normally distributed therefore mean and standard deviations were used to summarise the data. Percentages were used to describe the proportions of the population in each weight status category across age and gender. Past differences in BMI between groups at single time points were assessed using Analysis of Variance (ANOVA) with Bonferroni adjustments.

Forecasting framework – Functional Data Analysis

The FDA approach was applied to model and forecast average BMI, overweight and obesity prevalence rates. Generally, this approach involved four interrelated steps that can be summarised as follows: (a) model the reported discrete data by smoothing technique and construct smooth continuous functional observations. This emphasizes patterns in the data by minimizing short-term deviations due to observational errors, such as measurement errors or inherent system noise; (b) apply functional decomposition technique onto the smoothed functional observations to estimate the time-invariant basis functions and the associated time series coefficients. This decomposition is obtained by transforming the data to a new set of variables, or principal components that are uncorrelated and ordered so that the first few retain most of the variation present in all of the original dataset; (c) A standard time series technique to model and forecast the time series coefficients; and (d) combine the resulting time series forecasts with the time-invariant basis functions and generate forecasts of BMI, overweight and obesity for each year.

To implement these steps, following the convention in FDA, the observed average BMI or overweight and obesity prevalence rates for age x in year t, $y_t(x)$, are described as $y_t(x) = f_t(x) + \sigma_t(x)\varepsilon_t(x)$. The $f_t(x)$ is an underlying BMI smooth function of x observed with error, $\varepsilon_t(x)$ is an independently and identically distributed standard normal random variable and $\sigma_t(x)$ allows the variance to change with age and year according to the nature of the data. The second equation $f_t(x) = \mu(x) + \sum_{k=1}^{K} \beta_{t,k}\varphi_k(x) + e_t(x)$ describes the dynamics of $f_t(x)$ evolving through time. In this equation, $\mu(x)$ is the mean of smooth BMI curves $f_t(x)$ across years and $e_t(x)$ is the model error. The age component $\varphi_k(x)$ is a set of orthogonal basis functions or principal components which modifies the main time trend according to whether change at a particular age is faster or slower than the main trend and in the same or opposite direction). The model assumes that $\varphi_k(x)$ is invariant over time. The time component, $\beta_{t,k}$ are time series coefficients which capture the overall time trend in $f_t(x)$ at all ages. The model makes no assumptions about the functional form of the trend in $\beta_{t,k}$.

Although a number of methods have been used (17-20), the age-gender BMIs for each year were smoothed using weighted regression splines (11) to estimate the age–BMI curves. Since the BMI increased rapidly up to certain age and then declined, the BMI curves were assumed to concave with age. To capture the concave trends in BMI, constrained concavity (21) applied to smooth curves were used according to the method of Hyndman and Ullah (11). The use of weighted regression splines has a number of advantages in that: (a) the smoothness conditions can easily be adopted to the nature of the BMI data analysed, thereby reducing the noise in the BMI curves; and (b) the underlying process generating the age–BMI curves is then continuous and smooth. Once the required smoothed functions are generated, the resulting series were subsequently decomposed into optimal number of orthogonal functional principal components (FPC) and their associated time series coefficients using FPC technique (11). As all parameters on the right-hand side of second equation are unobservable, fitting the model using the ordinary least square method is impossible. To overcome the situation, FPC decomposition was applied to the smoothed BMI curves.

Finally, given that time series coefficients are uncorrelated, we generated forecast for each time series separately. To keep the forecasts within acceptable confidence bounds, we limited the forecast interval to 7 years or 28 quarters, and generated forecasts on BMI for each quarter from 2013 to 2019. An exponential smoothing state space model selection algorithm (22,23) was used for forecasting BMI time series coefficients. Combine the forecasted time series coefficients with their corresponding basis functions to obtain forecast of BMI. All analyses were performed using R version 13.0 (24,25).

Forecast accuracy

The accuracy of forecast was evaluated by computing the integrated squared prediction error, $ISPE_n(h) = \int_x e_{n,h}^2(x)dx$ where $e_{n,h}(x) = y_{n+h}(x) - \hat{y}_{n,h}(x)$ which denotes the prediction error. In designing the accuracy measures for the future age-specific BMI, an out-of-sample test was performed (26). An out-of-sample evaluation of forecast accuracy begins with the division of the time series set into a fit period and a test period. The fit period is used to identify and estimate an appropriate model, based on a set of the observed data for that period and does not involve any predictions. The test period also uses observed data but this is compared to predictions arising from the model generated for the fit period and so measures the model's prediction accuracy. Based on the fitting period 2003–2010, the FDA forecasts of BMI for 2011–2012 were directly compared with the actual data for 2011–2012 through averaging of the Integrated Squared Forecast Error (ISPE) (11).

Results

1. BMI

Table 1 shows the trends in BMI, by age and gender, over the period 2003-2012. The average BMI of males has increased from 26.7kg/m^2 in 2003 to 27.2kg/m^2 in 2012 (P=0.009) and from 25.8kg/m^2 to 26.4kg/m^2 for females (P=0.007). Average BMI generally increased with age (P<0.001). In males BMI peaked in the 45-54 year age group and females in the 55-64 year age groups, before decreasing in the older age groups. Over 10 years, South Australians aged 18-24 consistently reported the lowest BMI. With one exception, males in 2012, the average BMI for this age group has been below 25 (Table 1).

