The Analysis and Interpretation of Performance Data for Area Health Services in New South Wales

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EXECUTIVE SUMMARY

The primary objective of the Analysis and Interpretation of Performance Data for Area Health Services (AIPA) project is, through exploratory statistical analysis, to recommend a robust, scientific trend prediction methodology for use by the NSW Department of Health when setting health targets for key health indicators at the area health services level.

This review of current trend setting methods used to monitor and assess progress towards targets has been undertaken in conjunction with the Centre for Statistical and Survey Methodology at the University of Wollongong. This report reviews how objectives and targets are set, clarifies the statistical properties of the current methods, identifies improvements to the analysis and interpretation of survey based performance measures using relatively simple statistical methods, identifies more sophisticated methods that might be useful, and compares possible model-based methods of trend analysis for healthy lifestyle indicators by area health service.

Of interest to this project are the following 8 healthy lifestyle indicators:

- Risk alcohol drinking
- Overweight or obesity
- Obesity
- Recommended fruit consumption
- Adequate physical activity
- Current smoking
- Recommended vegetable consumption
- 3 or more servings of vegetables per day

These indicators are collected through the NSW Population Health Survey for the area health services. The Survey has collected information on these healthy lifestyle indicators annually since 2002. Data are also available for 1997 and 1998. Based on the annual data from 2002 onwards, monthly time series estimates for the state and each area can be produced.

It is important to set reasonable annual targets for the future performance of the area health services, based on current trends in these healthy lifestyle indicators. The current sample size provides reasonably resilient annual state estimates but this is not the case for the area health services, which are more volatile.

The 2006 area health service reports were released in April 2007. They include, for each indicator, the actual prevalence estimates, with 95% confidence intervals, as well as a smoothed line and predictions for 2007 using the Holt exponential smoothing model. For comparisons between years and target setting, it is advisable to use the predicted prevalence estimates and the forecast estimates for 2007.

Using the currently available 5 years of monthly data (2002–2006), linear regression analysis has detected evidence of seasonality in some indicators and statistically significant changes over time at the state level. Statistically significant changes over time have also been detected at the health area level but it is difficulty to detect seasonality. There is no evidence of variation of the seasonal effect or linear trends between the health areas and so use of a regression model with constant seasonal effects and linear trends can help in assess trends. There is clear evidence of differences in the prevalence levels between health areas.

As more data becomes available in the future, the X11 based trend is a useful smoother, which can supplement the regression analysis and help identify non-linear trends.

1. INTRODUCTION

The NSW Health Survey Program monitors health behaviours, health status, use of and satisfaction with health services, and other factors that influence the health of the people of New South Wales. The core activity of the program is the New South Wales Population Health Survey, which is designed to produce estimates at the level of the 8 area health services. These estimates and data from other sources can be used to monitor trends in important indicators and in setting and assessing the achievement of performance targets.

The estimates obtained from the survey are subject to sampling variability, which needs to be accounted for when interpreting the trends and progress towards achieving targets. This report reviews how current objectives and targets are set and clarifies the statistical properties of the current methods used to monitor and assess progress towards targets. The report also identifies improvements to the analysis and interpretation of survey based performance measures using relatively simple statistical methods. More sophisticated methods that might be useful are also identified.

The healthy lifestyle performance indicators for the area health services (alcohol risk drinking behaviour, current smoking, overweight or obesity, obesity, adequate physical activity and recommended fruit and vegetable intake) are collected through the New South Wales Population Health Survey. Information on these healthy lifestyle indicators have been collected annually in the NSW Population Health Survey since 2002 and are available for 1997 and 1998.

Setting reasonable annual targets for future performance of area health services on the basis of current trends in these healthy lifestyle indicators are of great importance and interest. The current sample size provides reasonably resilient annual state estimates, but this is not the case for health areas.

The purpose of this report is to explore new ways to monitor progress and set targets on the healthy lifestyle indicators by health area. This report reviews current methods used to monitor and assess progress towards targets. A comparison of possible model-based smoothed trends is undertaken for health area healthy lifestyle indicators. Model-based smoothing trend analysis methods are identified which can be used to predict health area risk factor prevalence estimates.

This report includes the following:

- review of how current objectives and targets are set;
- clarification of the statistical properties of the current methods;
- identification of improvements to the analysis and interpretation of survey based performance measures using relatively simple statistical methods;
- identification of more sophisticated methods that might be useful;
- comparison of possible model-based trend analysis methods for health area healthy lifestyle indicators.

2. NSW POPULATION HEALTH SURVEY

2.1 Sample Design

The NSW Population Health Survey is a telephone survey of the population of usual residents of NSW in private households. The survey was first conducted in 1997 and 1998 when a sample of approximately 17,000 adults was selected throughout the calendar year. The population was stratified into 17 strata corresponding to the 17 area health services that existed at that time. Approximately equal sample sizes were used in each stratum to give approximately the same accuracy on the area level estimates. The sample was reintroduced in 2002 with a total sample of approximately 13,000 adults and 3,000 children and has been conducted ever since. Following the reorganisation into 8 area health services, the sample was redesigned to achieve a minimum of 1000 adult respondents in each of the new areas. The areas were reorganized into 8 during 2004 and the sample was reduced during 2004 but because it was partway during the year the stratification was not changed until the beginning of 2005. The 2004 report reported on the new areas following the weighting adjustment to the new areas. In 2005 and 2006, approximately equal sample sizes have been obtained in each of the current health areas. For previous years the sample sizes vary between areas because of the merger of areas.

A sample of households is selected using Random Digit Dialling (RDD). One person is selected at random from the usual residents in the selected household. Children are included in the survey with the information provided by a person aged over 16. Table 1 gives the responding sample for the state for each year that the survey has been conducted. All the key measures for which targets are set refer to adults and so it is the adult sample size that is relevant to them.

Table 1: Summary of NSW Population Health Survey Sample Sizes

	1997	1998	2002	2003	2004	2005	2006
Adults	17543	17494	12622	13008	9786	11500	7962
Total	17543	17494	15442	15837	11830	13704	10346

The sampling frame is created by using 4 digit prefixes that contain working residential numbers (WRNs) in the Electronic White Pages (EWPs). Banks of 10 contiguous numbers with no numbers in the EWP are removed from the sampling frame. To improve the efficiency of the data collection the frame is matched with the Yellow Pages to remove business numbers.

The stratification of the sampling frame according to area health services is achieved by geocoding all the numbers present in the EWP using the listed address. Telephone numbers not listed in the EWP with the same prefix are allocated to the area with the highest proportion of numbers listed in the EWP.

The resulting eligible numbers are then randomly ordered and divided into regions. The survey is spread throughout the year, by enumerating approximately a quarter of the sample each quarter. Numbers are called with an aim of achieved a prescribed sample of 250 respondents in each area. However, the responding sample in each quarter will not be exactly 25% of the annual sample. At the state level there is no sample in January. At the area level there are an additional 11 instances of months with no sample.

2.2 Sample Weighting

In general sample weighting procedures serve three purposes. They are designed to:
- account for different chances of selection,
- adjust for variation of the sample from the population due to random selection,
- adjust for potential non-response bias.

The different chances of selection are accounted for by using the inverse of the probability of selection. In this survey the selection probabilities vary because:
- different sampling fractions are used to select telephone numbers in each region,
- the probability of selection of a household is proportional to the number of telephone lines connected,
- selecting 1 person per household means that a person's selection probability is inversely proportional to the number of usual residents in the selected household.

The weighting procedure used accounts for the variation in selection probabilities. It also adjusts to the age-sex population structure as given by ABS population estimates. The weighting is carried out on a quarterly basis, although monthly estimates can be produced.

2.3 Design Effects

The effect of the sample design and weighting on sampling variances can be conveniently summarised through the design effect (*deff*), which is the ratio of the variance of an estimate to the variance that would have been obtained is a Simple Random Sample (SRS) of the same size had been used. An attractive feature of the *deff* is that it is scale invariant and can be compared across different variables. For each area, there has been no stratification and an approximation that can be useful is $deff \approx 1 + CV_w^2$, where CV_w is the coefficient of variation of the weights. This formula rests on some assumptions.

The variation in weights increases the standard errors of estimates. In the 2005 survey the coefficient of variation of the weights within a health area varied from 0.67 to 0.79, suggesting a design effect of around 1.45 to 1.62. Because of the variation in sampling fractions between areas, the CV of the weights across the state is 0.97 suggesting a *deff* of 1.94.

Standard error and confidence intervals that account for the stratification and weighting are produced using PROC SURVEYMEANS in SAS. The variables for which performance is monitored and targets are set are listed in section 3. The *deff* varies a little across the variables. For 2005 the *deff* averaged across the six indicators and the 8 health areas was 1.54 and at the state level it was 1.89. In subsequent calculations we will assume a *deff* of 1.5 for health area estimates and 1.9 for state estimates. Comparison of the factor $1 + CV_w^2$ with the estimated *deff* showed reasonable consistency.

3. CURRENT APPROACH TO SETTING TARGETS AND MONITORING PROGRESS

The indicators that are the main focus of monitoring and target setting are for persons aged 16 years and over:

- Risk alcohol drinking behaviour
- Overweight and obesity (that is, BMI of 25 and over)
- Obesity (that is, BMI of 30 and over)
- Recommended fruit consumption (that is, 2 or more serves per day)
- Adequate physical activity (that is, 150 minutes per week over 5 separate occasions)
- Current smoking (that is, daily or occasional smoking)
- Recommended vegetable consumption (that is, 5 serves or more per day)
- Three or more serves of vegetables

In 2004 requests for “dashboard indicators” occurred from the Performance Branch as part of the “dashboard” process. Staff in the area health services then began contacting the NSW Health Survey Program regarding setting targets for their area with regard to the healthy lifestyle indicators. The suggested targets were:

- Smoking and risky alcohol consumption should go down;
- Overweight and obesity should not continue to increase;
- Fruit and vegetables should go up.

Actual values were required so it was suggested a small amount in the appropriate direction should be added i.e. +1%.

4. ANALYSIS AND INTERPRETATION OF SURVEY-BASED PERFORMANCE MEASURES

Because the estimates used in monitoring are based on a sample survey they may differ from the values that would have been obtained from a census using the same methods. This is reflected in the standard error (SE). For reasonable sample sizes the distribution of the sample estimates will be approximately normal and so there is a 95% chance the sampling error is less than 2 standard errors, a 66% chance it is less than one standard error, a 50% chance it is less than 0.7 SEs. Typically we assess estimates by considering 95% confidence intervals.

For estimates based on small samples we cannot assume normality of their distribution and asymmetric confidence intervals can be produced.

4.1 Standard Errors on Estimates of Prevalence Levels.

To illustrate the possible SEs, Table 2 summarises the SEs on estimates of levels corresponding to a prevalence of 10%, 20% and 50% for sample sizes of 8,000, 1000, 250, 80, corresponding roughly to annual state and area estimates respectively and quarterly and monthly area estimates for the current sample size. Design effects of 1.90 for state estimates and 1.5 for area estimates have been assumed. These are the average values found in 2005. SEs for previous years may be a bit smaller than indicated by Tables 2 because of the larger sample sizes used.

Table 2: SEs on prevalence estimates–percentage points

	Prevalence		
Sample Size	10%	20%	50%
8,000	**0.46**	**0.62**	**0.77**
1,000	**1.16**	**1.55**	**1.94**
250	**2.32**	**3.10**	**3.87**
80	**4.11**	**5.48**	**6.85**

A prevalence of 10% approximates the proportion of adults consuming 5 or more serves of vegetables a day, 20% the level of smoking and most of the remaining indicators are around 50%. The SEs on the annual state level estimates are around 0.5% to 0.8% and at the area level they vary between 1% and 2%. These results show that the area level estimates will have SEs about 2.5 times the SEs of the corresponding state level estimates. The quarterly and monthly area level estimates have SEs of between 2% and 7%.

4.2 Standard Errors on Estimates of Changes in Prevalence Levels.

To assist in interpreting what these SEs mean we need to consider how survey estimates can be used to assess performance and trends. There are several ways that a continuing survey such as the NSW Population Health Survey can be used. For health area *r* let $\hat{Y}_{rm}$ be the survey estimate at month *m*, $\hat{Y}_{rq}$ the estimate for quarter *q* and $\hat{Y}_{ra}$ the estimate for year *a* and in general the estimate for time period *t* is $\hat{Y}_{rt}$. State estimates are denoted $\hat{Y}_t$.

A key feature of a repeated survey is the ability to provide estimates of change, such as

$$\hat{Y}_t - \hat{Y}_{t-s} = \Delta^{(s)}\hat{Y}_t .$$

The focus is often on s=1, but for a survey repeated on a monthly basis changes for s=2, 3, 12 are also commonly examined. For annual estimates changes over the last 3 years and since some base period may be examined.

Since the samples at different time periods have no overlap they are effectively independent and so

$$Var(\Delta^{(s)}\hat{Y}_t) = Var(\hat{Y}_t) + Var(\hat{Y}_{t-s}) \qquad (1)$$

Table 3 gives the SEs on estimates of changes when both estimates are based on the indicated sample size. These results suggest that in looking at changes between years we should expect SEs of about 1% for state level estimates and 2 to 3% on area level estimates. Remember that 95% confidence intervals are obtained be adding and subtracting twice the SE to the estimate.

Table 3: SEs on estimates of change between prevalence estimates: percentage points

	Prevalence		
Sample Size	10%	20%	50%
8,000	**0.65**	**0.87**	**1.09**
1,000	**1.64**	**2.19**	**2.74**
250	**3.29**	**4.38**	**5.48**
80	**5.81**	**7.75**	**9.68**

Table 4 gives the SE when the comparison is between the current estimate and the average of the 1997 and 1998 base year estimates. These are slightly smaller than the corresponding SEs in Table 3 because of the larger sample size in the base years.

Table 4: SEs on estimates of change from base years

	Prevalence		
Sample Size	10%	20%	50%
8,000	**0.51**	**0.68**	**0.85**
1,000	**1.29**	**1.72**	**2.15**
250	**2.58**	**3.43**	**4.29**
80	**4.55**	**6.07**	**7.59**

There may also be interest in changes in the rate of change, such as

$$\Delta^{(s)}\hat{Y}_t - \Delta^{(s)}\hat{Y}_{t-k} = \hat{Y}_t - \hat{Y}_{t-s} - (\hat{Y}_{t-k} - \hat{Y}_{t-k-s}).$$

If s=k this becomes

$$\Delta^{(s)}\hat{Y}_t - \Delta^{(s)}\hat{Y}_{t-s} = \hat{Y}_t - 2\hat{Y}_{t-s} + \hat{Y}_{t-2s}.$$

4.3 Using Probabilities of Changes of Correct Sign or Statistical Significance

To assist in interpreting the impact of sampling errors on estimates of changes we can look at two aspects;

- the probability that the change is in the correct direction;
- the probability that the change is statistically significant.

Both of these probabilities depend on the true change $Y_t - Y_{t-s} = \Delta^{(s)} Y_t$.

We assume that the sample size is large enough so that the distribution of the sample estimates are approximately normal so that $\frac{\Delta^{(s)}\hat{Y}_t - \Delta^{(s)} Y_t}{\sqrt{Var(\Delta^{(s)}\hat{Y}_t)}}$ and $\frac{\Delta^{(s)}\hat{Y}_t - \Delta^{(s)} Y_t}{\sqrt{\hat{V}ar(\Delta^{(s)}\hat{Y}_t)}}$ both have a standard normal distributions. Let Z have a standard normal distribution and $\Phi(x) = \Pr ob(Z \le x)$ is the associated cumulative distribution function. The probability that the estimated change if positive is

$$\Pr(\Delta^{(s)}\hat{Y}_t > 0) = \Pr\left(\frac{\Delta^{(s)}\hat{Y}_t - \Delta^{(s)} Y_t}{\sqrt{Var(\Delta^{(s)}\hat{Y}_t)}} > \frac{-\Delta^{(s)} Y_t}{\sqrt{Var(\Delta^{(s)}\hat{Y}_t)}}\right) = 1 - \Phi\left(\frac{-\Delta^{(s)} Y_t}{\sqrt{Var(\Delta^{(s)}\hat{Y}_t)}}\right) \qquad (3)$$

Using a two-sided 95% confidence interval the estimated change will be treated as statistically significant if $abs\left(\frac{\Delta^{(s)}\hat{Y}_t}{\sqrt{\hat{V}ar(\Delta^{(s)}\hat{Y}_t)}}\right) > 1.96$. The probability of this occurring is approximately

$$\Phi\left(-1.96 - \frac{\Delta^{(s)} Y_t}{\sqrt{Var(\Delta^{(s)}\hat{Y}_t)}}\right) + 1 - \Phi\left(1.96 - \frac{\Delta^{(s)} Y_t}{\sqrt{Var(\Delta^{(s)}\hat{Y}_t)}}\right) \qquad (4)$$

However, this includes the possibility of a statistically significant change of the incorrect direction. The probability that the change is statistically significant and in the correct direction is more relevant. If we have no prior belief on the direction of the change this would be, for a positive true change

$$1 - \Phi\left(1.96 - \frac{\Delta^{(s)} Y_t}{\sqrt{Var(\Delta^{(s)}\hat{Y}_t)}}\right) \qquad (5)$$

For a given true change and known variance of the estimates involved we can use (3) and (5) to examine these probabilities. Tables 5 to 8 give a simple example for estimates of change when the prevalence is 20% and 50% for sample sizes of 8,000 (*deff*=1.9) and 1000 (*deff*=1.5), and an annual increase of 0.5, 1 and 2 percentage points for analysis of change over s=1, 2, 3 years.

Table 5: Prob (%) of change of correct sign, for prevalence of 20%

	Analysis of Change over								
	1 year			2 years			3 years		
	Annual Rate of Change (%)			Annual Rate of Change (%)			Annual Rate of Change (%)		
Sample Size	0.5	1	2	0.5	1	2	0.5	1	2
8,000	**72**	**87**	**99**	**87**	**99**	**100**	**96**	**100**	**100**
1,000	**59**	**68**	**82**	**68**	**82**	**97**	**75**	**91**	**100**

Table 6: Prob (%) of statistically significant change of correct sign, for prevalence of 20% – two sided 5% test

Sample Size	1 year			2 years			3 years		
	Annual Rate of Change (%)			Annual Rate of Change (%)			Annual Rate of Change (%)		
Sample Size	0.5	1	2	0.5	1	2	0.5	1	2
8,000	**8**	**21**	**63**	**21**	**63**	**100**	**41**	**93**	**100**
1,000	**5**	**7**	**15**	**7**	**15**	**45**	**10**	**28**	**78**

Table 7 : Prob (%) of change of correct sign, for prevalence of 50%

	Analysis of Change over								
	1 year			2 years			3 years		
	Annual Rate of Change (%)			Annual Rate of Change (%)			Annual Rate of Change (%)		
Sample Size	0.5	1	2	0.5	1	2	0.5	1	2
8,000	**68**	**82**	**97**	**82**	**97**	**100**	**93**	**100**	**100**
1,000	**57**	**64**	**77**	**64**	**77**	**93**	**71**	**86**	**99**

Table 8 : Prob (%) of statistically significant change of correct sign, for prevalence of 50 % – two sided 5% test

	1 year			2 years			3 years		
	Annual Rate of Change (%)			Annual Rate of Change (%)			Annual Rate of Change (%)		
Sample Size	0.5	1	2	0.5	1	2	0.5	1	2
8,000	**7**	**15**	**45**	**15**	**45**	**96**	**28**	**79**	**100**
1,000	**4**	**6**	**11**	**6**	**11**	**31**	**8**	**19**	**59**

These results suggest that if the underlying rate of change is 1% a year then there is a reasonably high chance that at the NSW level the survey estimates will correctly indicate the direction after 1 or 2 years and produce a statistically significant results after 3 years. At the health area level there is a reasonably high chance that the survey estimates will correctly indicate the direction after 2 or 3 years and produce a statistically significant results well after 3 years.

Tables 9 give the size change needed to have a 90% chance of the estimated change being in the correct direction and also the size needed to have an 80% chance of a statistically significant change in the correct direction, for prevalence of 10%, 20% and 50%. These results are for comparing two years with the indicated sample sizes. Table 10 give corresponding results for comparisons with the average of the two base years.

Table 9: Changes (%) needed for change of correct sign, statistically significant, for prevalence of 10, 20, and 50%

Sample Size	90% Chance Correct Sign			80% Chance Stat Sig		
	Prevalence			Prevalence		
	10%	20%	50%	10%	20%	50%
8,000	**0.84**	**1.12**	**1.39**	**1.83**	**2.44**	**3.05**
1,000	**2.10**	**2.80**	**3.51**	**4.60**	**6.13**	**7.67**

The results suggest that at the state level true changes of about 1% give a high chance of the estimated change being in the correct direction. At the area level changes of around 3% are needed. To have about an 80% chance of obtaining statistical significance at the state level a true change of about 3% is needed, whereas at the area level a true change of about 7% is needed. At the area level we would expect change of 3% or 7% to take several years to occur, which suggests that analysis should examine changes over at least 3 years.