Figure 1 shows the results of the functional data analysis showing the past rate of change in BMI by age and gender (Figures 1b and 1e) and the forecast coefficients for projecting future trends (Figures 1c and 1f). The first basis function indicates that the rate of change in BMI from 2003-2012 has differed by gender. Past trends show the greatest rate of increase has occurred in females aged 25-34 years (Figure 1b). The peak in the basis function curve is more gradual and slightly lower in males than females, with the peak occurring over the 25-34 and 35-44 year age groups and dropping off more gradually with age than for females (Figure 1e). Based on these past trends, the forecast coefficients for males and females suggest a continuing positive increase in BMI through to 2019 (Figures 1c and 1f).

Figures 2a and 2b shows the results of the forecasting analysis for BMI by gender and age group through to 2019, with each line representing the forecasted average BMI for the quarter (four per year), and the change in colour indicating a new year. The forecast models suggest from 2013 to 2019 BMI will continue to increase. Specifically, the average BMI will increase from 27.2 in males in 2012 to 28.0 in 2019 (0.8kg/m^2), and from 26.4 to 27.6 (1.2kg/m^2) in females. The projections (2013-2019) suggest marked increases are expected in some age groups, particularly females around 30 years of age where an increase of over $1 kg/m^2$ is expected by 2019 (Figure 3a).

2. Overweight

Figure 4a shows a notable disparity in the prevalence of overweight between males and females across all years from 2003 to 2012. In 2012, 45.6 percent of males were considered overweight and 27.9 percent of females. The increase in prevalence of overweight with age is more gradual in females than males (Figures 5a and 5d), but the greatest rate of change in prevalence between 2003 and 2012 has occurred in the 25-34 year age groups in both genders.

The prevalence of overweight in males overall has remained stable; 46.5 percent in 2003 and 45.6 percent in 2012. For females, the prevalence was 27.9 percent in 2003 and 2012 with a small increase in the years between (Supplementary Table 2). Based on these past trends, the forecast coefficient for males and females is a flat line along the zero value (data not shown). The forecasting analysis of overweight by gender and age group shows little increase in the prevalence of overweight through to 2019. Forecasting analysis suggests the prevalence of overweight across the population will be 46.1 percent in males and 30.1 percent in females.

3. Obesity

Different from overweight, the prevalence of obesity has tracked closely between males and females from 2003 of 2012 (Figure 4b). A gradual increase in the prevalence of obesity has been observed, from 17.2 percent in males in 2003 to 21.6 percent in 2012, and 19.5 percent to 23.1 percent in females. An increase in obesity prevalence with age is also evident, with the highest prevalence observed in the 55-64 year age group for both males and females (Supplementary Table 2).

The results of the FDA show a clear peak in the rate of change in obesity for females in the 25-34 year age group (Figure 5b), compared to a more rounded peak across the 25-34 and 35-44 year age groups for males (Figure 5e). The rate of increase in obesity prevalence slowed with age. Based on these trends, the forecast coefficients suggest a continuing increase in population prevalence of obesity through to 2019 (Figures 5c and 5f). Overall, the forecast model suggests the prevalence of obesity in males is expected to increase by 7.1 percentage points (21.6 to 28.7 percent) and 6.1 percentage points in females (23.1 to 29.2 percent). Generally, the increase in obesity is gradual over the forecast years for males and females (Figures 2e and 2f). The greatest increase in the prevalence of obesity is expected for females aged 25-34 years where the prevalence could reach 33 percent. The greatest increase in males is in the mid 30s to mid 40s (Figure 3b), where the prevalence of obesity may reach almost 35 percent.

Discussion

The obesity epidemic is considered one of the greatest public health challenges confronting Australia and other industrialised countries (26-28). The rise in prevalence of obesity over the last decade presented in this paper supports national and international data (1-2, 7-8). However, to our knowledge, this is the first application of FDA to estimate future increase in BMI and obesity. FDA is a novel, innovative trend forecasting tool which uses smoothing and noise reduction data techniques that should result in more accurate projections of obesity than alternative approaches, such as regression models. We suggest that without major intervention the *average* BMI of the Australian adult population will continue to increase (~0.5kg/m^2 by 2019, but up to 1kg/m^2 in some groups) and the prevalence of obesity could reach 33-34 percent in some sub-groups of the population. The estimates of the prevalence of overweight and obesity for 2019 were 67 percent (60 percent in females and 75 percent in males), two percent higher than previous projections (1). This trajectory of predicted weight gain among adults, particularly in younger age groups, will have serious impacts on individuals' quality of life. The number of years lived with obesity has been shown to be associated with risk of cardiovascular disease related and all-cause mortality (29). With more of the population becoming obese and at a younger age, the consequences of obesity will exert more pressure on over-stretched health care systems.

Action is needed to ensure individuals stay within their weight status category and avoid the upwards slide into the overweight or obese categories. Forecasting suggests that while overweight will plateau, overweight as a precursor to obesity is still of concern, particularly for men where 45 percent are currently overweight. While this data are cross-sectional in nature and do not track weight gain in individuals, the upward shift in BMI of the population towards obesity has also been shown in longitudinal studies. The AusDiab study recruited 11,247 Australian adults (aged 25+ years) in 1999-2000 and followed them over a 12-year period (~55 percent of sample participated in follow-up data collection). The annual incidence of overweight was 2.6 percent and the annual incidence of obesity was 1.3 percent. For those individuals who were normal or overweight at baseline, 28.4 percent had progressed to a higher BMI category during follow-up. The reverse was not common; that is few obese individuals moved to a lower BMI category at follow-up (30).

Increases in BMI and obesity prevalence over the adult years for women relate to the reproductive transitions - during pregnancy (in the 30s) and menopause years (in the 50s) (31). The rate of increase in obesity has been highest for women of mid-childbearing age (32), and notably in our study this increase occurred at a faster rate than men at this age; however for men it stays elevated through the 30s and into their mid 40s. Longitudinal studies have also demonstrated that the rate of weight gain is highest amongst this age group of adults and declines with age (30,33). In the AusDiab study, the average weight gain over 12 years was 2.6kg for all age groups, however weight gain for those aged 25-34 years at baseline was 6.7kg compared to 0.4kg for those aged 55-64 years at baseline (30).

While our data is limited to the South Australian population, the Australian Longitudinal Study on Women's Health is a national population-based study, which also shows the rate of increase in BMI in greatest for young women of child bearing age (34). Excess weight gain during pregnancy and failure to return to pre-pregnancy weight within six months postpartum are predictors of long-term obesity (35-36) and many women cite pregnancy as one of the life-course events associated with the advent of weight gain in adulthood. Our projections suggest that, in the future, Australian mothers will be starting their pregnancy journey from a heavier baseline, which will further exacerbate weight management at this life stage. Further to this, there is a link between maternal obesity and an increased risk of obesity in their children meaning future generations will be at a greater risk of obesity (37). The FDA approach can effectively model the age-related changes in BMI over time, and therefore allow predictions for specific age groups to be made (11). The ability to identify sub groups across the whole population at greatest risk of obesity over time allows primary and secondary interventions to be targeted to particular life stages.

Strengths and limitations

This is the first published application of FDA to forecast overweight and obesity in an Australian or international population. The approach of initially smoothing the data and then using the smoothed observations for modelling and prediction estimation is a major methodological improvement to fit linear/non-linear trends of observed prevalence rates. A second strength of the FDA approach is the improved modelling of inconsistent increases in prevalence rates over time, and allows unstable trend and high variability of prevalence rates across ages to be captured in projections.

The key strength of the data used in this modelling is the standardised data collection method used across many years, in a large representative sample. However, in population surveys a common limitation is the use of self-reported height and weight which are subject to misreporting (38-39), and using self-reported measurements could underestimate the prevalence of overweight and obesity by 5 percent or more in males and female adults (40). Therefore in the context of our results, it is likely that the estimates of BMI and weight status are a conservative estimate of obesity, and the future prevalence may be even greater than projected.

Our forecasting models have used data collected continuously over ten years for South Australia, which is one jurisdiction, and accounts for 7.5 percent of the total Australian population. There are some differences in the demographic characteristics of South Australia compared to the Australia more generally, mainly as a consequence of the slightly older population (median age 39 vs 37 years nationally) (13) which influence estimates of overweight and obesity slightly, but we believe the forecasting is valuable more broadly given the widespread nature of obesity. Further forecasting analysis will examine other demographic sub-groups, as the most disadvantaged groups have been identified to be at greater risk of overweight and obesity (41-42). Also, a random telephone survey approach was used to collect data for this study and has been used extensively in the past. The increasing community reliance on the mobile network is thought not to impact on health estimates in telephone surveys (43), however this needs to be monitored to ensure telephone surveyed samples continue to be representative of the wider community.

The BMI, overweight and obesity may be varied for changing the policy in public health setting. The FDA forecasting did not take into account the impact of change in public health policy within an obesogenic environment, especially at state level. Although observational errors have been reduced through smoothing technique in the cases of changing rates over time, the change in public health policy may impact on the accuracy of the model.

Further research and action

The worldwide obesity epidemic indicates that poor diet and lack of physical activity are replacing smoking as the key behavioural determinants of preventable disease (2, 44). A vision for Australia to be the healthiest country by 2020 has been proposed but progress on implementing the full scope of the recommendations to reduce obesity has been limited (45). A comprehensive and integrated program of action to control population weight gain, at the level of the individual and environment, have been suggested (46-47), with strategies largely in line with the more recent nutrition and physical activity recommendations from the World Health Organization to prevent and manage non-communicable diseases that are major contributors to preventable mortality and morbidity (28). Obesity needs to be at the forefront of all government agendas. Past trends and future projections in Australia would suggest a major investment or shake up in the approach is required to attenuate the anticipated increase in diseases associated with increases in overweight and obesity.

Acknowledgments

This study uses data from the South Australian Monitoring and Surveillance System (SAMSS), which is managed by Population Research and Outcome Studies at the University of Adelaide, for the South Australian Department for Health and Ageing.

Funding

This work was supported by the South Australian Department for Health and Ageing who provided funding to establish the Physical Activity and Nutriton Observatory: Research and Monitoring Alliance (PANORAMA). All authors (except SU) were part of PANORAMA.

The authors declare no conflicts of interest.

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Figure 1. Principal Components From the Functional Data Analysis (FDA) for Male and Female BMI: the Mean BMI (Figures 1a and 1d), the First Basis Function (Figures 1b and 1e) and the Coefficient Associated with the First Basis Function (Figures 1c and 1f).