Table 10: Changes needed for change of correct sign, statistically significant, for prevalence of 10, 20, 50%, comparison with base years

Sample Size	90% Chance Correct Sign			80% Chance Stat Sig		
	Prevalence			Prevalence		
	10%	20%	50%	10%	20%	50%
8,000	**0.66**	**0.87**	**1.09**	**1.43**	**1.91**	**2.39**
1,000	**1.65**	**2.20**	**2.75**	**3.61**	**4.81**	**6.01**

Because the SEs for comparison with the base years are a little smaller the size change needed to have a reasonable chance of a change of the correct sign or a statistically significant change are somewhat lower. As time goes on comparisons with the base years will be less useful in reflecting current trends.

5. GRAPHICAL PRESENTATION OF CONFIDENCE INTERVALS ON IMPORTANT CHANGES

It would be useful to use simple graphical methods to communicate how to interpret changes in the series of estimate to users and analysts.

Suppose the main focus is on $\Delta^{(s)}\hat{Y}_t$. An approximate 95% confidence interval for $\hat{Y}_t$ can be constructed as $\hat{Y}_t - 2\sqrt{\hat{V}ar(\hat{Y}_t)}$ to $\hat{Y}_t + 2\sqrt{\hat{V}ar(\hat{Y}_t)}$, where $\hat{V}ar(\hat{Y}_t)$ is an estimate of the variance of accounting for the sample design. Similar confidence interval can be constructed for $\hat{Y}_{t-s}$.

Plotting these intervals for each time point is valid for indicating the confidence interval for each estimate. However, if users examine whether or not these confidence intervals overlap to assess the statistical significance of the change then they will be in error, as they imply a confidence interval of

$$\hat{Y}_t - \hat{Y}_{t-s} - 2\left(\sqrt{\hat{V}ar(\hat{Y}_t)} + \sqrt{\hat{V}ar(\hat{Y}_{t-s})}\right) \text{ to } \hat{Y}_t - \hat{Y}_{t-s} + 2\left(\sqrt{\hat{V}ar(\hat{Y}_t)} + \sqrt{\hat{V}ar(\hat{Y}_{t-s})}\right)$$

instead of an appropriate interval of

$$\hat{Y}_t - \hat{Y}_{t-s} - 2\left(\sqrt{\hat{V}ar(\Delta^{(s)}\hat{Y}_t)}\right) \text{ to } \hat{Y}_t - \hat{Y}_{t-s} + 2\left(\sqrt{\hat{V}ar(\Delta^{(s)}\hat{Y}_t)}\right),$$

where $Var(\Delta^{(s)}\hat{Y}_t)$ is given by (1). Using the inappropriate confidence interval will lead to a loss of power, that is it may lead to some differences that are statistically significant not be designated as such. It is equivalent to using a 0.05^2 =0.005 significance level in the testing or equivalently a 99.75% confidence interval for the change.

Assume $Var(\hat{Y}_t) \approx Var(\hat{Y}_{t-s})$. If we scale the original confidence intervals on the estimates of levels by a factor of $\sqrt{\frac{1}{2}}$, that is use

$$\hat{Y}_t - \sqrt{2}\sqrt{\hat{V}ar(\hat{Y}_t)} \text{ to } \hat{Y}_t + \sqrt{2}\sqrt{\hat{V}ar(\hat{Y}_t)},$$

then the confidence interval for $\hat{Y}_t - \hat{Y}_{t-s}$ implied by looking at whether the intervals overlap is appropriate.

When the two variances are different each of the original confidence intervals can be scaled by a factor of $\frac{\sqrt{1+k_{t,t-s}}}{1+\sqrt{k_{t,t-s}}}$, where $k_{t,t-s} = \frac{\hat{V}ar(\hat{Y}_{t-s})}{\hat{V}ar(\hat{Y}_t)}$. The appropriate scale factor now depends the particular time periods being compared.

6. ANALYSIS USING REGRESSION

6.1 Overview

Monthly estimates can be produced from the survey, although for January there is no sample at the state level and another 11 cases there is no sample for some months at the area level. Monthly estimates will have high SEs associated with them and cannot be analysed by themselves or by looking at changes between any two months as shown by the SEs in Tables 2 and 3. However, analysis of the time series of monthly estimates may provide further insights into the patterns of change and trend in the date. In a five yearly period we will only have 5 annual estimates, but will have 55 monthly estimate albeit with higher variances associated with them. Analysis of monthly estimates may reveal important changes more quickly and enable better assessments of trends than analysis of annual estimates.

A relatively straightforward way to investigate the properties of the monthly times series is to use a regression approach. The basic model can include terms reflecting trend and the possibility of seasonal effects relating to the month of the year.

The monthly trend, T_t, can be included as

1. no trend, $T_t = \beta_0$
2. linear, $T_t = \beta_0 + \beta_1 t$
3. quadratic, $T_t = \beta_0 + \beta_1 t + \beta_2 t^2$
4. cubic time trend, $T_t = \beta_0 + \beta_1 t + \beta_2 t^2 + \beta_3 t^3$

Changes in the true level of the variable of interest may not follow such well-behaved functions of time. A potentially useful approach is to include a term for each year. If no other terms are in the model then this analysis would be similar to a direct analysis of each of the annual estimates. The main difference is that the standard error on the yearly effects is estimated from the variability of the monthly estimates not directly from the sample and thus captures the variability of the true population values as well as the sampling errors. Hence we can compare the directly estimated SEs with those associated with a simple regression model with year effects included. A potential advantage is that in a regression model we can include other terms which may reduce the variability.

Another option is to have a moving 12-month effect so that we can update the analysis of annual change each month. It is similar to analysis of non-overlapping 12 month moving averages. This procedure is a crude form of filter based trend analysis, which will be discussed in more detail in section 7. It is a lagged indicator of current trends.

If the analysis up to the current year or 12 months has accepted the hypothesis of no trend then we can fit a model with an intercept and a term for the latest year or 12 months.

Given that the main additional terms we will include in the model are monthly seasonal effects, which average out to zero over any 12 months, the advantage of the regression approach may be small unless other terms are added. Its main value may come when area level analysis is involved.

If a particular intervention has been identified then a term can be added to the regression model that can then be tested to see if there is any evidence of the intervention having an effect. A simple approach is to put in a simple level shift. As the impact of an intervention may take time to accumulate and also may dissipate more complicated intervention models can be used, involving linear and quadratic terms.

Seasonality is an issue when monthly data are analysed. Potential seasonality can be included in the analysis by including an indicator variable for each month, with one month deleted as reference month. Seasonal factors may reflect true seasonal factors and also consistent measurement effects in the survey. The main interest is in whether there is evidence of seasonality. If there is no seasonality then the analysis is simplified. If seasonality is present, then including its effect in the analysis will reduce the residual variability and improve the analysis of trends. An advantage of monthly analysis is that it allows earlier detection of changes in trends than would be possible by annual analysis or monthly analysis of annual or 12 month effects. In SAS PROC GLM the variable indicating month can be declared as a CLASS variable. This automatically creates the required indicator variables and produces ANOVA tables that allow testing of the presence of seasonality.

As usual the statistical significance of each term in the model and the R^2 associated with the model can be examined. This enables testing for presence of seasonality and trend. As the estimates have a component of sampling error there is always going to be an appreciable degree of random variation in the estimates, which will limit the amount of variation that can be explained by any model. The primary interest is initially in whether the terms in the model are statistically significant. A model that finds no evidence of any trend is still a useful model as it says that the indicator in question is stable. Monitoring should then be focussing on checking on whether there is any evidence of a change from this situation.

A key output from the regression analysis is the estimated root mean squared error (RMSE) of the residuals. This RMSE is important in determining how the analysis can help detect important changes. The residual variation in the regression analysis includes sampling error and other sources of variation. Hence comparison of the RMSE with the sampling SE can indicate the level of other sources of variation.

In these analyses we need to recognise that the sample based estimate is composed of the true value, Y_t, and sampling error, e_t.

$$\hat{Y}_t = Y_t + e_t \qquad (1)$$

The variance of the sampling error of $\hat{Y}_t$ will depend on the sample size, n_t, and design effect, d_t, and the sampling variance of the variable in the population, σ_t^2, so

$$Var_p(\hat{Y}_t) = d_t \frac{\sigma_t^2}{n_t} \qquad (2)$$

Since all the indicators of interest are expressed as proportions, $\sigma_t^2 = Y_t(1 - Y_t)$, and so

$$Var_p(\hat{Y}_t) = d_t \frac{Y_t(1 - Y_t)}{n_t} \qquad (3)$$

The effective sample size is $n_t^* = \frac{n_t}{d_t}$ and so

$$Var_p(\hat{Y}_t) = \frac{Y_t(1 - Y_t)}{n_t^*} \qquad (4)$$

(The p subscript is used to denote that the variance is that associated with using a probability sampling scheme.)

The residuals can also be examined, including analysis of the autocorrelations and partial autocorrelations. The presence of such autocorrelations may indicate the presence of short terms effects or trends in the true level of the series. Writing the true value in terms of a systematic component, μ_t, and random term, η_t, then $Y_t = \mu_t + \eta_t$. Because the sample has no overlap between months, the sampling errors should be uncorrelated. Any observed autocorrelation should be due to autocorrelation in η_t. The systematic component is what we try to model using trend and seasonal terms.

The regression analysis ignores the information that is potentially available on sampling errors. If we can assume that the sampling error is much larger than the variance of the finite population values, then we can incorporate them in the regression analysis using a weight matrix. The weights are analysis weights not sampling weights.

The sample sizes vary for several reasons. The sample design and annual sample size was changed in conjunction with the change from 17 to 8 health areas. Monthly sample sizes are not tightly controlled so there is variation in monthly sample sizes. Variation in sample sizes will lead to variation in the residual variance. Standard regression analysis assumes constant residual variance. It is straightforward to use weighted least squares, which in SAS is achieved by specifying a weight variable, W_t. This corresponds to the assumption that the residual variance is of the form $V(\hat{Y}_t) = \theta^2 W_t^{-1}$. Thus by setting $W_t = n_t$ we can easily account for the variation in the sample sizes. The associated estimated RMSE will estimate θ.

If the design effect and true value are constant over the time period being analysed, then $\theta^2 = dY(1 - Y)$. If the design effects and true values vary we can still interpret the RMSE^2 as an estimate of the average of the $d_t Y_t(1 - Y_t)$ terms. Hence, RMSE^2 divided by $\overline{Y}(1 - \overline{Y})$ should indicate the average design effect and this will be a useful comparison.

The discussion ignored the variation that η_t might contribute. The comparisons suggested above will indicated with this source of variation is appreciable compared with the variation contributed by the sampling error. More sophisticated approaches can be developed to estimate the relative contribution of the sampling error and other sources to the variability of the monthly time series.

This approach could be taken a step further by also accounting for variation in the design effects and setting $w_t = n_t^*$. For each estimate the effective sample size can be determined by dividing the actual sample size by the estimated *deff*. The analysis weight is then the inverse of the effective sample size. Estimated design effects would be needed for this and that may introduce another source of variation, so should only be done if the design effects vary. The design effects are partly due to the selection of one person per selected household and this factor is determined by the coefficient of variation of household size, which should not vary appreciably over time. The design effect will also be affected by changes in stratification and associated selection probabilities. Hence, we would expect the change in stratification associated with the reduction in health areas to change the design effect of the state and area level estimates. This suggests using an average design effect for the two designs. Once the *deff* has been included in the effective sample size, a comparison of the RMSE[2] with $\bar{Y}(1-\bar{Y})$ should give a factor of about 1 if the variation of η_t is small compared with the variance of the sampling error.

The regression analysis also assumed that the distribution of the residuals errors are, at least approximately, normally distributed. For an Simple Random Sample (SRS) the number of cases contributing to the estimated proportion, $n_t\hat{Y}_t$, would have a binomial distribution, B(n_t, Y_t). To account for the design effect we could assume that $n_t^*\hat{Y}_t$ is B(n_t^*, Y_t). Provided $n_t^* Y_t$ (and $n_t^*(1-Y_t)$) is at least 5 the binomial distribution can be reasonably approximated by a normal distribution.

While normality may not be an issue, there is a final issue since (3) implies that the residual variance depends on Y_t. If these value do not vary much then this issue is not important, but we do not need to constrain the analysis to models in which the true values do not vary much. In this application we would not expect large changes in these values. By using Generalised Linear Models this dependence of the variance on Y_t can be accounted for. In SAS the GENMOD procedure can be used. This procedure allows specification of a binomial distribution. A link function, $g(.)$ can also be specified such that $g(E(\hat{Y}_t))$ is a linear function of the explanatory variables. The identity link function allows for a model similar to the linear regression analysis described above. For indicators taking values away from the boundaries of 0 and 1, such an approach is reasonable. The usual link function used with the binomial distribution is $g(y) = \log\left(\frac{y}{1-y}\right)$, which stays in the interval (0,1).

The main feature of this approach is that is models the implied sample counts and allows $V(\hat{Y}_t) = \phi\frac{Y_t(1-Y_t)}{n_t}$. The parameter ϕ is called the scale factor. If the sample counts vary precisely as predicted with a binomial distribution, $\phi = 1$ and the model can be fitted with this restriction. More generally $\phi > 1$, which is called overdispersion, as it occurs when the sample values vary more than implied by the binomial distribution. Clearly ϕ is related to the design effect. There are two approaches that can be considered. One is where were the counts are $n_t\hat{Y}_t$ and sample size n_t, in which case $\hat{\phi}$ is another estimate of the average design effect. Another approach is to take the counts as $n_t^*\hat{Y}_t$ and sample size n_t^*, in which case we would expect the scale factor to be approximately 1, unless there is overdispersion in the true values.

6.2 State Level Analysis

Based on the discussion above the following analyses of the monthly series were performed.
1. Cubic trend in time and monthly seasonal factors
2. Year terms and monthly seasonal factors

The analysis was done using weighting by sample size in each month.

To allow assessment if the statistical significance of the seasonal factors as an overall effect, they were treated as a CLASS variable in PROC GLM. This was also be done for the year effect. The analysis did not include the indicator obesity and three of more serves of vegetables to reduce the size of the analysis and because similar indicators are included.

Table 11 summarises the results, by giving the *p* value for the linear, quadratic and cubic components of the trend and seasonal part of the model, the RMSE, R^2 and the Durbin Watson statistic (DW) for model 1. The *p* value associated with the year terms from model 2 is also given. The results are based on 55 months as the January sample sizes were zero and were weighted by sample size. The p-value associated with a year effect in a model that also included a seasonal components is also given in column 6. Shading is used to indicate effects that are statistically significant at the 5% level.

Table 11: Summary of Cubic Regression Models

Variable	Mean	Linear *p*value	Quad *p*value	Cubic *p*value	Year *p*value	Seasonal *p*value	RMSE	R^2	DW
Risk alcohol drinking	34.26	0.01	0.15	0.12	<.01	0.20	78.56	0.42	2.35
Overweight or obesity	48.43	<.01	0.27	0.83	<.01	0.01	65.76	0.56	2.20
Recommended fruit consumption	48.81	<.01	0.13	0.44	<.01	0.01	84.81	0.64	1.93
Adequate physical activity	49.61	<.01	0.22	<.01	<.01	0.12	98.30	0.67	1.54
Current smoke	20.70	<.01	0.01	0.50	<.01	0.52	61.41	0.51	2.14
Recommended vegetable consumption	8.44	0.33	0.28	<.01	<.01	0.78	50.17	0.44	1.28

The results in Table 11 suggest seasonality for overweight or obesity and recommended fruit consumption. The analysis is also detecting year effects for each variable and linear trends for all variables except recommended vegetable consumption. Some evidence of quadratic or cubic trends in case of adequate physical activity, current smoking and recommended vegetable consumption respectively, although for reasons of stability we will subsequently fit only linear trends or year effects. The analysis is also detecting year effect for each variable. Examination of year effects can also help assess major departures from consistent changes in the one direction. More subtle non-linear trends can be examined using filter-based method covered in section 7.

Table 12 shows the estimated year effects relative to 2002 for a model that also included seasonal effects. There appears to be good consistency in the general direction of the changes when examined over several years, although for recommended vegetable consumption there is some oscillation. The level of recommended vegetable consumption is less than 10% and so the sampling SEs are higher relative to the level of the estimates than for the other indicators. In general there will be less reliability in the analysis of this indicator.

Table 12 : Year Effects Compared with 2002 (Seasonal Effects Included)

Variable	2003	2004	2005	2006
Risk alcohol drinking	1.13	0.66	-2.25	-1.86
Overweight or obesity	1.92	1.97	3.61	4.31
Recommended fruit consumption	0.63	0.38	4.42	6.83
Adequate physical activity	-1.92	4.77	5.18	7.63
Current smoke	0.67	-0.92	-1.47	-3.86
Recommended vegetable consumption	2.15	0.92	-0.21	1.94

The regression models were reanalysed dropping the quadratic and cubic terms and the statistical significance of the linear and seasonal terms in the model are given in Table 13. As for Table 11 the results in Table 13 suggest seasonality for overweight and obesity and recommended fruit consumption. The analysis is also detecting year effect for each variable as shown in Tables 11 and 12. The value of the Durbin-Watson statistic suggests some autocorrelation in the residuals for recommended fruit consumption, which could be investigated by further time series modelling.

Table 13: Summary of Linear Regression Models

Variable	Mean	Linear *p*value	Seasonal *p*value	RMSE	R^2	DW
Risk alcohol drinking	34.26	0.01	0.31	82.04	0.33	2.00
Overweight or obesity	48.43	<.01	0.01	64.68	0.55	2.18
Recommended fruit consumption	48.81	<.01	0.02	86.71	0.60	1.73
Adequate physical activity	49.61	<.01	0.26	109.14	0.58	1.30
Current smoke	20.70	<.01	0.54	64.72	0.43	1.81
Recommended vegetable consumption	8.44	0.52	0.95	61.71	0.11	0.93

To assess the sort of reliability obtained from a regression approach in Table 14 we compare the SE on the year effect estimate from the regression model (col 2) with that likely to arises from the direct sampling SE on the difference between 2002 and 2006 (col 3). The SE of the year effect from the regression is a little higher as should be expected as they reflect additional sources of variation and are in the range 0.9% to 1.4%. Columns 4 and 5 give the SEs on the linear trend for the cubic model and the model with a linear trend only. The instability caused by the inclusion of the quadratic and cubic terms is evident. The SE for the linear only model are around 0.025% on the estimate of monthly change, which corresponds to around 0.3% on the annual rate of change and a confidence interval of +/- 0.6% on the annual rate of change.

Table 14 : SEs on 2002 to 2006 change and linear effect (Seas Inc)

Variable	Sampling SE on year	SE on year Reg Model	SE Linear from cubic model	SE Linear Only
Risk alcohol drinking	1.02	1.13	0.25	0.024
Overweight or obesity	1.07	0.98	0.22	0.019
Recommended fruit consumption	1.05	1.18	0.27	0.025
Adequate physical activity	1.05	1.38	0.32	0.032
Current smoke	0.88	0.90	0.20	0.019
Recommended vegetable consumption	0.50	0.77	0.16	0.018

These analyses were rerun using PROC GENMOD with the binomial distribution and SCALE=DEVIANCE option. We used $n_t\hat{Y}_t$ as the number of events and n_t as the number of trials. Use of the effective sample size approach requires further analysis the design effects. Both linear and logistics link function were used. Results are summarised in Table 15, which gives the p-values on terms and the estimated scale factor (Disp). For comparison the term $\mathrm{RMSE}^2/\bar{Y}(1-\bar{Y})$ is also shown (Disp2) and they are comparable. The *deff* estimates in 2005 are also shown and is generally smaller, which is expected as it does not reflect sources of variation additional to sampling error.

Table 15: Summary of Generalised Linear Models, Linear Link

Variable	Linear *p*value	Seasonal *p*value	Disp	Disp2	Deff 2005
Risk alcohol drinking	0.01	n.a	3.10	3.00	1.98
Overweight or obesity	<.01	n.a	1.67	1.68	1.94
Recommended fruit consumption	<.01	n.a	3.02	3.01	1.94
Adequate physical activity	<.01	n.a	4.74	4.76	1.93
Current smoke	<.01	n.a	2.65	2.55	2.08
Recommended vegetable consumption	0.54	n.a.	4.98	4.93	1.45

Table 16 gives the results using a logit link. Similar results are obtained.