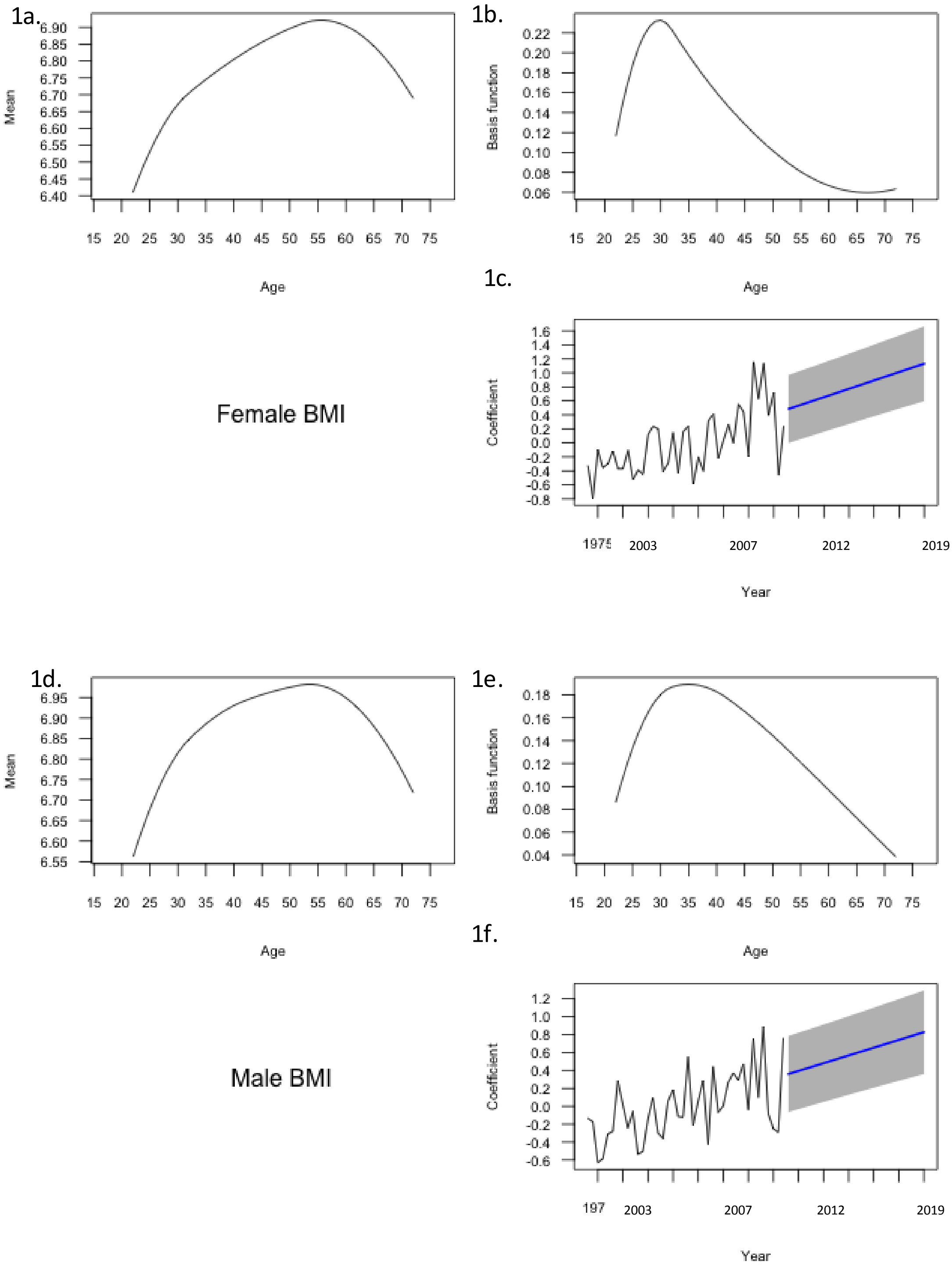
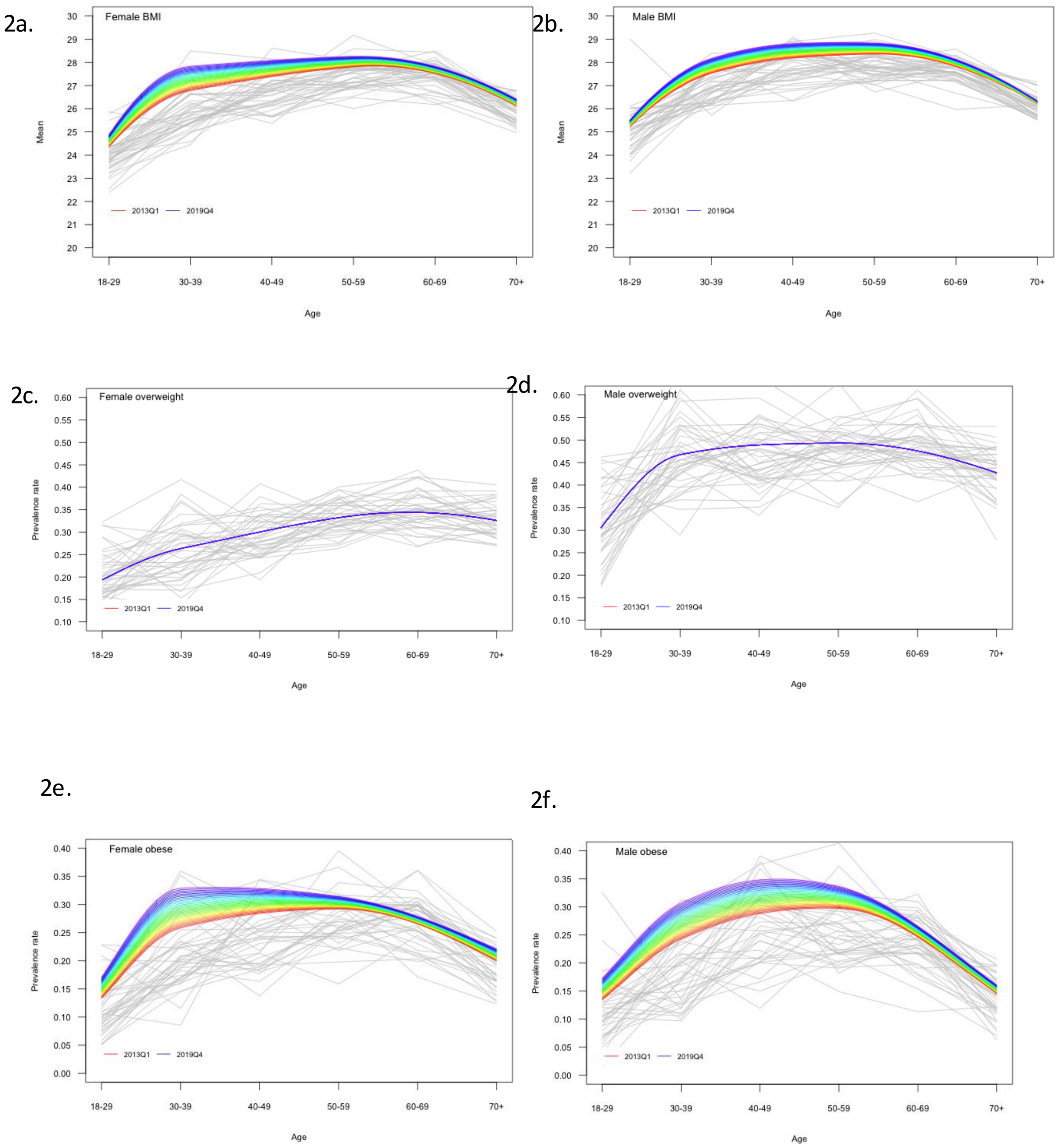
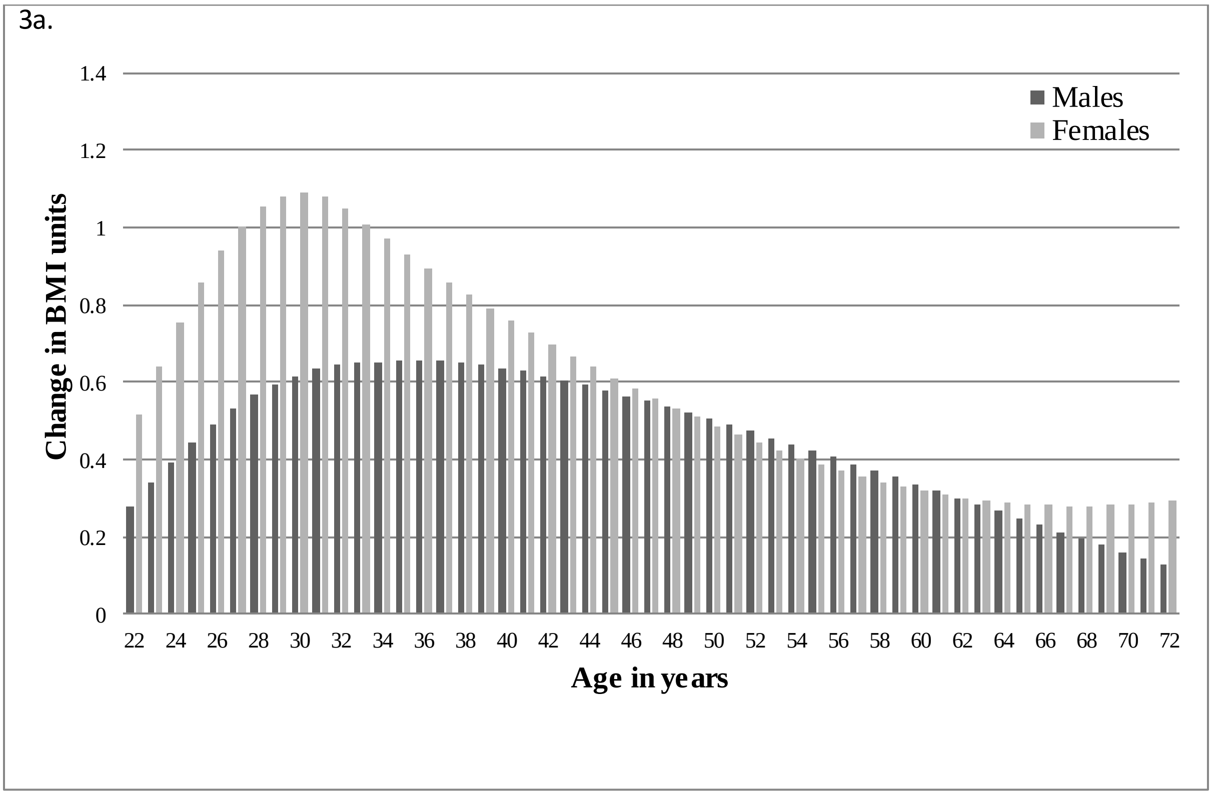