Table 16: Summary of Generalised Linear Models, Logit Link

Variable	Linear *p*value	Seasonal *p*value	Disp
Risk alcohol drinking	0.01	n.a	3.10
Overweight or obesity	<.01	n.a	1.67
Recommended fruit consumption	<.01	n.a	3.02
Adequate physical activity	<.01	n.a	4.74
Current smoke	<.01	n.a	2.70
Recommended vegetable consumption	0.54	n.a	4.98

Table 17 summarises the estimated regression coefficients on the linear time effect from a model with the quadratic and cubic terms included, the linear only model and the GENMOD model using linear and logit link. Seasonal terms are included in all the models. The results from the linear only regression are comparable with those from GENMOD using a linear link as the linear model has multiplied the proportions by 100. Notice that, with the exception of overweight and obesity, the linear trends are all in the desirable direction. Also the data have not been age-standardised. The corresponding annual rates of change vary from 0.14% to 2.43% in absolute values.

Table 17. Estimated Coefficients on Time

Variable	Linear Reg In Cubic	Linear Only	GEMMOD Linear	GENMOD Logistic
Risk alcohol drinking	0.507	-0.064	-0.0006	-0.0029
Overweight or obesity	0.249	0.095	0.0009	0.0038
Recommended fruit consumption	-0.272	0.152	0.0015	0.0061
Adequate physical activity	-0.870	0.203	0.0020	0.0081
Current smoke	0.184	-0.0848	-0.0009	-0.0052
Recommended vegetable consumption	0.782	0.0115	0.0001	0.0014

In summary, the results show that a regression based analysis of NSW data can estimate year effects with SEs around 0.9% to 1.4% and annual rates of change with a SE of around 0.3%.

6.3 Area Level Analysis

For the health areas the linear regression analysis was repeated for each area separately. This enables separate linear trends and seasonal effects to be estimated for each area. It also allows for different degrees of variance of the residuals. We should expect variances to differ because of the different sampling variances of the estimates and the different population sizes that may affect the variation of the finite population values. Table 18(a) provides a summary of the p-values and other summary measures for Alcohol for each area:

Table 18(a): Summary of Linear Regression Models, Alcohol (Seas Inc)

Area	Mean	Linear *p*value	Seasonal *p*value	RMSE	R^2	DW
Sydney South West	28.93	0.48	0.89	62.80	0.13	1.97
South Eastern Sydney & Illawarra	35.81	0.57	0.01	60.93	0.41	2.05
Sydney West	28.28	0.01	0.30	53.11	0.34	1.92
North Sydney & Central Coast	37.07	0.06	0.45	66.29	0.26	1.58
Hunter & New England	37.17	0.38	0.67	82.37	0.19	1.62
North Coast	37.27	0.70	0.47	65.07	0.22	1.97
Greater Southern	40.40	0.42	0.56	67.55	0.21	2.22
Greater Western	37.83	0.23	0.82	46.81	0.17	1.42

The results in Table 18(a) only show statistically significant trends in one area and seasonality in a different area. This is partly a reflection of the smaller sample sizes. The estimated RMSEs are lower than for the NSW level analysis (see Table 13), which is partly due to the lower *deff* associated with area level estimates. The actual variances on each monthly estimate will be higher at the area level because the RMSE^2 is divided by around 80 rather than 660 as the approximate monthly sample size.

Results for the other indicators are given in Tables 18(b) to 18(f) in appendix A. These results and those given in Table 25 later, show that the linear regression analysis can detect linear trends at the area level provided that the annual rate of change exceeds about 1.3% .

Table 19 summarise the SEs on the estimates of the 2006 compared to the 2002 year effect and the linear trend for each area for risk alcohol drinking. For the year effect we see SEs in the range 2.5% to 3.3%, which compares with 1.0% for NSW based analysis. The SEs on the estimated annual rate of change are around 0.65% corresponding to 95% confidence intervals of +/-1.3%, which compares with+/- 0.56% at the NSW level.

Table 19: SEs on 2002–2006 year and linear effect, Risk alcohol drinking (Seas Inc)

Area	SE Year	Linear
Sydney South West	2.49	0.052
South Eastern Sydney & Illawarra	2.58	0.051
Sydney West	2.68	0.046
North Sydney & Central Coast	2.59	0.058
Hunter & New England	3.27	0.066
North Coast	2.53	0.056
Greater Southern	2.88	0.056
Greater Western	2.71	0.059
Common Slopes Model	0.99	0.020
State Model	1.13	0.024

A combined analysis was done where the data for all the areas is used. This approach has the advantage of allowing analysis and testing of area effects. By declaring area and month as CLASS variables in PROC GLM, it is relatively straightforward to test for difference between areas. Fixed area effects were incorporated in the regression analysis. The model used allowed for interactions between the time effect and areas and the seasonal effects and areas and area specific intercepts. This model allows for different regression models for each area:

1. Time+Area+Seasonal +Time*Area+ Seasonal*Area.

As variations in sample sizes are likely to be larger at the area level, the analysis was done using the sample size in each month for each area as the weight. We can then test for evidence of area effects on the seasonal effects and trend. By using the CLASS variable option the ANOVA tables provide overall tests of the significance of the three types of effects.

The value of this analysis is that it allows a formal testing of whether there is any evidence of area specific effects. We should expect differences in levels of the indicators of interest, due to say differences in the socio-demographic composition of the population in the area, as well as other difference, for example in weather. Differences in seasonal effects may also occur. The main interest is in whether the trend differs. If differences are found, then that is interesting. If differences are not found then we can improve the estimates for each area by appropriately using information from all areas.

Table 20 summarises the p-values of the terms in the model. The results in Table 20 show no statistically significant interactions, suggesting the time and seasonal effect do not vary across areas. The area effect is statistically significant suggesting there are differences in the prevalence rates between areas. Seasonality is detected for overweight or obesity, recommended fruit consumption and adequate physical activity.

Table 20: Significance of Interactions

Indicator	Time	Area	Seasonal	Time*area	Seas*area
Risk alcohol drinking	<.01	<.01	0.12	0.60	0.48
Overweight or obesity	<.01	<.01	0.02	0.13	0.59
Recommended fruit consumption	<.01	<.01	<.01	0.37	0.98
Adequate physical activity	<.01	<.01	<.01	0.68	0.95
Current smoke	<.01	<.01	0.55	0.95	0.39
Recommended vegetable consumption	0.11	<.01	0.73	0.78	0.60

The results in Table 20 indicates no interactions and so the model without interactions was fitted:

2. Time+Area+Seasonal.

This model assumes different intercepts between areas, but common slope for the linear time effect and seasonal terms for all the health areas. Table 21 summarises the results by giving the estimated area intercepts, which is the estimated level at the beginning of 2002. The intercepts may vary due to many factors, which can be the subject of further analysis.

Table 21: Summary of Areas Effect, common slopes model

Area	Risk alcohol drinking	Overweight or obesity	Recomm-ended fruit consumpt-ion	Adequate physical activity	Current smoker	Recomm-ended veg consump-tion
Sydney South West	26.06	50.96	48.79	40.92	28.35	9.79
South Eastern Sydney & Illawarra	32.95	49.69	51.47	46.13	26.42	11.49
Sydney West	25.41	55.22	46.91	36.67	28.68	8.71
North Sydney & Central Coast	34.20	46.75	52.67	44.49	23.35	14.22
Hunter & New England	34.26	57.33	48.41	40.18	27.65	12.71
North Coast	34.48	52.40	51.94	43.15	29.44	13.51
Greater Southern	37.62	57.55	45.40	41.01	28.73	12.42
Greater Western	34.74	59.51	43.71	38.63	29.65	12.16
NSW Intercept	30.54	54.93	49.44	40.44	27.13	9.74
p value area	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01

Table 22 gives the estimated common slope and the p value for the seasonal effects. The slope is statistically significant for all the indicators except smoking and seasonality is present for overweight or obesity, recommended fruit consumption and adequate physical activity.

Table 22: Summary coefficients in common slopes model

	Risk alcohol drinking	Overweight or obesity	Recomm-ended fruit consump-tion	Adequate physical activity	Current smoker	Recomm-ended veg consump-tion
Slope	-0.0684	0.0986	0.169	0.204	-0.0803	0.0214
p value slope	<0.01	<0.01	<0.01	<0.01	<0.01	0.06
p value seas	0.1184	0.0154	<0.01	<0.01	0.5442	0.7161

In summary, the results show that while the SEs on the monthly area level estimates are relatively high, they are capable of detecting linear trends and seasonality. A combined analysis gives no evidence of differences in the slope and seasonality across areas. Examination of the last two rows of Table 19 for risk alcohol drinking shows that the improvements in SEs that can be obtained by using the common slopes model for both the models where a year effect is used to reflect trend and when a linear time trend is used. The SE on the estimated year effect is 0.99% and on the estimated monthly rate of change it is 0.02%, which corresponds to 0.24% on the annual rate of change. The use of these models will be considered further in section 8.

The discussion so far has assumed that the analysis uses the monthly data from 2002. If monthly data for 1997 and 1998 are available then they can be included in the analysis. The main issue is handing the break in the series and the fact that the form of the trend is assumed for ten years, instead of five.

7. ASSESSMENT OF TRENDS USING MOVING AVERAGES AND FILTERS

When a monthly or quarterly repeated survey has been conducted for several years then a time series can be produced and analysed. Seasonally adjusted estimates are often produced to help interpretation of the time series, giving the series $\hat{x}_t$. Seasonal adjustment is not a linear process, but linear approximations are available. To assess the underlying pattern of change trend estimates can also be produced, which raises the question of what is trend? In some cases it is taken to be $\Delta^{(s)}\hat{y}_t$ or $\Delta^{(s)}\hat{x}_t$. The Australian Bureau of Statistics often produces seasonally adjusted estimates using the X11 procedure and trend estimates using Henderson moving averages applied to the seasonally adjusted series (ABS, 1987). Other options are available.

To examine the possible usefulness of seasonal adjustment and trend estimation we applied PROC X11 to the NSW and area level monthly time series. The options chosen regarding initial trend and seasonal filters were:

- 2x12 filter for the initial trend estimation
- 3x3 moving average for first estimation of seasonal factors
- 3x5 moving average for estimation of seasonal factors

There are issues with outliers, especially for area level seasonal adjustment. The issue of some months having no estimates was accounted for in this analysis by imputing the yearly average.

An advantage of these methods compared with the regression based approach described above is that they assume local smoothness of the trend, rather than making an assumption of a particular form of the trend over the entire length of the time series being analysed. This means that they can reflect smooth non-linear trends. Because the filter based methods do not make explicit model assumptions, a disadvantage is that it is not clear how to undertake analysis that simultaneously analyses the eight health areas. Each area can be analysed separately, but there is then no borrowing of strength across the areas. Approaches to trying to do this will be discussed in the next section.

A common opinion is:" the first time something happens it is a blip; the second is a coincidence; the third makes a trend" (*The Economist, 1990)*. This statement reflects what many users do, that is examine $\Delta^{(s)}\hat{y}_t$ for s=1, 2, 3. Ignoring seasonal adjustment it is possible to calculate the sampling variance on trend estimates and their movements.

The results are summarised by attached graphs, which suggest that the X11 based trend is useful smoother.

8. RANDOM EFFECTS BASED METHODS

Implicit in what the discussion so far is that the survey estimate $\hat{Y}_{rt}$ is unbiased for the true value Y_{rt}, so that $\hat{Y}_{rt} = Y_{rt} + e_{rt}$, where e_{rt} is the sampling error. So far we have taken the true values as fixed and unknown quantities that are in no way related across the health areas. Intuitively we might regard the state trend as reflecting an overall trend and focus on evidence from the survey on how each area is performing relative to the overall trend. We can also consider what evidence is there that the variation in trends between areas is more than can be explained by random variation. The test of the statistical significance of area interaction terms in section 6 is one way of examining area effects. However, this approach forces us to decide that say the linear trend for the areas are either exactly the same or completely unrelated.

There is also the potential to improve the estimates for a particular area by borrowing strength across the areas. To do so we need to start specifying a statistical model structure for the finite population values Y_{rt} that incorporates variation in the area specific intercepts and slopes. A simple model would be to assumes

$$Y_{rt} = \beta_{0r} + \beta_{1r}t + \varepsilon_{rt} \qquad (6)$$

where the area intercepts and slopes vary randomly around overall values β_0 and β_1. This is a similar model as used to generate the Table 20, expect that the coefficients are assume to vary randomly across areas. Common fixed seasonal effects are also included.

Table 23 gives the p-values associated with the random effects for the intercepts and slopes. They are all non-significant for the slopes, which is consistent with the fixed effects analysis summarised in Table 20, suggesting no difference in the slopes between areas. The p value for the fixed slope effect is also shown in Table 23 and is statistically significant for all variables, except recommended vegetable consumption.

Table 23: Summary of Random Effects (RE) Model (Seas Inc)

Indicator	p value-intercept RE	p value-slope RE	p value-slope fixed
Risk alcohol drinking	0.06	1.00	0.01
Overweight or obesity	0.05	0.25	0.01
Recommended fruit consumption	0.09	1.00	<0.01
Adequate physical activity	0.09	1.00	<0.01
Current smoke	0.13	1.00	<0.01
Recommended vegetable consumption	0.19	1.00	0.07

The model was reanalysed with the sloped treated as a fixed effect and intercepts as random. Such a model allows for differences in the prevalence level across health areas but assumes that they change over time in the same way for all health areas. For this model the random effects on the intercepts are statistically significant for all variables. The resulting slope estimates are given in the third column of table 24 and all are statistically significant, except for recommended vegetable consumption. For ease of comparison the slope estimates from the state estimate and the model with different area intercepts and common slopes analysed in section 6 are given in columns 2 and 4 respectively. There is very good consistency in the estimated slopes, which are the coefficients of the linear time effects.

Table 24: Comparison of Slope Estimates (Seas Inc)

Indicator	NSW Slope	Random intercept, Slope fixed	Area Intercepts Common Slope
Risk alcohol drinking	-0.0642	-0.0640	-0.0684
Overweight or obesity	0.0951	0.0875	0.0986
Recommended fruit consumption	0.1522	0.1659	0.1687
Adequate physical activity	0.2027	0.2043	0.2039
Current smoke	-0.0849	-0.0806	-0.0803
Recommended vegetable consumption	0.0115	0.0226	0.0214

To further investigate these results the estimated slopes from fitting a linear model with seasonal effects for each area and variable are given in Table 25. With only three exceptions the area specific slopes are in the same direction as the slope estimated from model with area specific intercepts and common slope and the slope estimated from NSW level data. Also, it is possible to obtain statistically significant slope estimates at the area level. Table 24 suggest that to obtain a statistically significant slope estimate at the area level it has to be about 0.11% or more, which corresponds to an annual rate of change of about 1.3%.

Table 25: Results of separate linear regressions, common slopes and NSW slopes models (Seas Inc)

Area	Risk alcohol drinking	Overweight or obesity	Recommended fruit consumption	Adequate physical activity	Current smoker	Recommended veg consumption
Sydney South West	-0.0275	0.0637	0.0850	0.1742	-0.1206	-0.0135
South Eastern Sydney & Illawarra	-0.0349	0.1603	0.1401	0.1259	-0.0793	-0.0139
Sydney West	-0.1042	0.1787	0.1359	0.2567	-0.0934	0.0121
North Sydney & Central Coast	-0.1067	0.0214	0.1632	0.2898	-0.0623	0.0119
Hunter & New England	-0.0630	0.0540	0.2809	0.2058	-0.0790	0.0559
North Coast	0.0152	0.2024	0.1335	0.2174	-0.0884	0.0285
Greater Southern	-0.0531	0.0887	0.1515	0.1735	-0.0831	0.0488
Greater Western	-0.1324	0.0576	0.2170	0.2019	-0.0392	0.0401
Common Slope	-0.0684	0.0986	0.1687	0.2039	-0.0803	0.0214
NSW Slope	-0.0642	0.0951	0.1522	0.2028	-0.0849	0.0115

The potential value of the different ways of analysing the NSW Population Health Survey can be summarised by looking at the SEs that are associated with different estimates using:

- separate models for each area,
- a model with common year or time effect but different prevalence level for each area,
- the model estimated from NSW level data.

Table 26 gives the SEs on the estimated change from 2002 to 2006 for these models where the trend is reflected as a year effect. The SEs vary between indicators but at the area level they are around 2.5%, whereas the NSW estimates have SEs around 1.2%. The model with common year effect gives SEs around 1.0%

Table 26: SEs on 2002 to 2006 change for separate regressions, common year effects and NSW models

Area	Risk alcohol drinking	Overweight or obesity	Recommended fruit consumption	Adequate physical activity	Current smoker	Recommended veg consumption
Sydney South West	2.45	2.59	2.10	2.94	1.74	1.39
South Eastern Sydney & Illawarra	2.58	2.19	3.69	2.48	2.07	1.43
Sydney West	2.30	2.56	3.22	2.72	2.02	1.43
North Sydney & Central Coast	2.68	2.59	2.79	2.96	2.47	1.37
Hunter & New England	3.27	2.53	2.93	3.06	1.95	1.64
North Coast	2.88	2.87	2.61	2.75	2.47	1.54
Greater Southern	2.71	3.03	2.87	2.61	2.39	1.98
Greater Western	3.15	2.42	2.57	2.52	2.05	1.63
Common Model	0.99	0.93	0.99	0.95	0.76	0.55
NSW Model	1.13	0.98	1.18	1.38	0.90	0.77

Table 27 gives the SEs on the estimated linear monthly trend. The SEs vary between indicators but when converted to an annual rate they are around 0.6%, whereas the NSW estimates have SEs around 0.3%. The model with common time effect gives SEs around 0.24% on the annual rate of change.

Table 27: SEs on slope coefficients for separate linear regressions, common slopes and NSW slopes models

Area	Risk alcohol drinking	Overweight or obesity	Recommended fruit consumption	Adequate physical activity	Current smoker	Recommended veg consumption
Sydney South West	0.0525	0.0529	0.0452	0.0598	0.0361	0.0292
South Eastern Sydney & Illawarra	0.0510	0.0437	0.0735	0.0551	0.0410	0.0308
Sydney West	0.0461	0.0512	0.0640	0.0566	0.0401	0.0298
North Sydney & Central Coast	0.0578	0.0528	0.0571	0.0604	0.0519	0.0314
Hunter & New England	0.0671	0.0541	0.0590	0.0636	0.0456	0.0335
North Coast	0.0581	0.0616	0.0596	0.0648	0.0516	0.0326
Greater Southern	0.0585	0.0656	0.0640	0.0616	0.0494	0.0405
Greater Western	0.0644	0.0482	0.0547	0.0546	0.0409	0.0337
Common Slope	0.0202	0.0190	0.0205	0.0204	0.0157	0.0115
NSW Slope	0.0237	0.0190	0.0250	0.0317	0.0186	0.0178

9. INCORPORATING COVARIATE INFORMATION

A further development would be adding covariates to the regression analysis using any information on related indicator series available from other sources. Such analysis could also be carried out using individual level. Such analyses are beyond the scope of this project.

10. SUMMARY AND IMPLICATIONS FOR INTERPRETATION OF PERFORMANCE INDICATORS

The analyses in this report show that direct analysis of the annual survey estimates can be usefully supported by analysis of the monthly estimates at both the NSW and health area level. The regression analyses using 5 years of monthly data can detect evidence of seasonality in some indicators and statistically significant changes over time at the state level. At the health area level statistically significant changes over time can be detected but it is difficulty to detect seasonality. There is a good level of consistency in the estimated linear trends across the health areas. There is no evidence of variation of the seasonal effect or linear trends between the health areas and so use of a regression model with constant seasonal effects and linear trends can help in assess trends. There is clear evidence of differences in the prevalence levels between health areas.

As the data for more time periods becomes available the suitability of the linear trend model will have to be carefully checked. X11 based trend is a useful smoother, which can supplement the regression analysis and help identify non-linear trends.

Analyses Based on Annual Survey Estimates

In looking at changes between annual estimates we should expect sampling SEs of about 1% for NSW level estimates and 2 to 3% on area level estimates. Remember that 95% confidence interval are obtained be adding and subtracting twice the SE to the estimate.

By taking into account the possible impact of sampling error we can conclude that at the NSW level true annual changes of about 1% give a high chance of the estimated change being in the correct direction. At the area level changes of around 3% are needed.

To obtain statistical significance of annual changes at the NSW level a true change of about 3% is needed, whereas at the area level a true change of about 7% is needed.

These results suggest that if the underlying rate of change is 1% a year then there is a reasonably high chance that at the NSW level the survey estimates will correctly indicate the direction after 1 or 2 years and produce a statistically significant results after 3 years. At the health area level there is a reasonably high chance that the survey estimates will correctly indicate the direction after 2 or 3 years and produce a statistically significant results well after 3 years, which suggests that analysis should examine changes over more than 3 years.