Figure 2. Functional Data Analysis Forecast of Female and Male BMI (2a & 2b), Overweight (2c & 2d) and Obesity (2e & 2f), From January 2013 to December 2019.



Female | Male

Figure 3: Forecasted Change in BMI (Figure 3a) and the Forecasted Change in Prevalence of Obesity (Figure 3b) From January 2013 to December 2019.



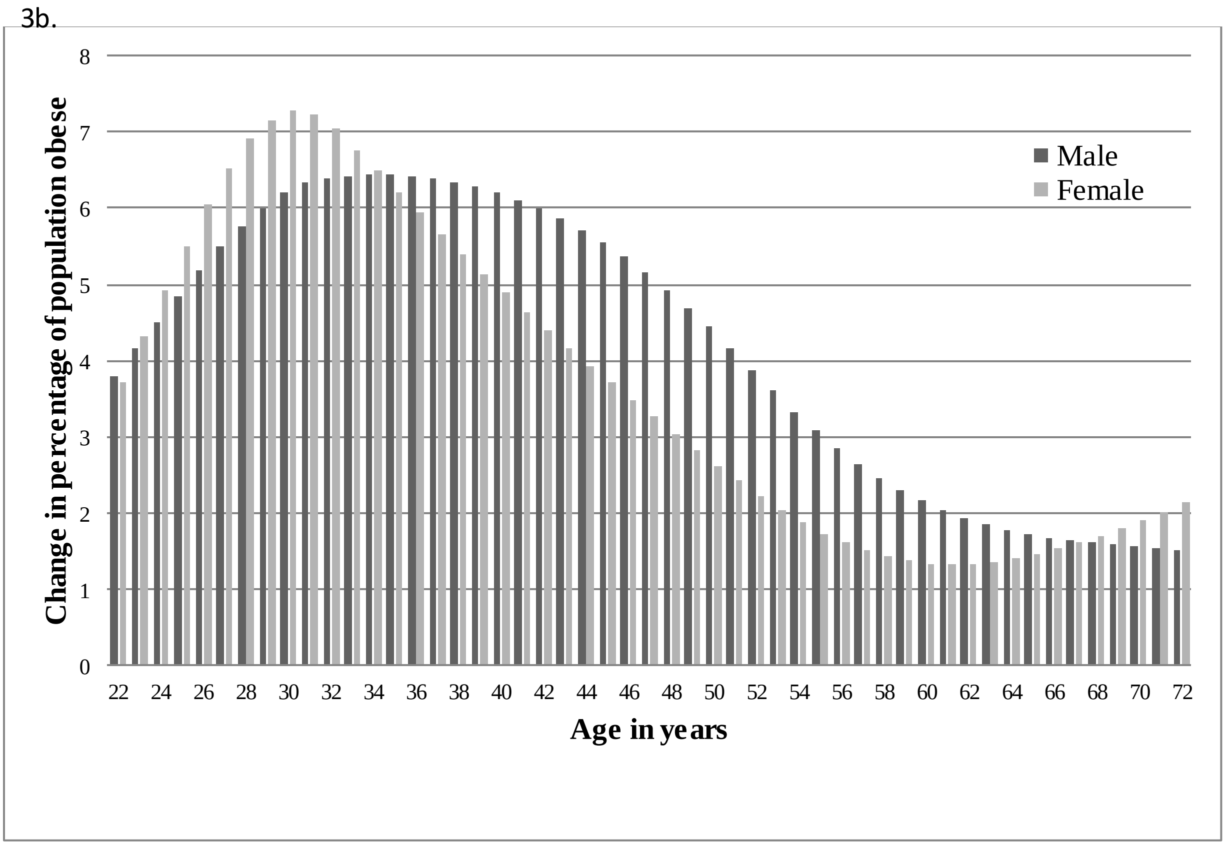
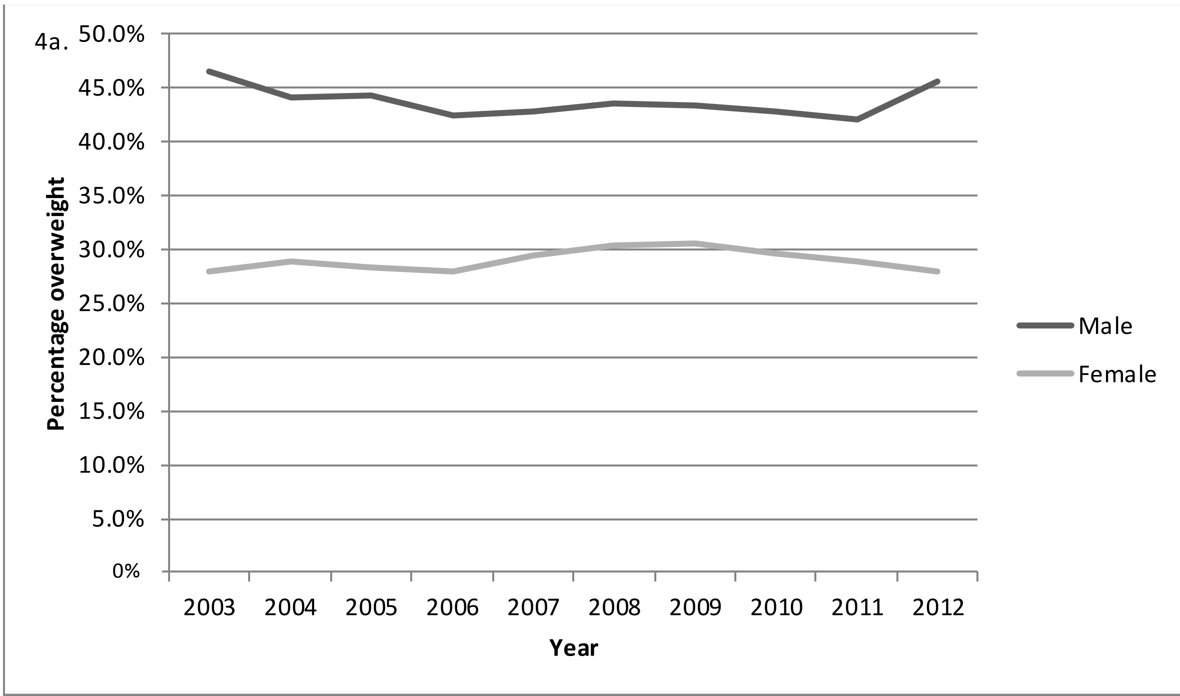


Figure 4: Prevalence of Overweight (Figure 4a) and Obesity (Figure 4b) in Males and Females, Using the South Australian Monitoring and Surveillance System, January 2003 to December 2012.