Analyses Based on Regression Modelling of Monthly Estimates

NSW Estimates

For the year effects SEs are in the range 0.9% to 1.4%. The SE for the linear only model based on 5 years of data are around 0.025% on the estimate of monthly change, which corresponds to around 0.3% on the annual rate of change and 95% confidence intervals of +/-0.6%. The corresponding annual rates of change vary from 0.14% to 2.43% in absolute values.

Area Level Estimates

For the year effect SEs are in the range 2.5% to 3.3%. The SEs on the estimated annual rate of change are around 0.65% corresponding to 95% confidence intervals of +/-1.3%.

To obtain a statistically significant estimate of the monthly rate of change at the area level it has to be about 0.11% or more over a 5-year period, which corresponds to an annual rate of change of about 1.3% or more.

The common slopes regression model gives SEs of about 1.0% on the estimated year effects and 0.24% on the estimated annual rate of change.

APPENDIX 1:

AREA LEVEL REGRESSION ANALYSES

Table 18(b): Summary of Linear Regression Models, BMI (Seas Inc)

Area	Mean	Linear *p*value	Seasonal *p*value	RMSE	R^2	DW
Sydney South West	47.00	0.58	0.16	62.31	0.29	2.26
South Eastern Sydney & Illawarra	45.76	<0.01	0.09	51.36	0.43	2.07
Sydney West	51.29	<0.01	0.28	57.83	0.37	2.26
North Sydney & Central Coast	42.97	0.71	0.65	59.69	0.18	1.23
Hunter & New England	53.31	0.36	0.42	85.23	0.24	2.07
North Coast	48.55	<0.01	0.41	68.31	0.36	1.20
Greater Southern	53.63	0.21	0.64	74.50	0.21	2.22
Greater Western	55.72	0.36	0.58	60.24	0.21	1.44

Table 18(c): Summary of Linear Regression Models, Recommended fruit consumption (Seas Inc)

Area	Mean	Linear *p*value	Seasonal *p*value	RMSE	R^2	DW
Sydney South West	43.38	0.02	0.17	54.27	0.35	1.92
South Eastern Sydney & Illawarra	50.96	0.08	0.75	87.87	0.20	2.02
Sydney West	46.42	0.03	0.59	73.62	0.26	2.14
North Sydney & Central Coast	52.23	<0.01	0.09	65.67	0.42	2.21
Hunter & New England	47.69	<0.01	0.43	72.45	0.48	1.94
North Coast	51.48	0.05	0.40	66.82	0.29	1.91
Greater Southern	44.92	0.02	0.81	74.04	0.24	1.46
Greater Western	42.70	<0.01	0.86	69.84	0.34	2.11

Table 18(d): Summary of Linear Regression Models, Adequate physical activity (Seas Inc)

Area	Mean	Linear *p*value	Seasonal *p*value	RMSE	R^2	DW
Sydney South West	49.02	<0.01	0.41	71.31	0.34	1.84
South Eastern Sydney & Illawarra	53.97	0.01	0.12	65.40	0.38	1.62
Sydney West	44.63	<0.01	0.81	64.97	0.39	1.97
North Sydney & Central Coast	52.47	<0.01	0.60	69.00	0.46	2.21
Hunter & New England	47.66	<0.01	0.48	77.58	0.36	2.40
North Coast	50.91	<0.01	0.30	72.34	0.39	1.67
Greater Southern	48.64	0.01	0.61	70.72	0.30	1.47
Greater Western	45.93	<0.01	0.76	69.26	0.33	0.89

Table 18(e): Summary of Linear Regression Models, Current smoke (Seas Inc)

Area	Mean	Linear *p*value	Seasonal *p*value	RMSE	R^2	DW
Sydney South West	21.72	<0.01	0.40	43.37	0.37	1.76
South Eastern Sydney & Illawarra	19.81	0.10	0.71	49.21	0.21	2.09
Sydney West	22.08	0.02	0.17	46.84	0.36	2.21
North Sydney & Central Coast	16.62	0.23	0.32	59.81	0.26	2.05
Hunter & New England	21.17	0.09	0.39	56.26	0.27	1.84
North Coast	22.86	0.14	0.25	58.16	0.30	2.07
Greater Southern	22.15	0.06	0.89	57.41	0.19	2.15
Greater Western	23.28	0.26	0.63	52.42	0.20	1.90

Table 18(f): Summary of Linear Regression Models, Recommended vegetable consumption (Seas Inc)

Area	Mean	Linear *p*value	Seasonal *p*value	RMSE	R^2	DW
Sydney South West	7.40	0.56	0.92	34.89	0.14	1.45
South Eastern Sydney & Illawarra	9.07	0.87	0.15	36.82	0.29	1.72
Sydney West	6.30	0.63	0.14	34.23	0.30	1.74
North Sydney & Central Coast	7.70	0.39	0.29	35.99	0.26	1.14
Hunter & New England	10.26	0.13	0.96	41.08	0.14	1.92
North Coast	11.08	0.39	0.76	36.51	0.17	1.89
Greater Southern	9.99	0.23	0.82	46.81	0.17	1.66
Greater Western	9.66	0.26	0.36	42.99	0.26	1.93

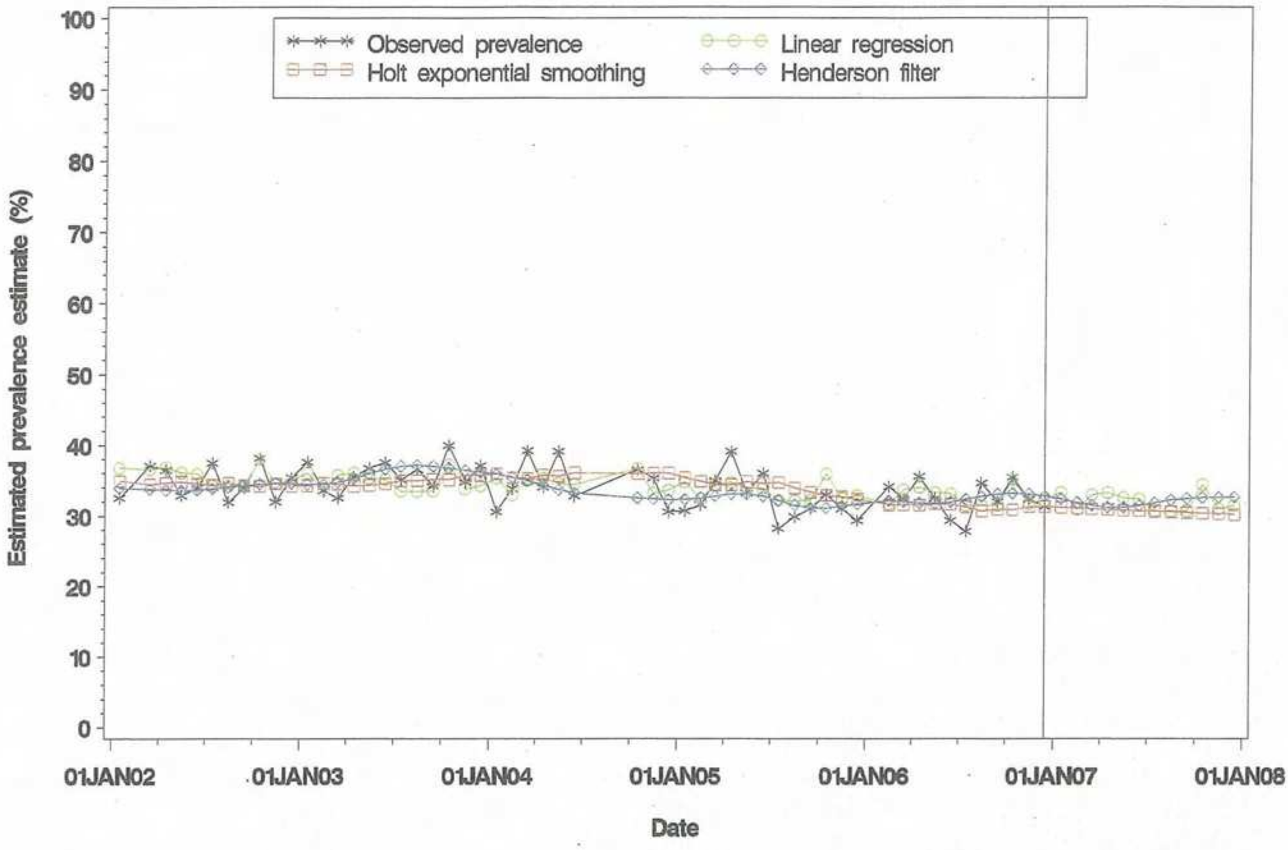
APPENDIX 2:

COMPARISON OF DIFFERENT PREDICTION METHODS FOR THE LIFESTYLE INDICATORS FOR NEW SOUTH WALES

Comparison of different prediction methods

Risk alcohol drinking, persons aged 16 years or over

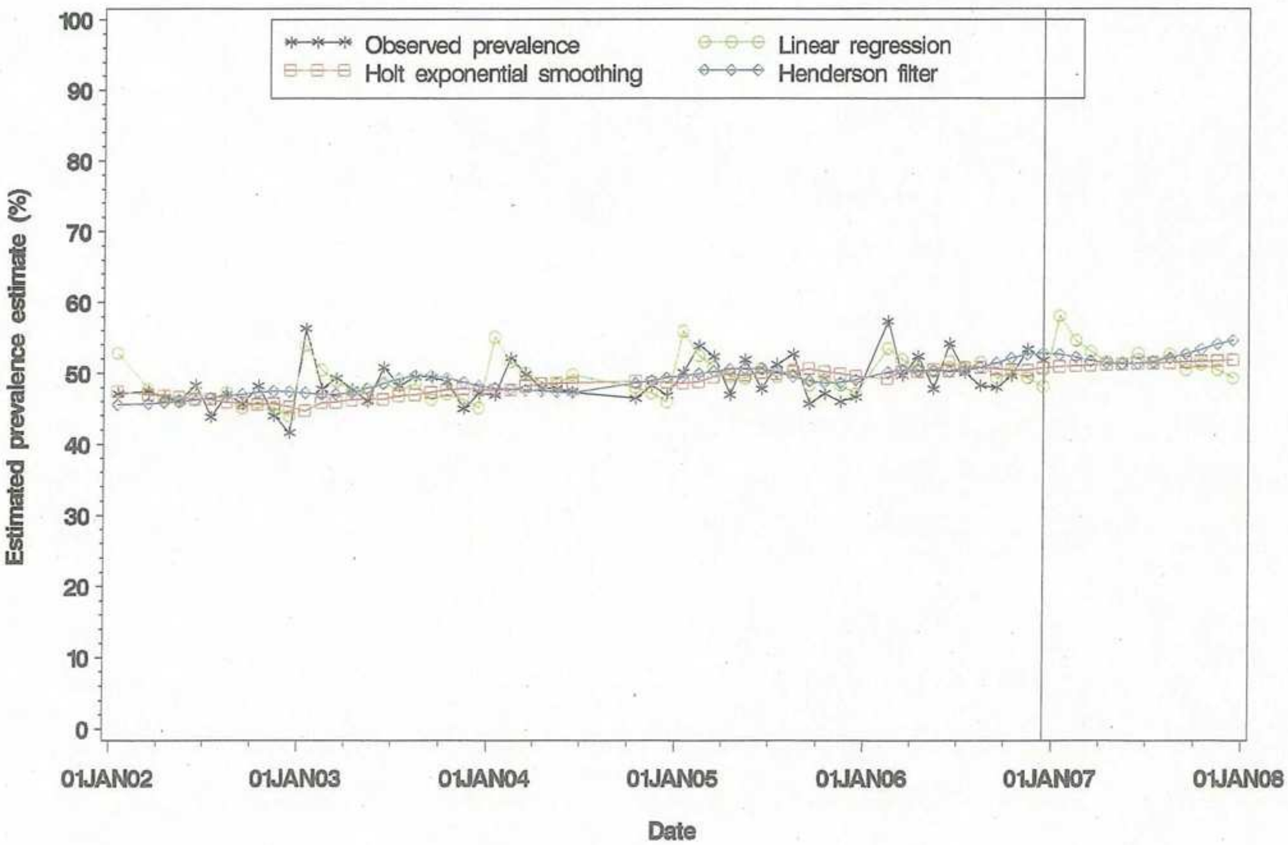
NSW, 2002–2006

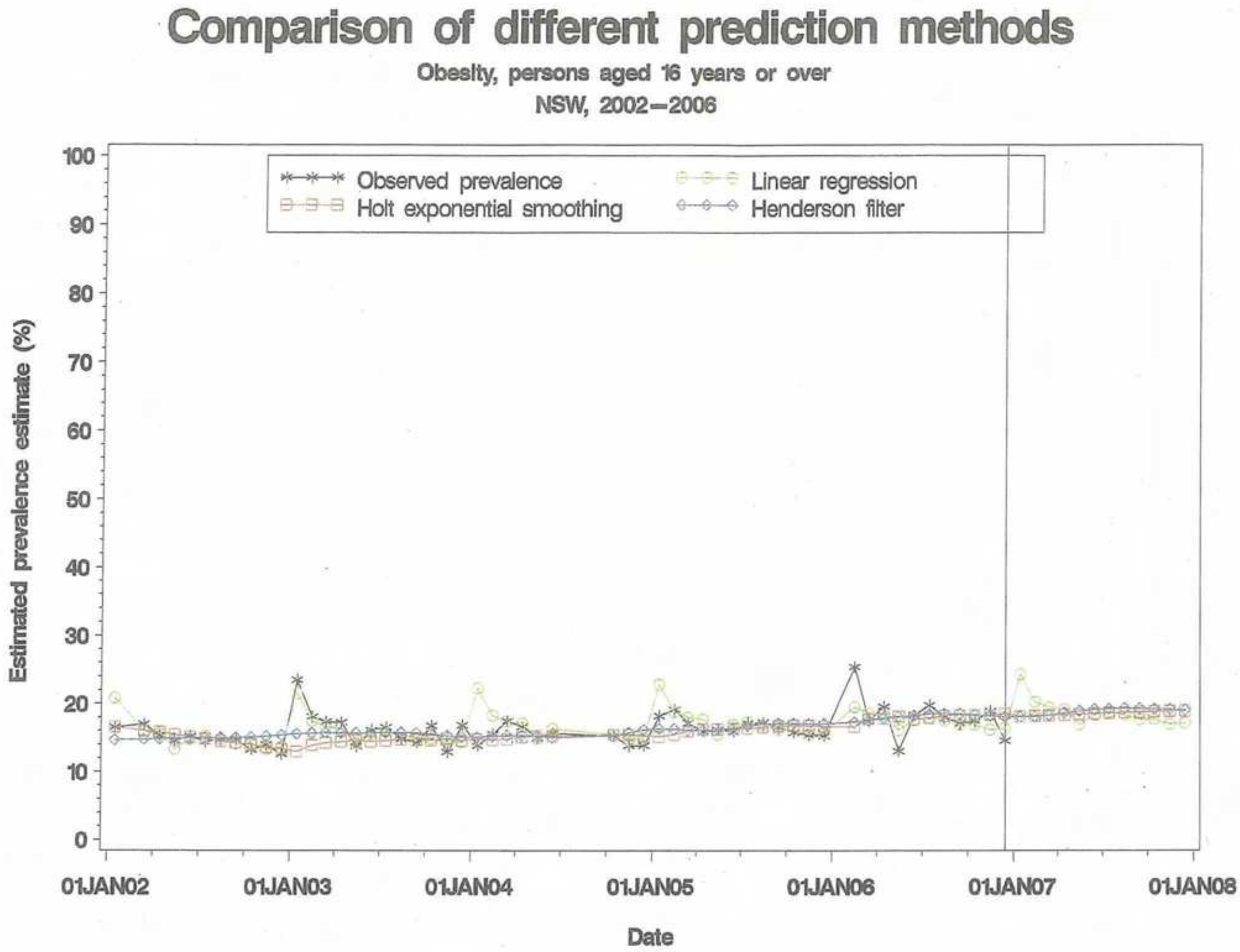


Comparison of different prediction methods

Overweight or obesity, persons aged 16 years or over

NSW, 2002–2006




Comparison of different prediction methods
Obesity, persons aged 16 years or over
NSW, 2002—2006
Observed prevalence
Holt exponential smoothing
Linear regression
Henderson filter
Estimated prevalence estimate (%)
0
10
20
30
40
50
60
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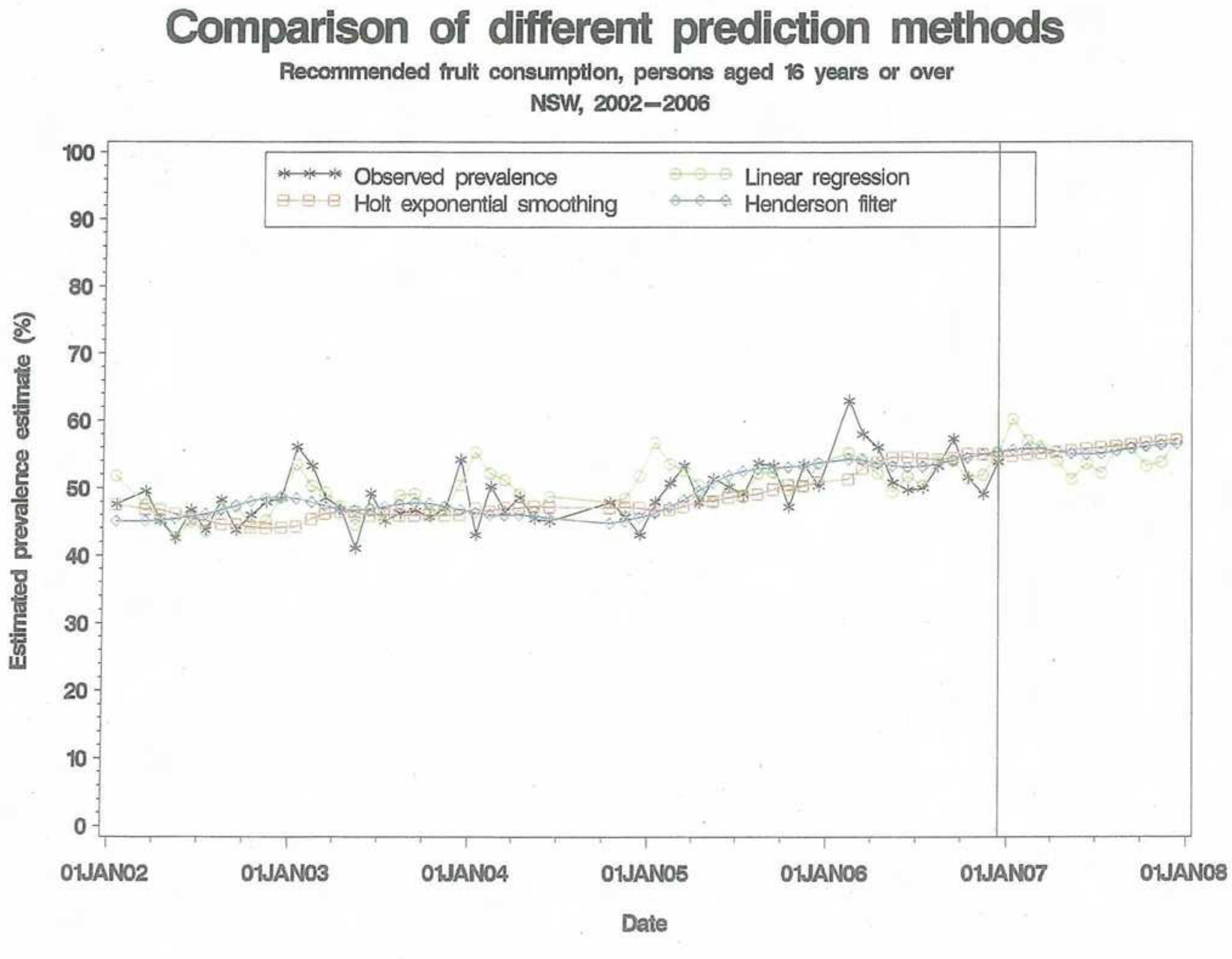
01JAN08
Date