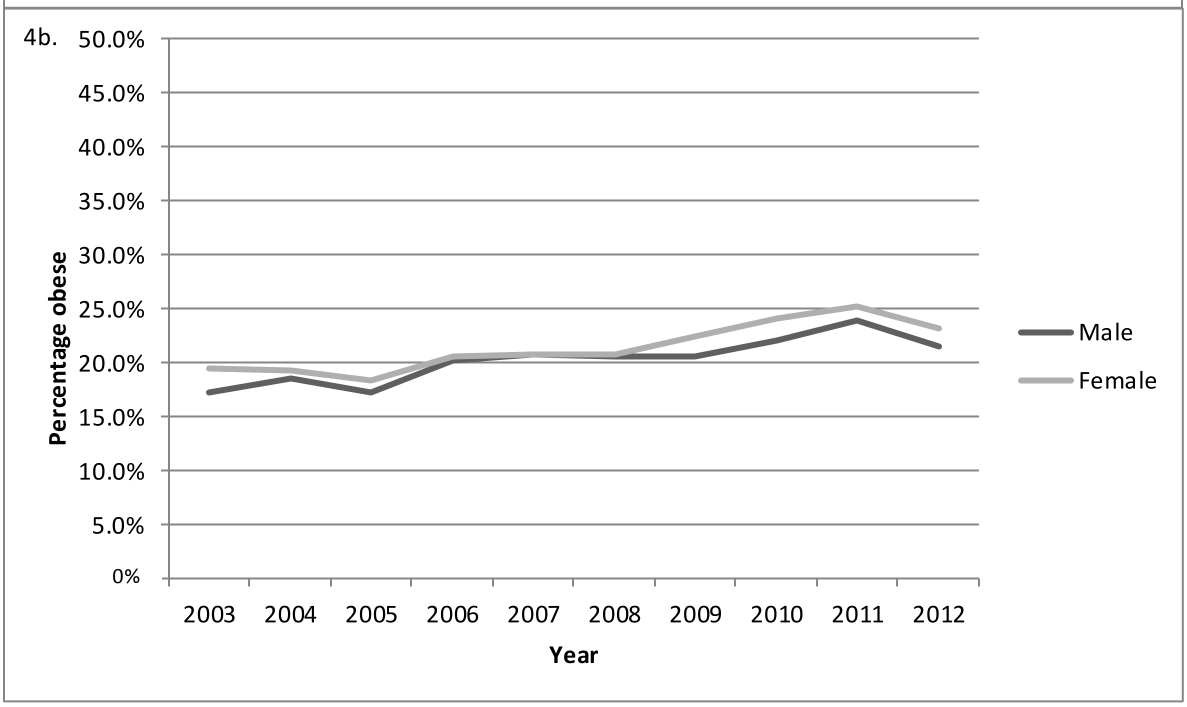


Figure 5. Principal Components From the Functional Data Analysis (FDA) for Male and Female Obesity: the Mean Prevalence of Obesity (Figures 5a and 5d), the First Basis Function (Figures 5b and 5e) and the Coefficient Associated With the First Basis Function (Figures 5c and 5f)