Comparison of different prediction methods
Recommended fruit consumption, persons aged 16 years or over
NSW, 2002—2006
Observed prevalence
Holt exponential smoothing
Linear regression
Henderson filter
Estimated prevalence estimate (%)
0
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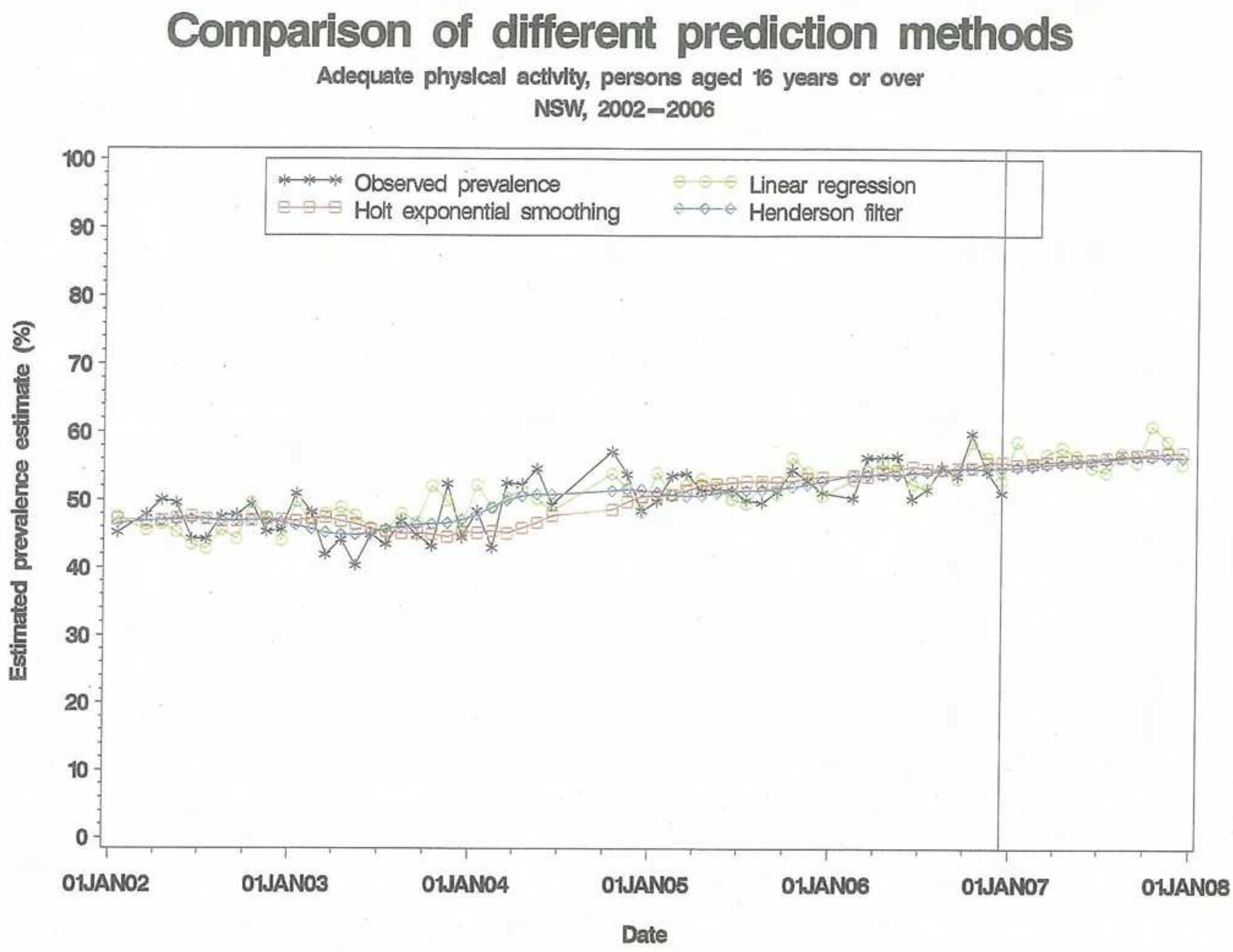
Date



Comparison of different prediction methods
Adequate physical activity, persons aged 16 years or over
NSW, 2002–2006
Observed prevalence
Holt exponential smoothing
Linear regression
Henderson filter
Estimated prevalence estimate (%)
100
90
80
70
60
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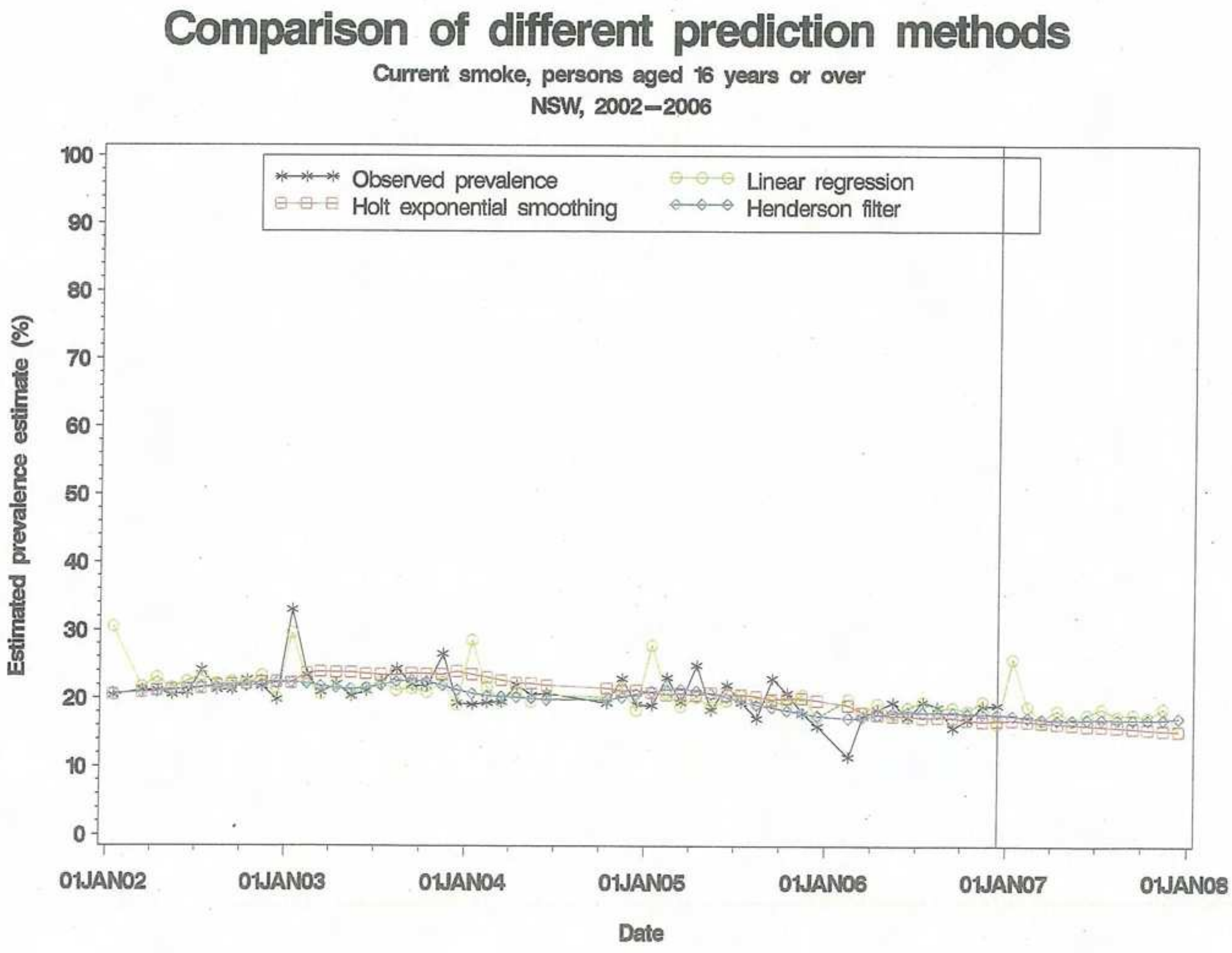
Date



Comparison of different prediction methods
Current smoke, persons aged 16 years or over
NSW, 2002–2006
Observed prevalence
Holt exponential smoothing
Linear regression
Henderson filter
Estimated prevalence estimate (%)
100
90
80
70
60
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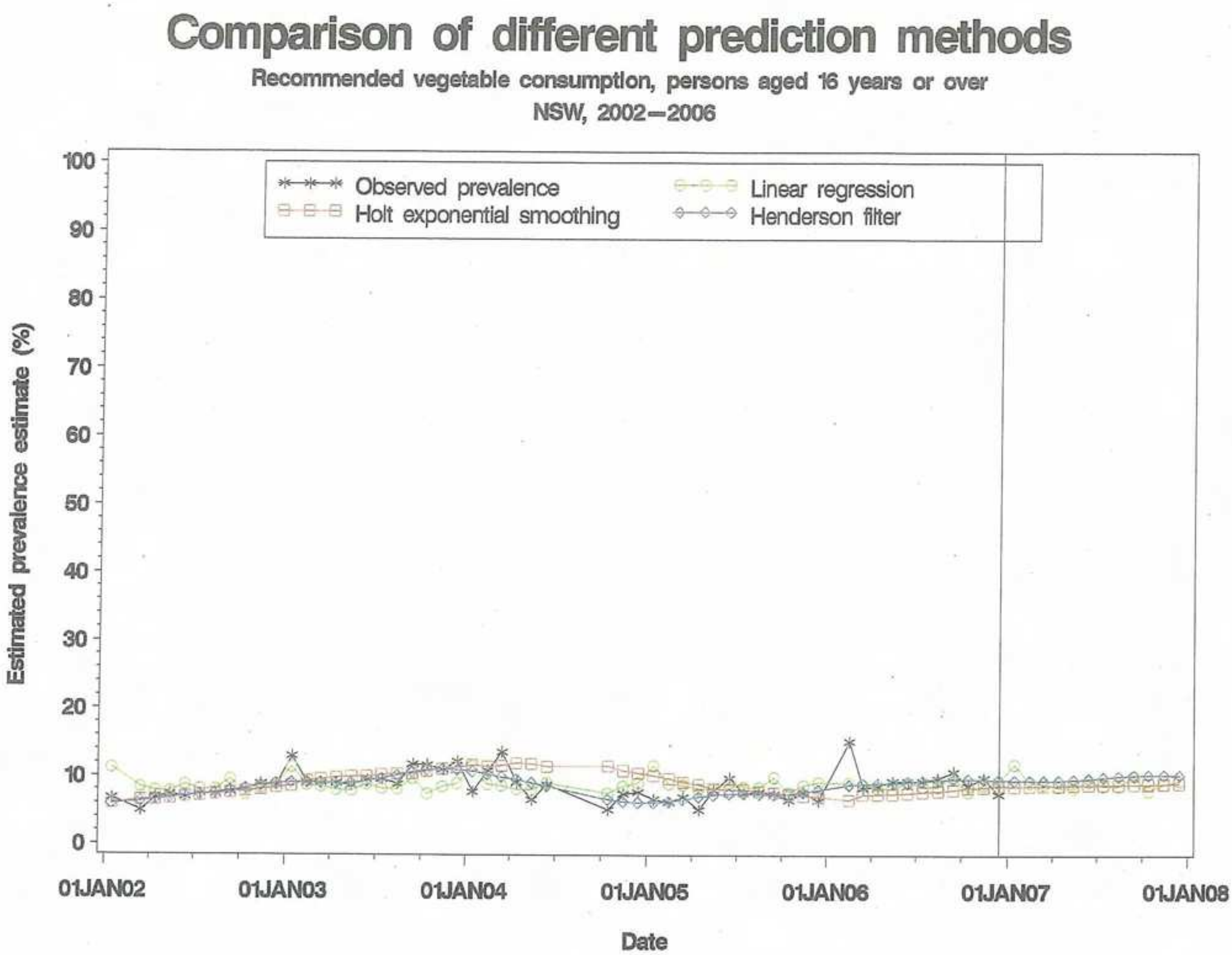
Date



Comparison of different prediction methods
Recommended vegetable consumption, persons aged 16 years or over
NSW, 2002—2006
Observed prevalence
Holt exponential smoothing
Linear regression
Henderson filter
Estimated prevalence estimate (%)
100
90
80
70
60
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40
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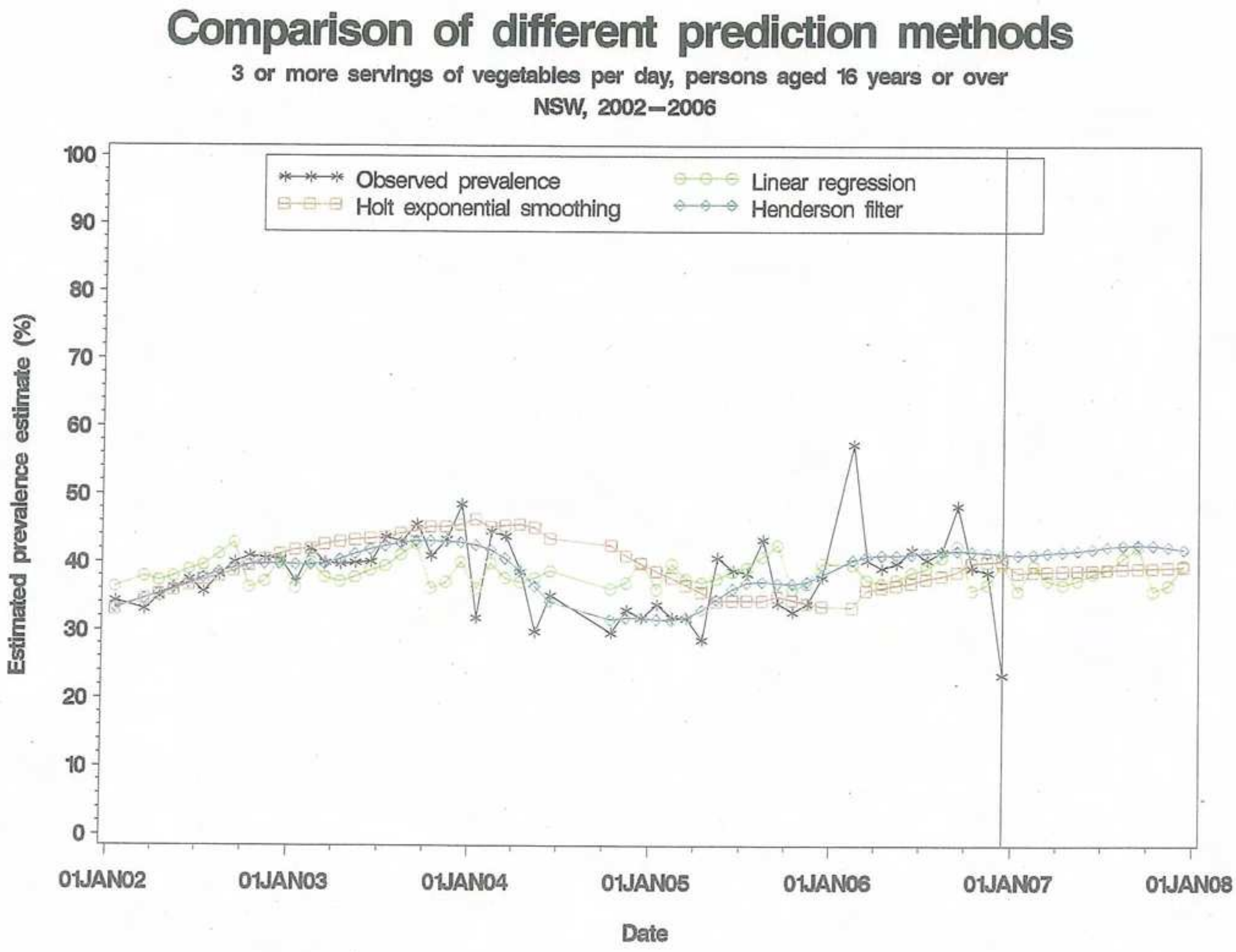
Date



Comparison of different prediction methods
3 or more servings of vegetables per day, persons aged 16 years or over
NSW, 2002—2006
Observed prevalence
Holt exponential smoothing
Linear regression
Henderson filter
Estimated prevalence estimate (%)
100
90
80
70
60
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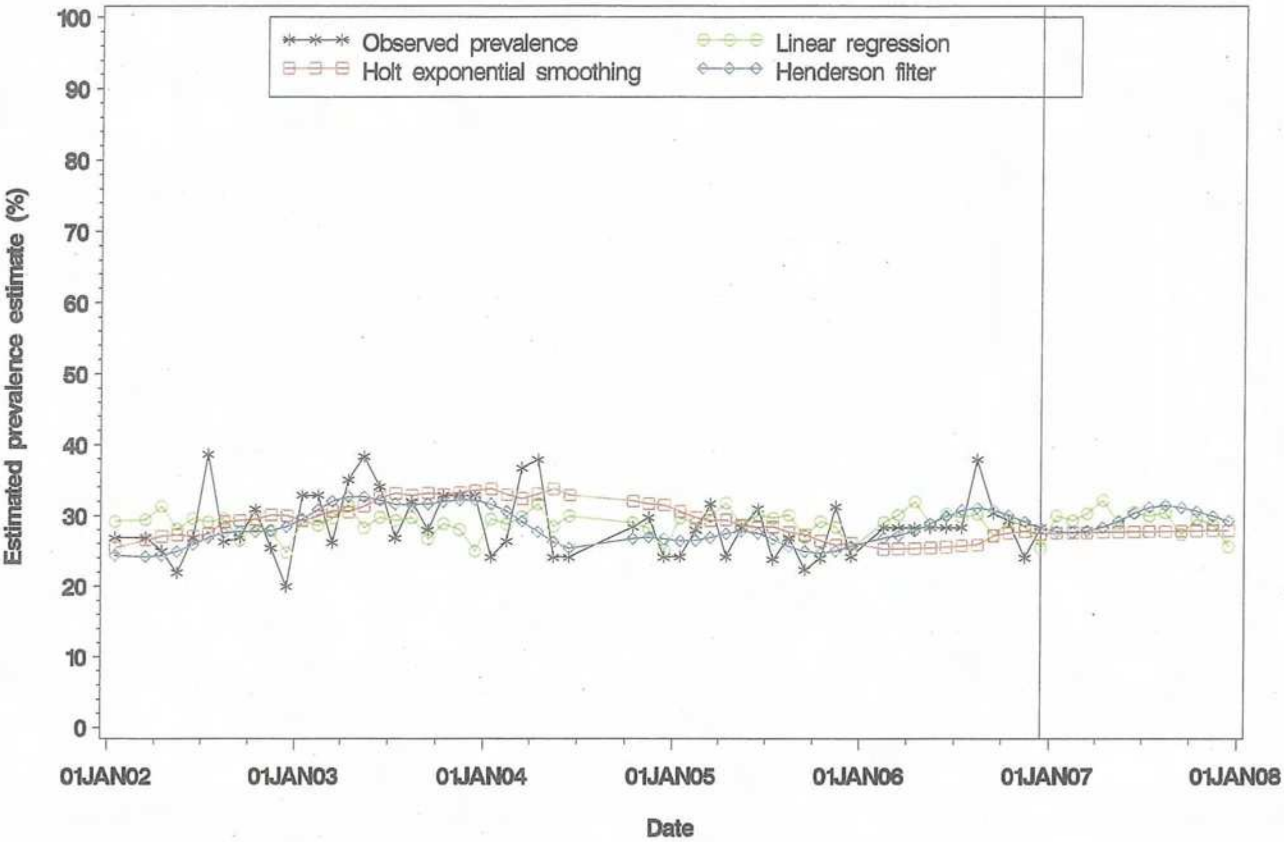
01JAN07
01JAN08
Date

APPENDIX 3:

COMPARISON OF DIFFERENT PREDICTION METHODS FOR THE LIFESTYLE INDICATORS FOR EACH AREA HEALTH SERVICE

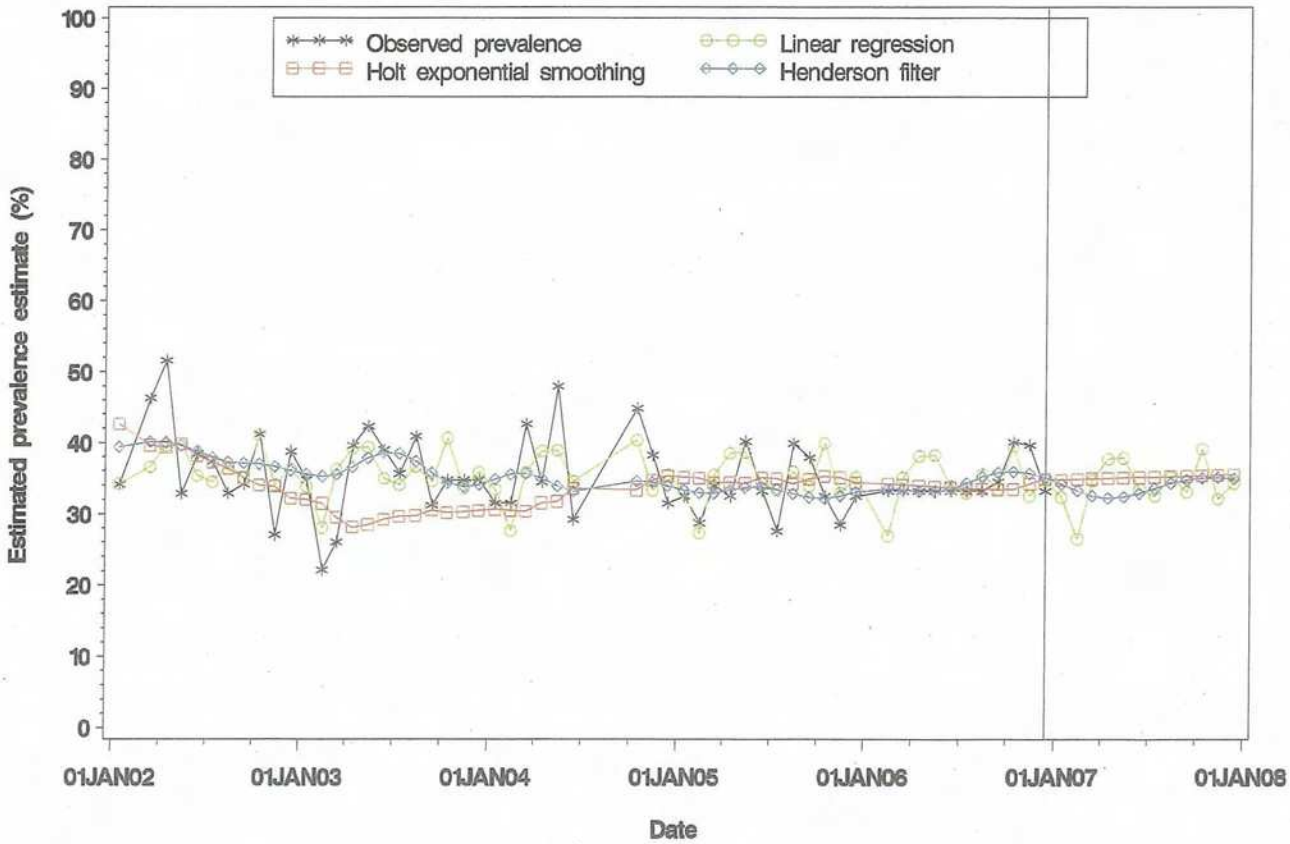
Comparison of different prediction methods

Risk alcohol drinking, persons aged 16 years or over
Sydney South West AHS, 2002–2006



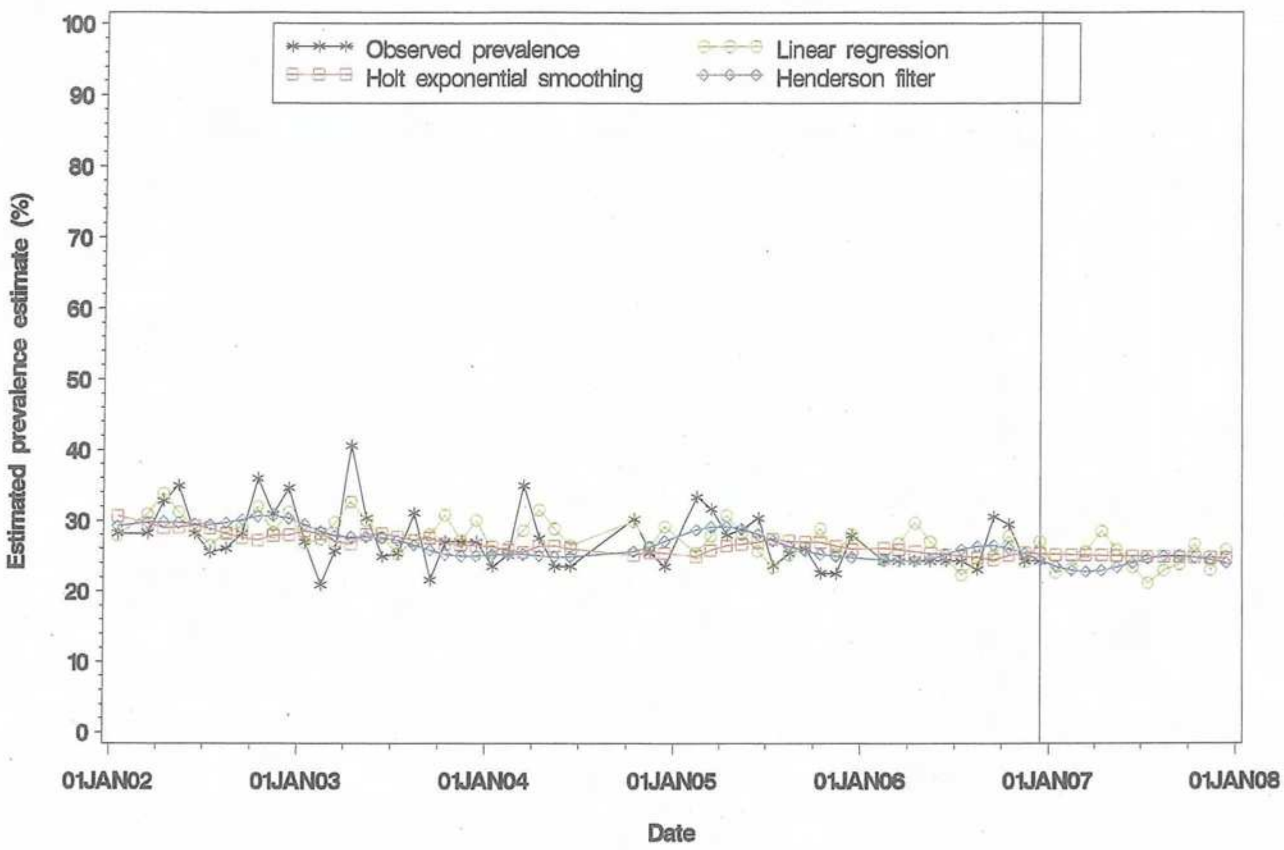
Comparison of different prediction methods

Risk alcohol drinking, persons aged 16 years or over
South Eastern Sydney & Illawarra AHS, 2002–2006



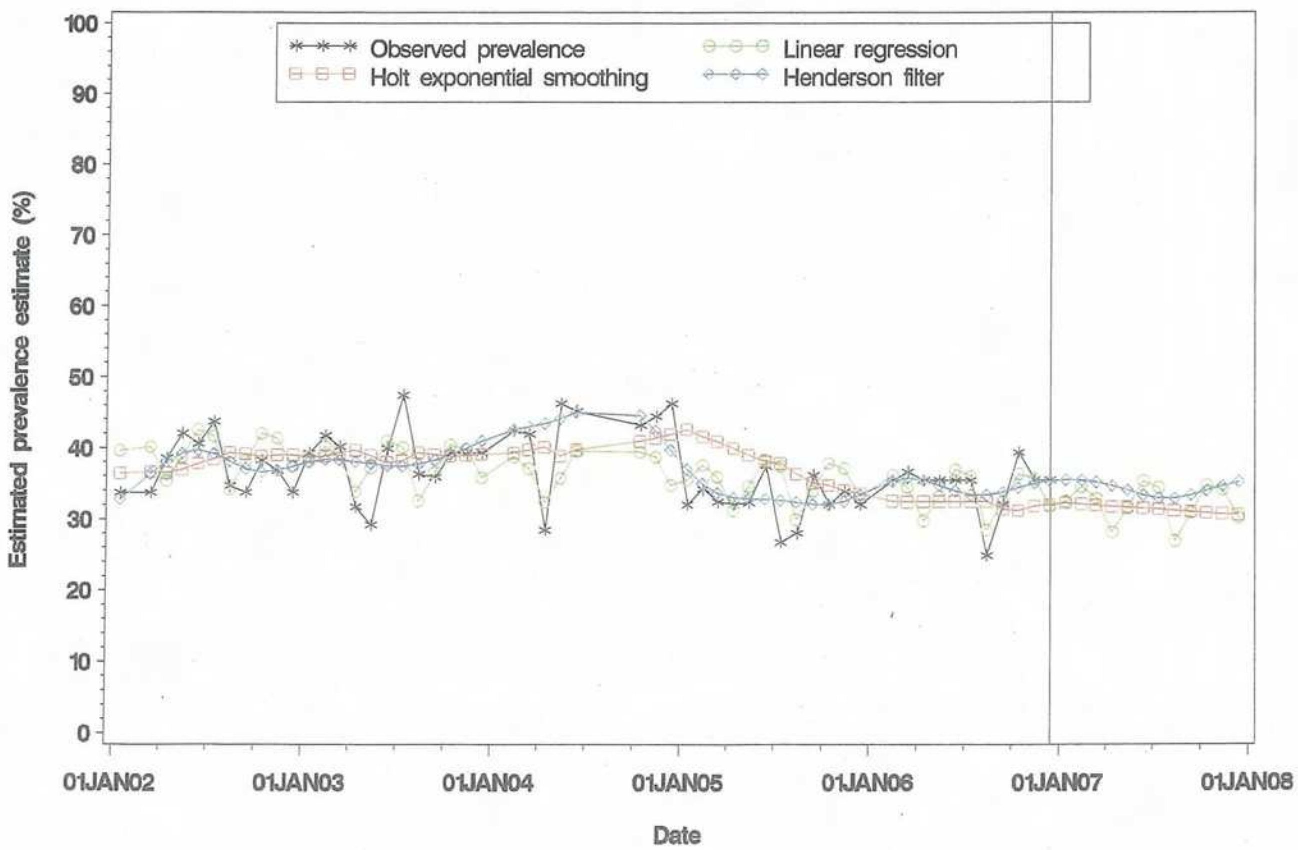
Comparison of different prediction methods

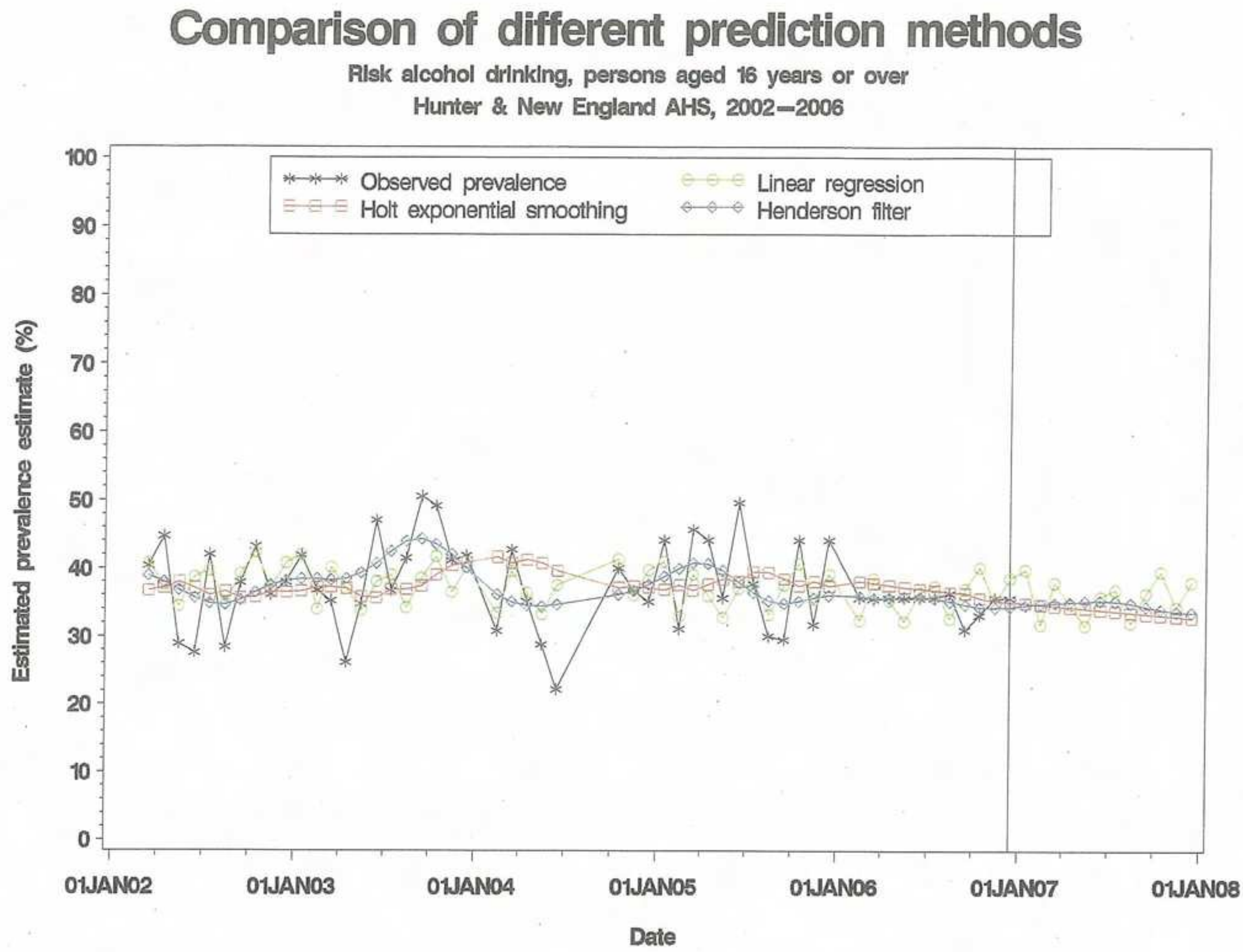
Risk alcohol drinking, persons aged 16 years or over
Sydney West AHS, 2002–2006



Comparison of different prediction methods

Risk alcohol drinking, persons aged 16 years or over
Northern Sydney & Central Coast AHS, 2002–2006




Comparison of different prediction methods
Risk alcohol drinking, persons aged 16 years or over
Hunter & New England AHS, 2002–2006
Observed prevalence
Holt exponential smoothing
Linear regression
Henderson filter
Estimated prevalence estimate (%)
0
10
20
30
40
50
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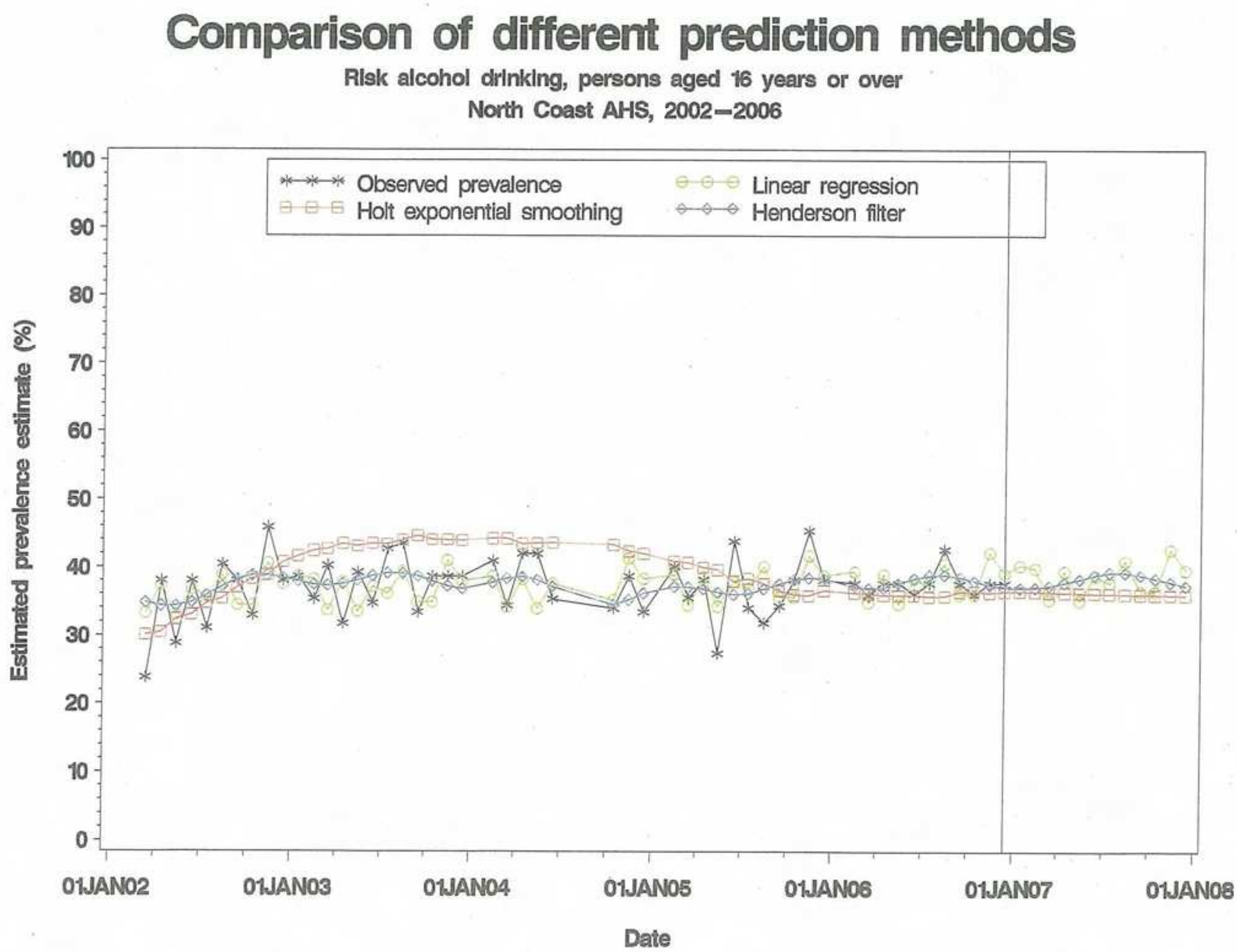
Comparison of different prediction methods
Risk alcohol drinking, persons aged 16 years or over
North Coast AHS, 2002–2006
Observed prevalence
Holt exponential smoothing
Linear regression
Henderson filter
Estimated prevalence estimate (%)
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10
20
30
40
50
60
70
80
90
100
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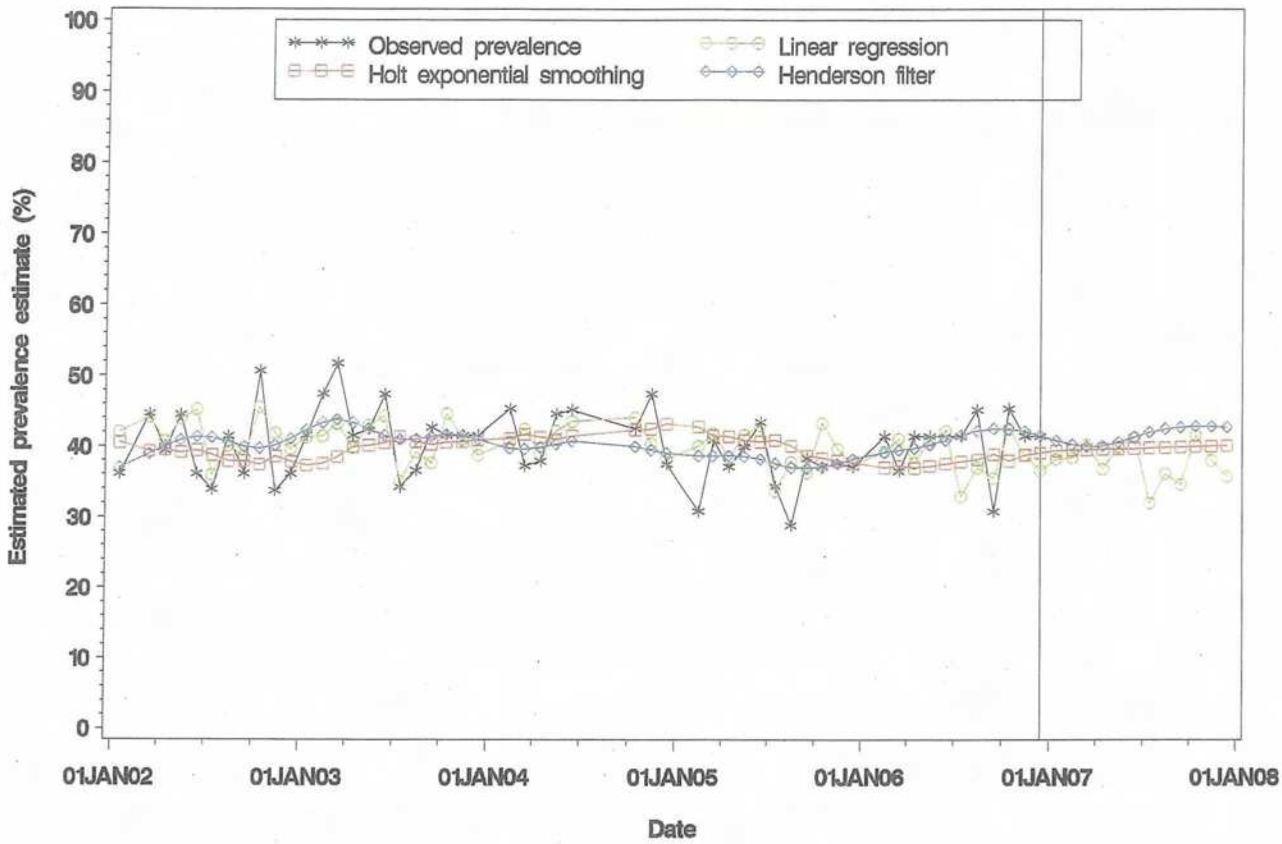
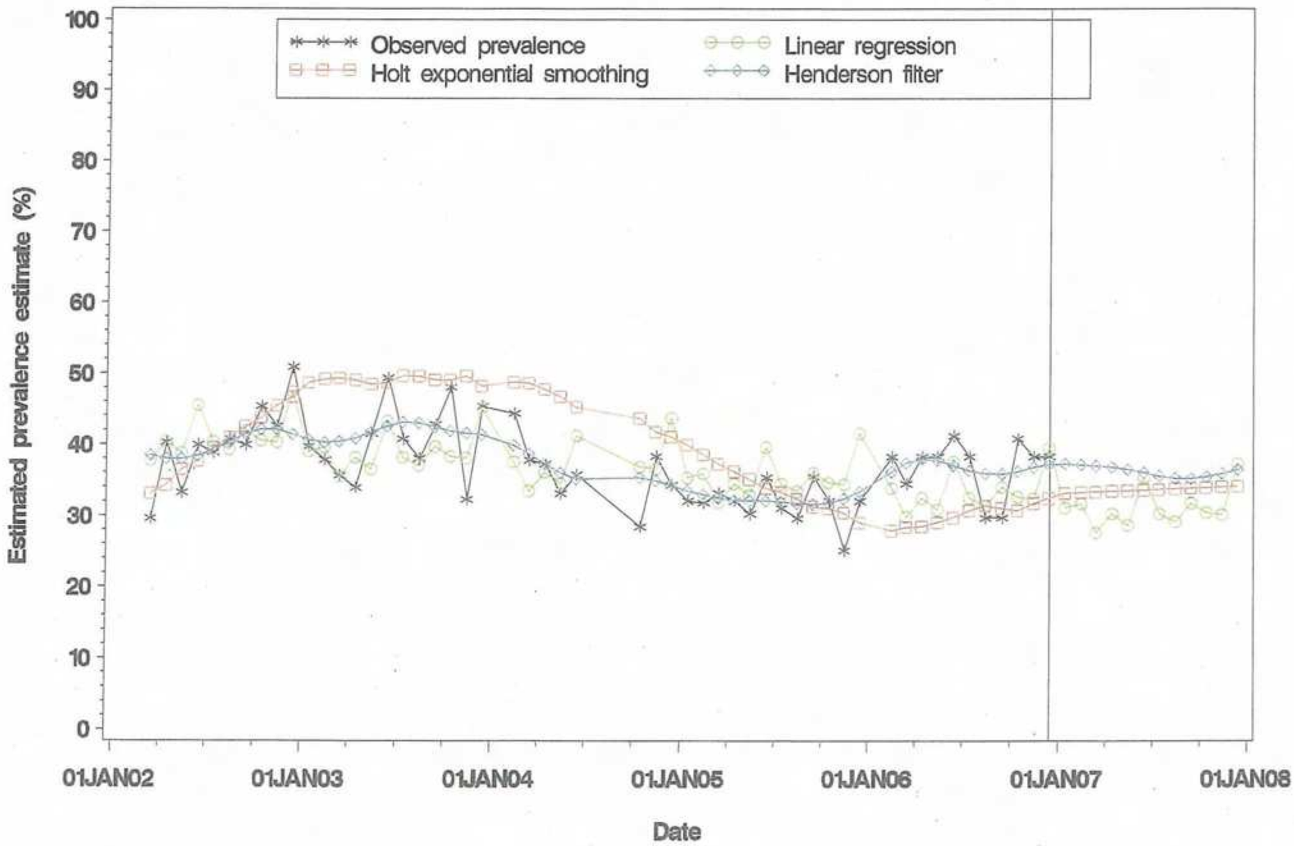
Comparison of different prediction methods

Risk alcohol drinking, persons aged 16 years or over
Greater Southern AHS, 2002–2006



Comparison of different prediction methods

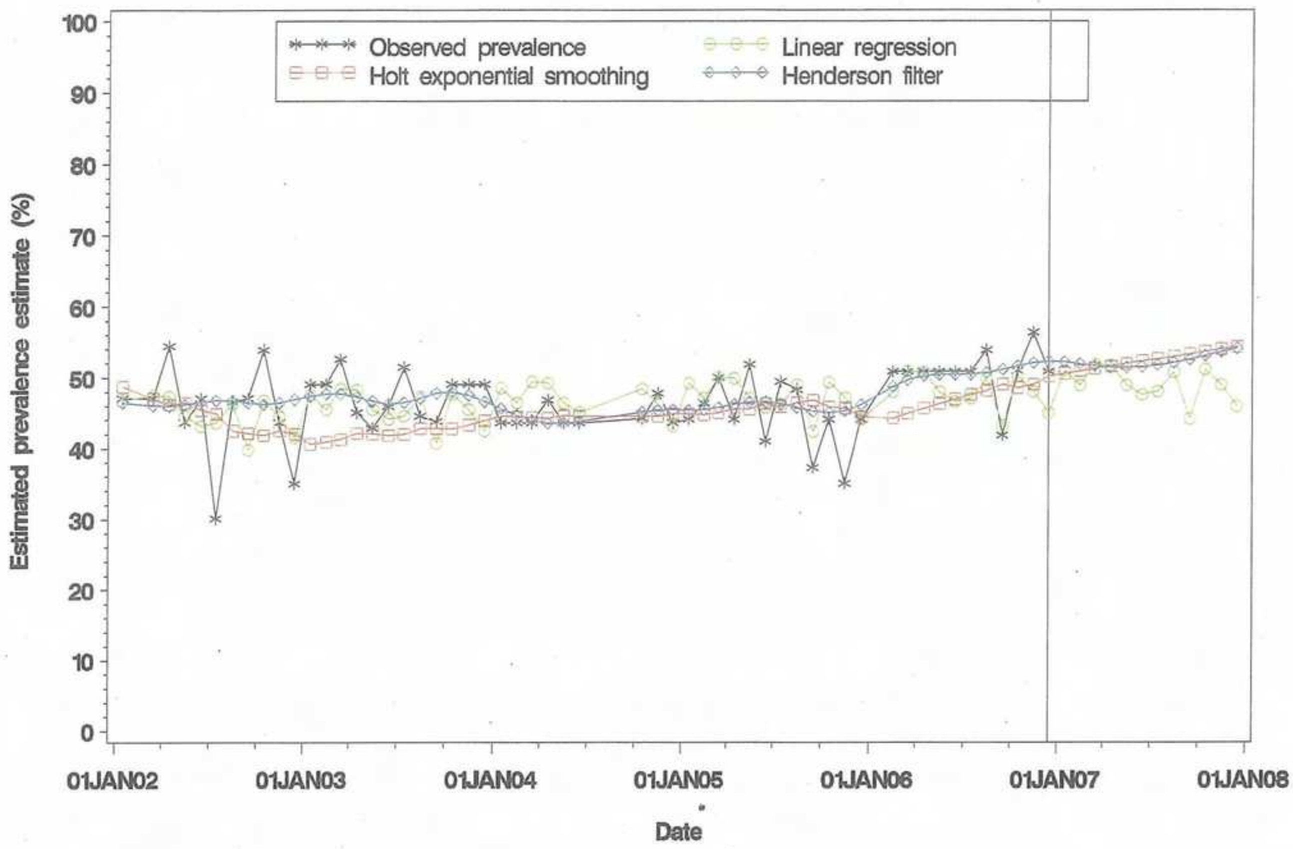
Risk alcohol drinking, persons aged 16 years or over
Greater Western AHS, 2002–2006



Comparison of different prediction methods

Overweight or obesity, persons aged 16 years or over

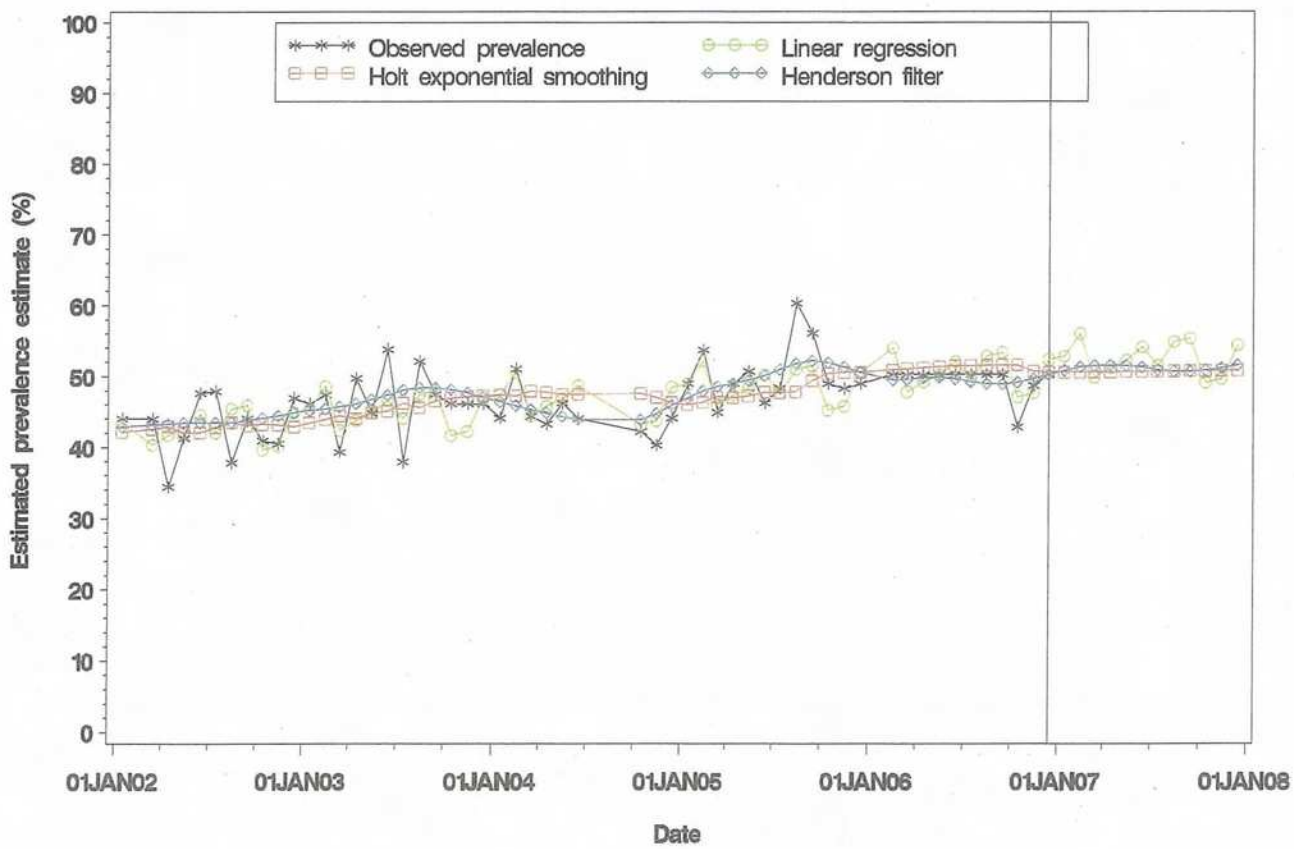
Sydney South West AHS, 2002–2006



Comparison of different prediction methods

Overweight or obesity, persons aged 16 years or over

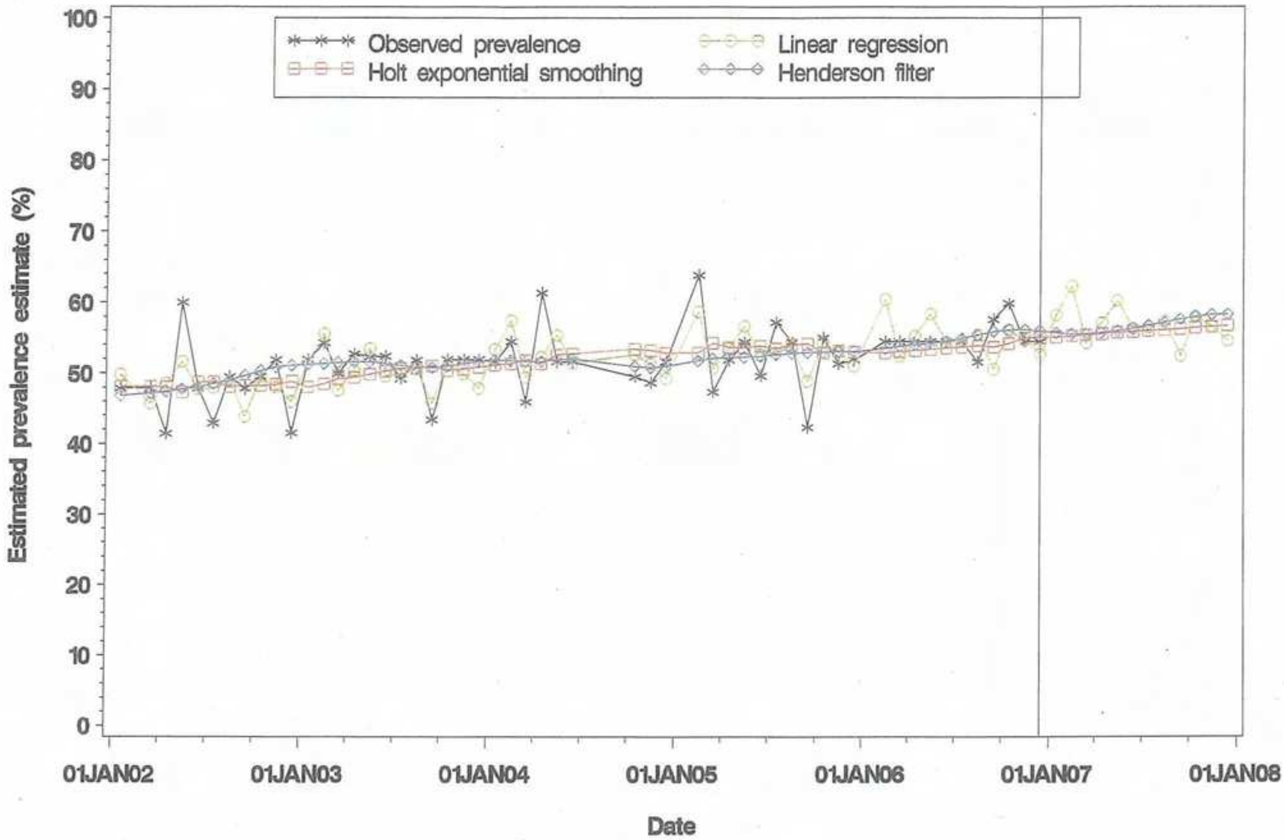
South Eastern Sydney & Illawarra AHS, 2002–2006



Comparison of different prediction methods

Overweight or obesity, persons aged 16 years or over

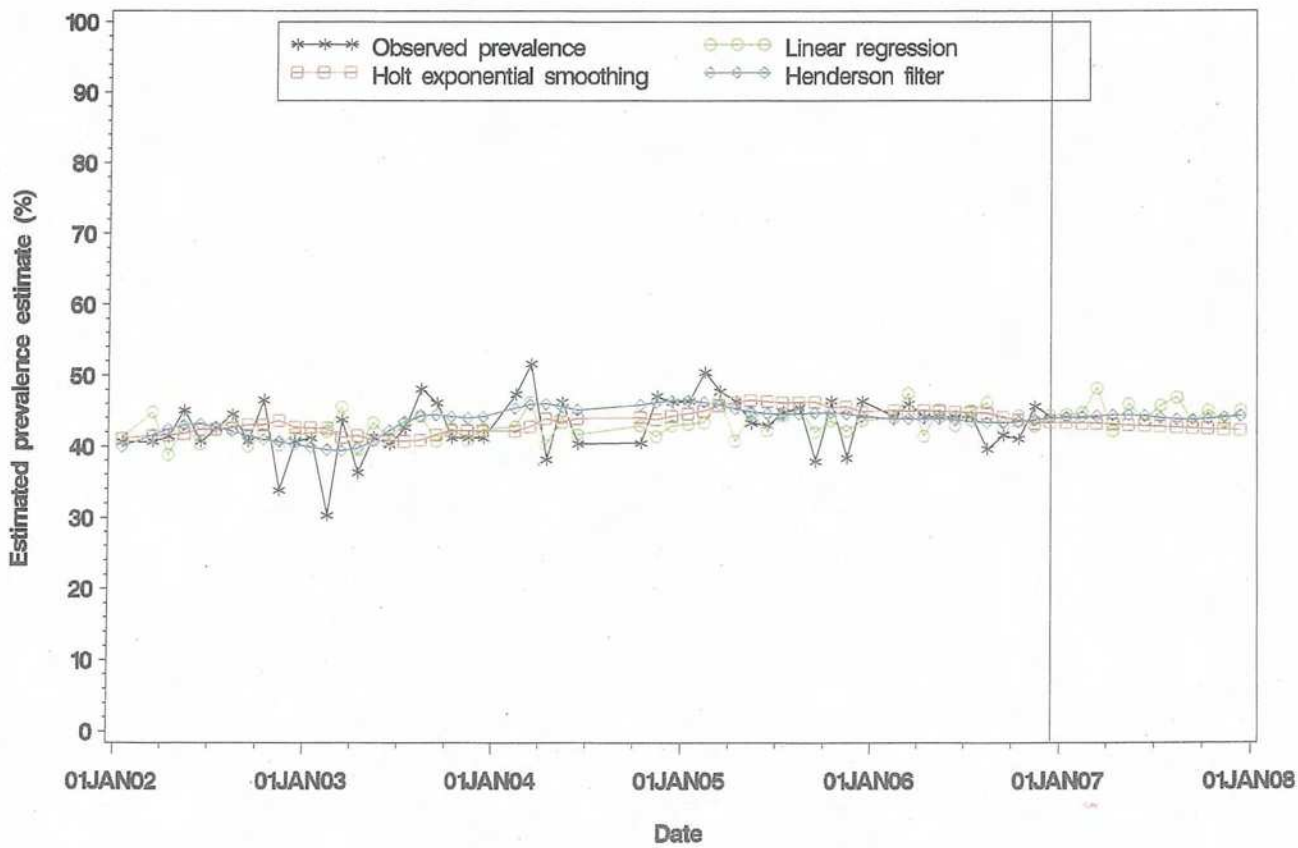
Sydney West AHS, 2002–2006



Comparison of different prediction methods

Overweight or obesity, persons aged 16 years or over

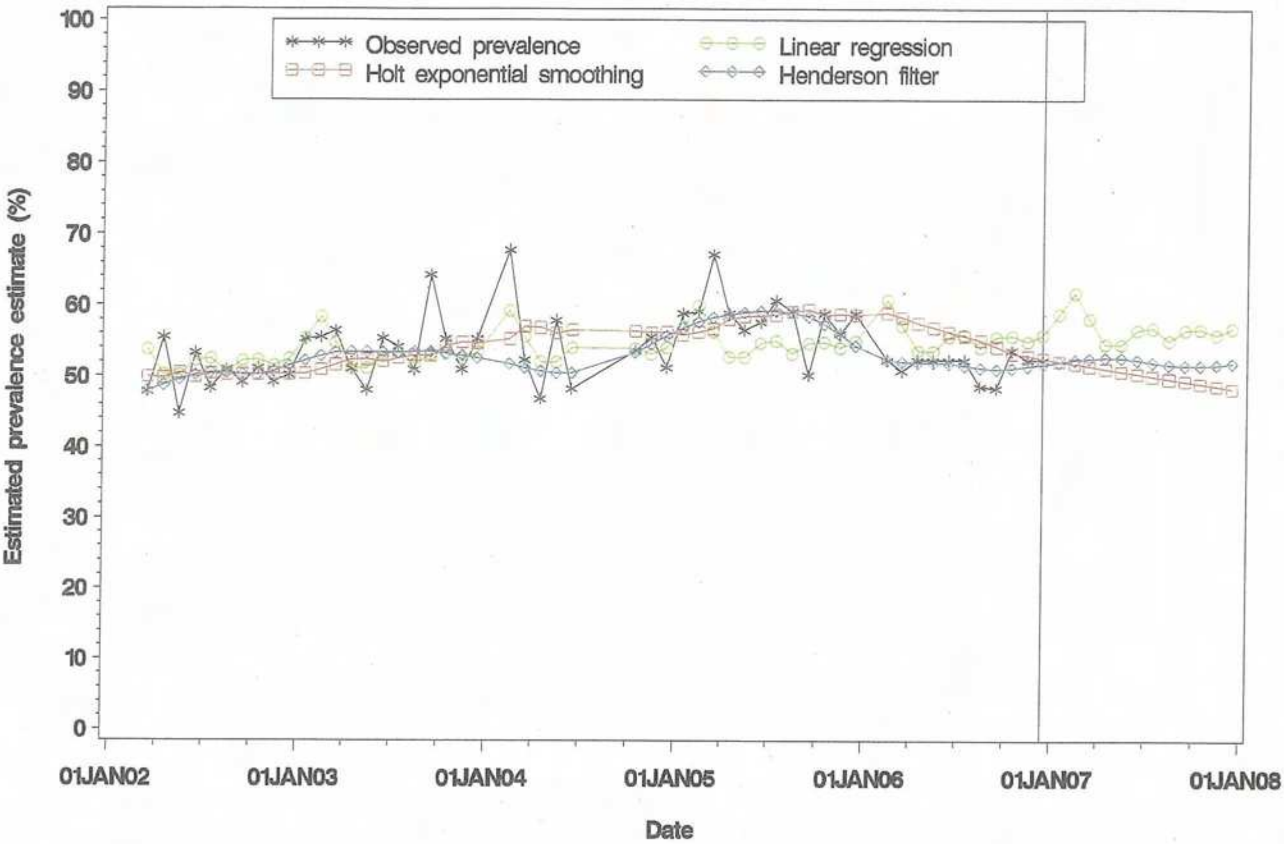
Northern Sydney & Central Coast AHS, 2002–2006