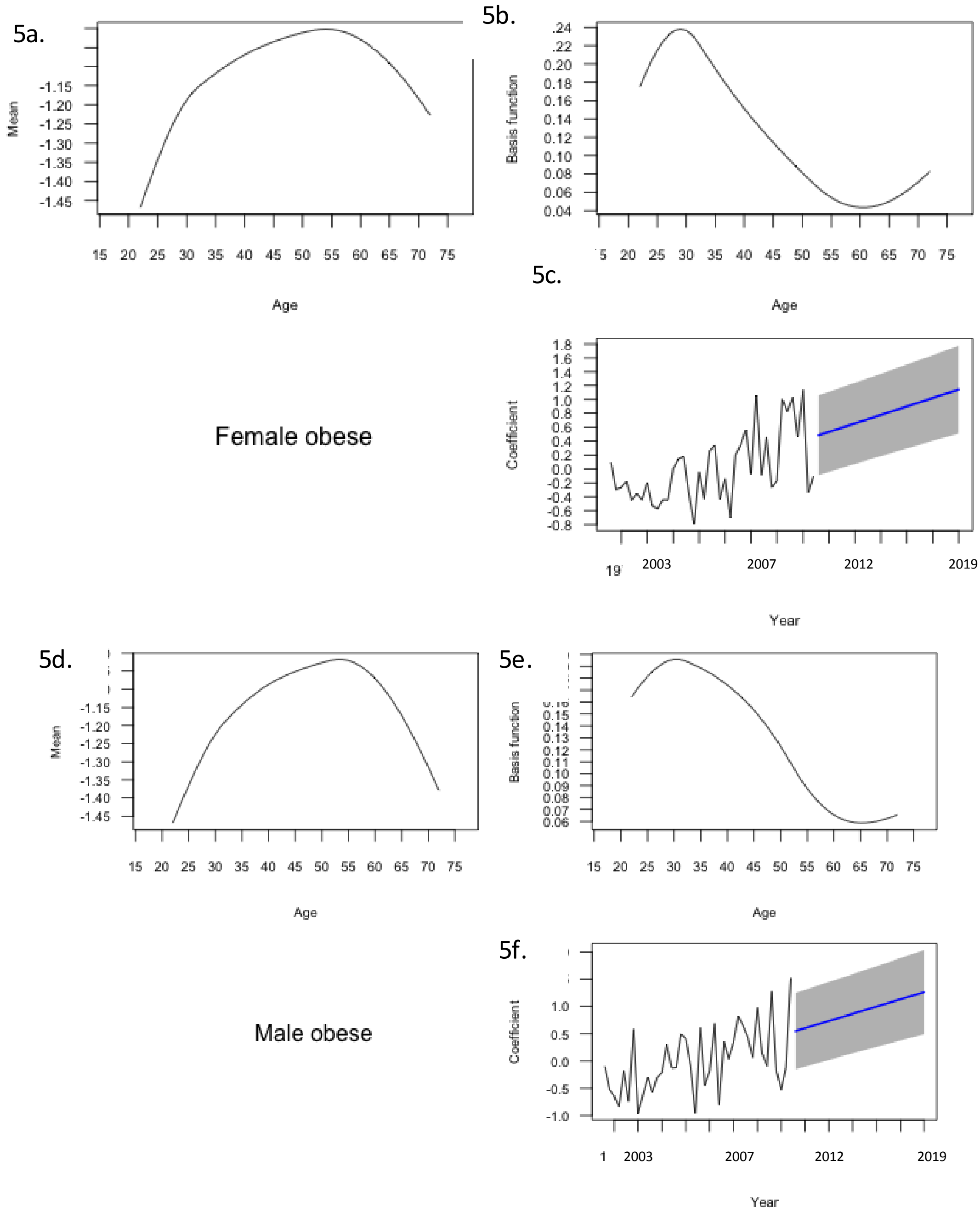


Table 1: Average Body Mass Index by Age and Gender Groups, Using the South Australian Monitoring and Surveillance System, January 2003 to December 2012.

		2003		2004		2005		2006		2007	
	Age group	Mean	(SD)	Mean	(SD)	Mean	(SD)	Mean	(SD)	Mean	(SD)
Male	18-24	24.94	(4.10)	23.83	(3.75)	24.19	(5.13)	24.50	(4.39)	23.60	(3.59)
	25-34	26.16	(4.02)	26.26	(4.13)	26.01	(3.78)	26.30	(4.45)	26.29	(4.52)
	35-44	27.34	(5.43)	27.54	(4.38)	26.86	(4.24)	27.37	(4.25)	27.91	(4.37)
	45-54	27.73	(4.69)	27.67	(4.95)	27.37	(4.42)	27.69	(4.76)	27.88	(4.26)
	55-64	26.99	(4.59)	27.82	(4.34)	27.55	(4.30)	27.73	(4.62)	27.78	(4.34)
	65+	26.25	(3.82)	26.26	(4.28)	26.47	(4.96)	26.13	(4.06)	26.49	(4.02)
Overall males		26.68	(4.60)	26.74	(4.53)	26.52	4.56)	26.76	(4.54)	26.86	(4.44)
Female	18-24	23.27	(5.40)	23.00	(4.28)	23.24	(4.53)	23.04	(4.36)	22.99	(4.19)
	25-34	25.35	(5.86)	24.91	(5.45)	24.83	(5.41)	25.17	(5.50)	25.22	(5.29)
	35-44	25.98	(5.71)	25.92	(5.91)	25.89	(5.76)	26.74	(5.70)	26.45	(6.34)

	45-54	26.39	(5.59)	26.64	(5.49)	27.09	(6.43)	26.54	(5.77)	27.47	(6.20)
	55-64	26.89	(5.37)	27.32	(5.42)	27.10	(5.81)	27.61	(5.73)	27.49	(5.68)
	65+	26.07	(5.30)	26.09	(4.91)	25.74	(5.48)	26.07	(5.19)	26.24	(5.10)
Overall females		25.78	(5.64)	25.80	(5.46)	25.79	(5.78)	26.03	(5.59)	26.21	(5.76)

Table 1: continued

		2008		2009		2010		2011		2012	
	Age group	Mean	(SD)	Mean	(SD)	Mean	(SD)	Mean	(SD)	Mean	(SD)
Male	18-24	23.73	(4.43)	24.71	(4.29)	24.24	(3.92)	24.31	(5.17)	25.02	(4.82)
	25-34	26.85	(4.70)	25.86	(4.10)	26.77	(4.89)	26.76	(4.54)	27.06	(5.01)
	35-44	27.76	(4.76)	27.81	(4.73)	27.79	(4.59)	28.28	(4.98)	26.95	(4.70)
	45-54	28.25	(4.65)	28.19	(5.40)	28.20	(4.75)	28.51	(5.53)	28.01	(4.63)
	55-64	27.86	(4.81)	28.11	(4.89)	27.65	(4.53)	28.31	(4.75)	27.91	(4.58)
	65+	26.42	(4.42)	26.73	(4.61)	26.97	(4.83)	26.74	(4.65)	27.23	(4.76)
Overall males		27.02	(4.83)	27.04	(4.86)	27.12	(4.77)	27.34	(5.12)	27.18	(4.82)

Female	18-24	23.23	(4.87)	22.88	(4.59)	23.60	(4.80)	23.38	(5.11)	23.39	(5.10)
	25-34	25.24	(4.74)	26.16	(5.50)	25.62	(5.51)	26.19	(7.45)	25.40	(6.34)
	35-44	25.88	(5.69)	26.62	(5.69)	26.63	(5.62)	27.74	(6.91)	26.58	(5.84)
	45-54	27.35	(5.74)	27.43	(5.70)	27.81	(6.04)	28.20	(6.65)	27.42	(6.36)
	55-64	27.58	(5.58)	27.26	(5.51)	27.87	(5.89)	27.62	(5.57)	27.78	(5.85)
	65+	26.42	(5.68)	26.48	(5.35)	26.85	(5.69)	26.71	(5.43)	26.58	(5.29)
Overall females		26.12	(5.60)	26.37	(5.60)	26.60	(5.80)	26.88	(6.43)	26.40	(5.98)