Comparison of different prediction methods

Overweight or obesity, persons aged 16 years or over

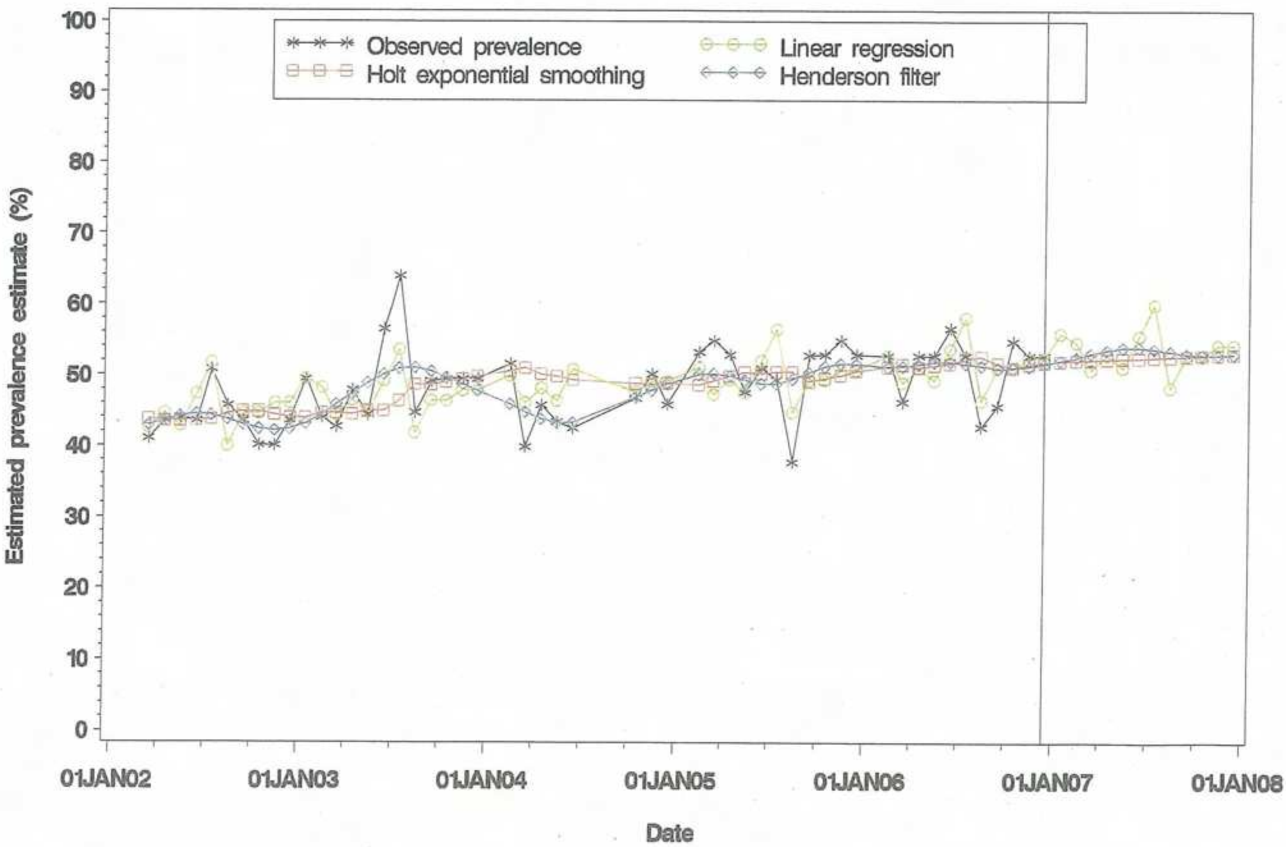
Hunter & New England AHS, 2002–2006



Comparison of different prediction methods

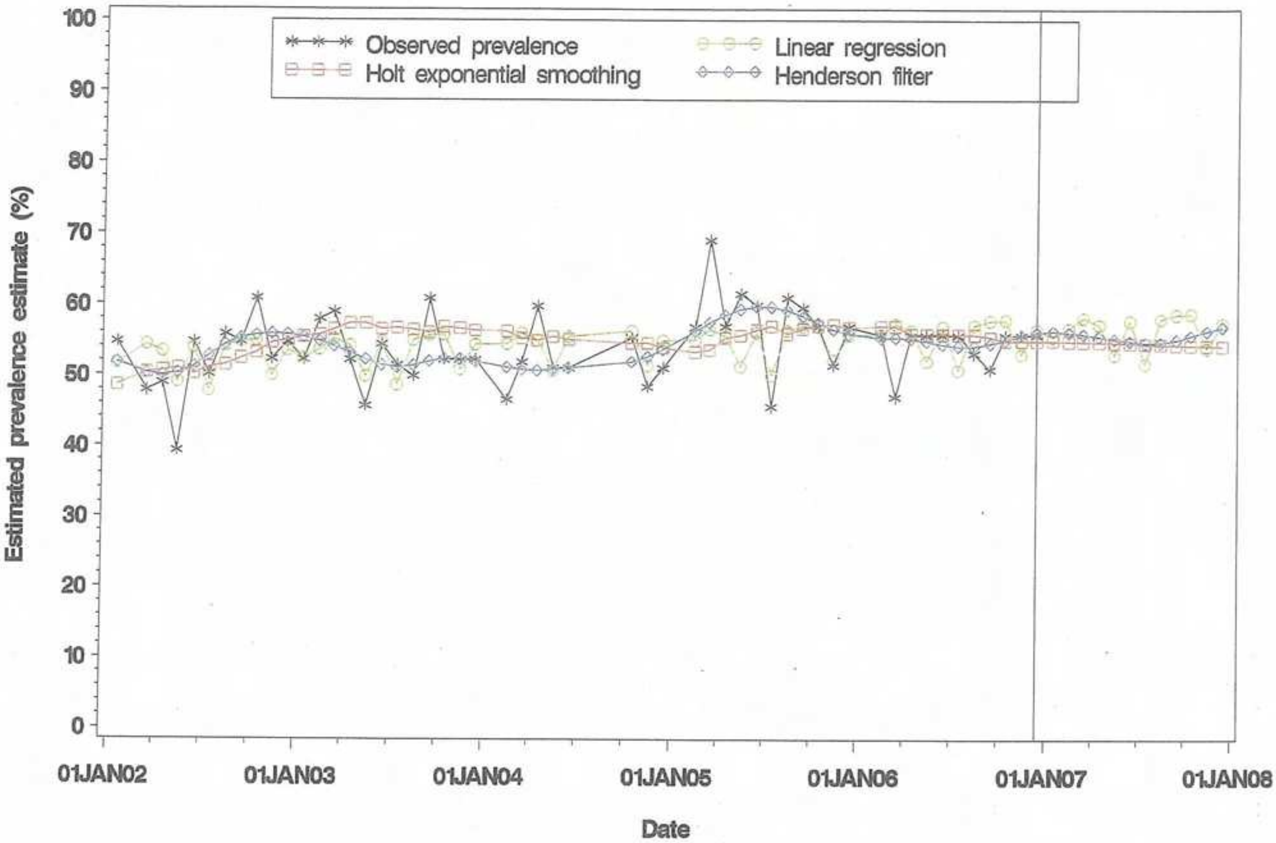
Overweight or obesity, persons aged 16 years or over

North Coast AHS, 2002–2006



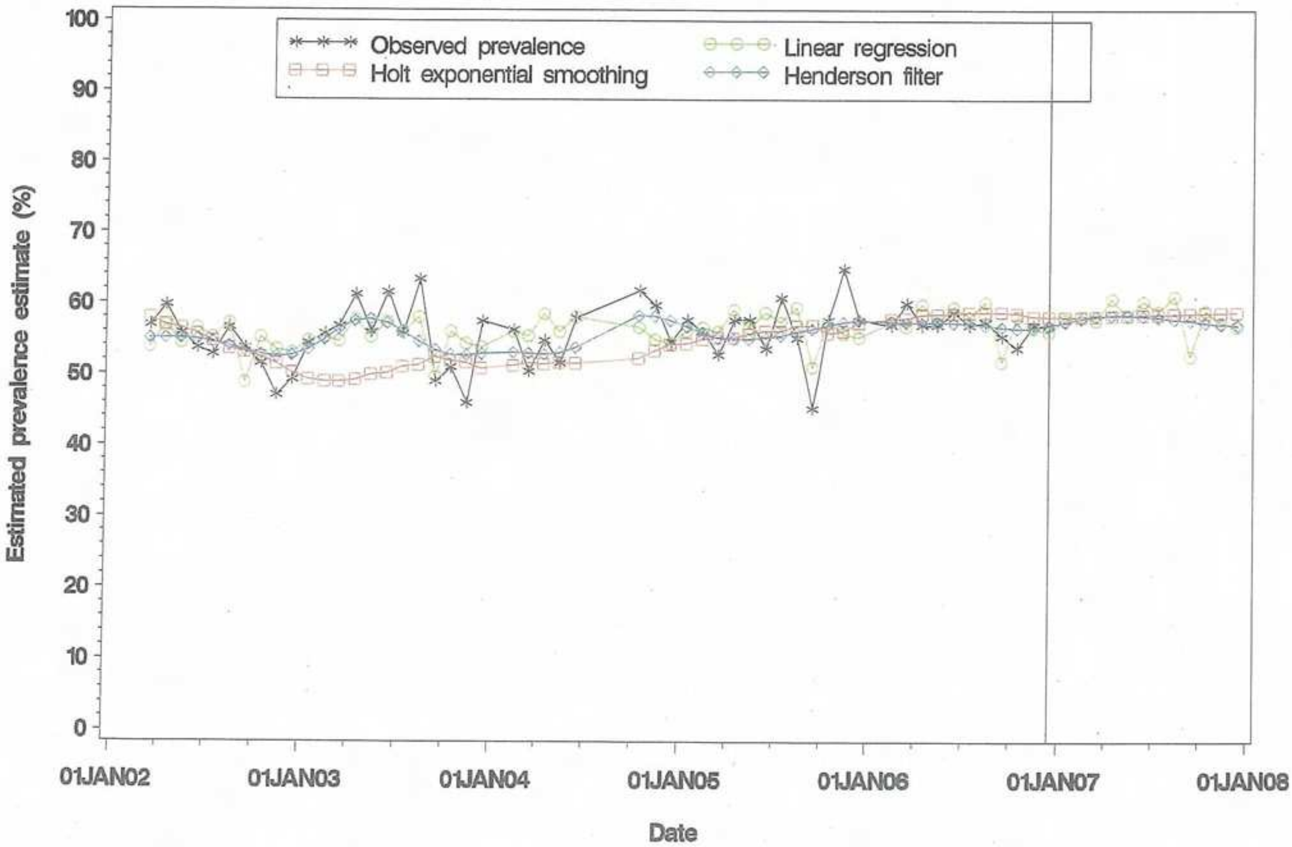
Comparison of different prediction methods

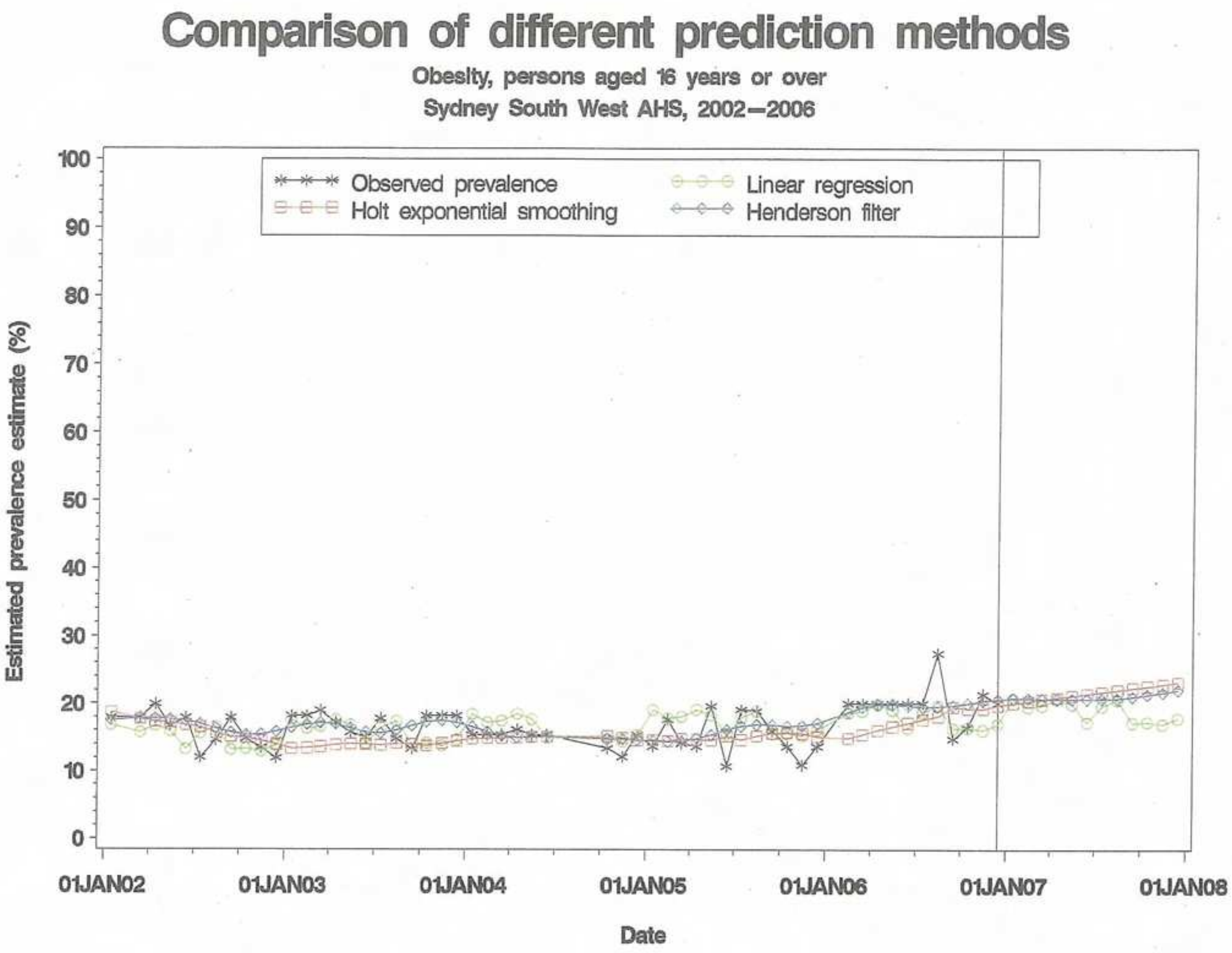
Overweight or obesity, persons aged 16 years or over
Greater Southern AHS, 2002–2006



Comparison of different prediction methods

Overweight or obesity, persons aged 16 years or over
Greater Western AHS, 2002–2006




Comparison of different prediction methods
Obesity, persons aged 16 years or over
Sydney South West AHS, 2002–2006
Observed prevalence
Holt exponential smoothing
Linear regression
Henderson filter
Estimated prevalence estimate (%)
100
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80
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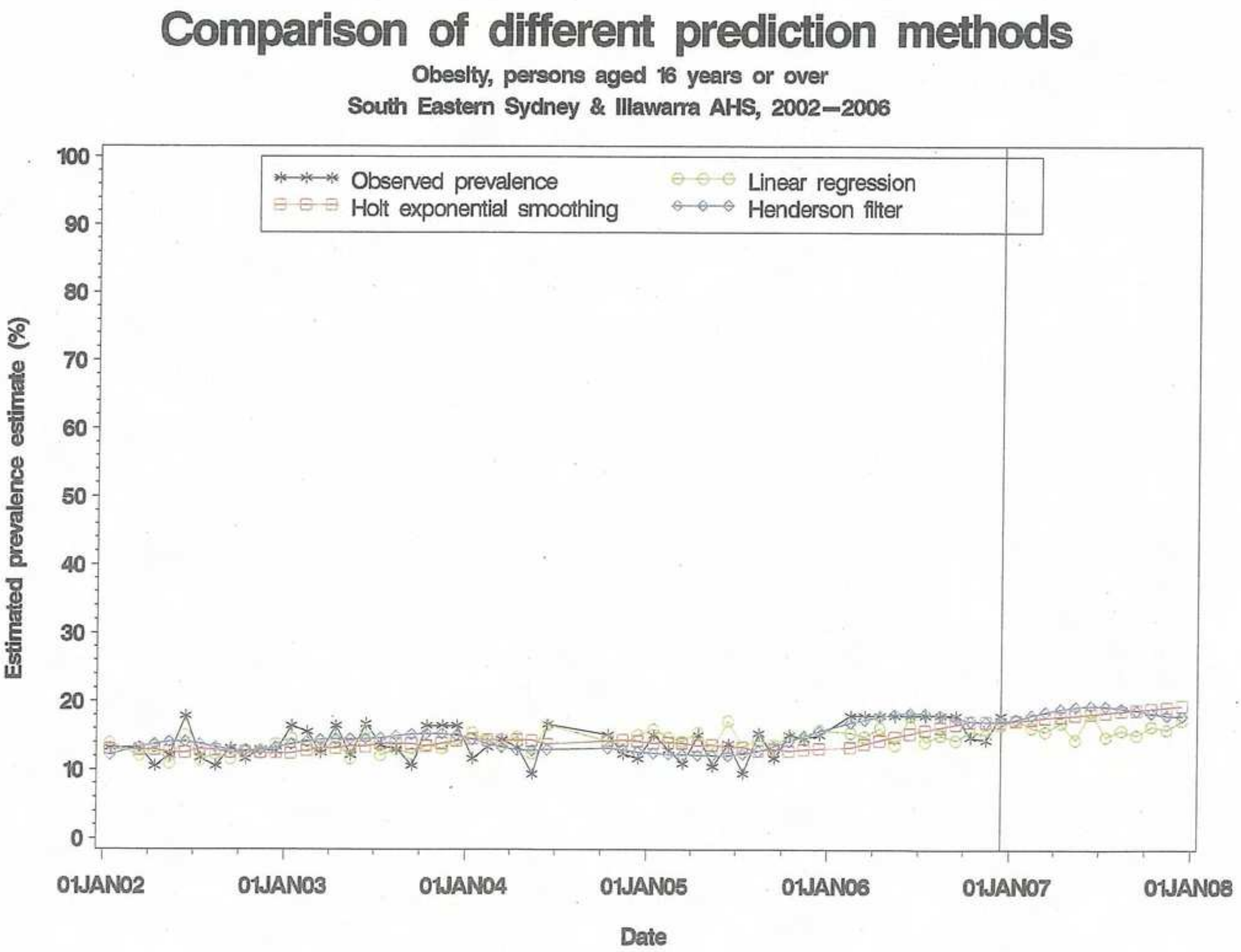
Date


Comparison of different prediction methods
Obesity, persons aged 16 years or over
South Eastern Sydney & Illawarra AHS, 2002–2006
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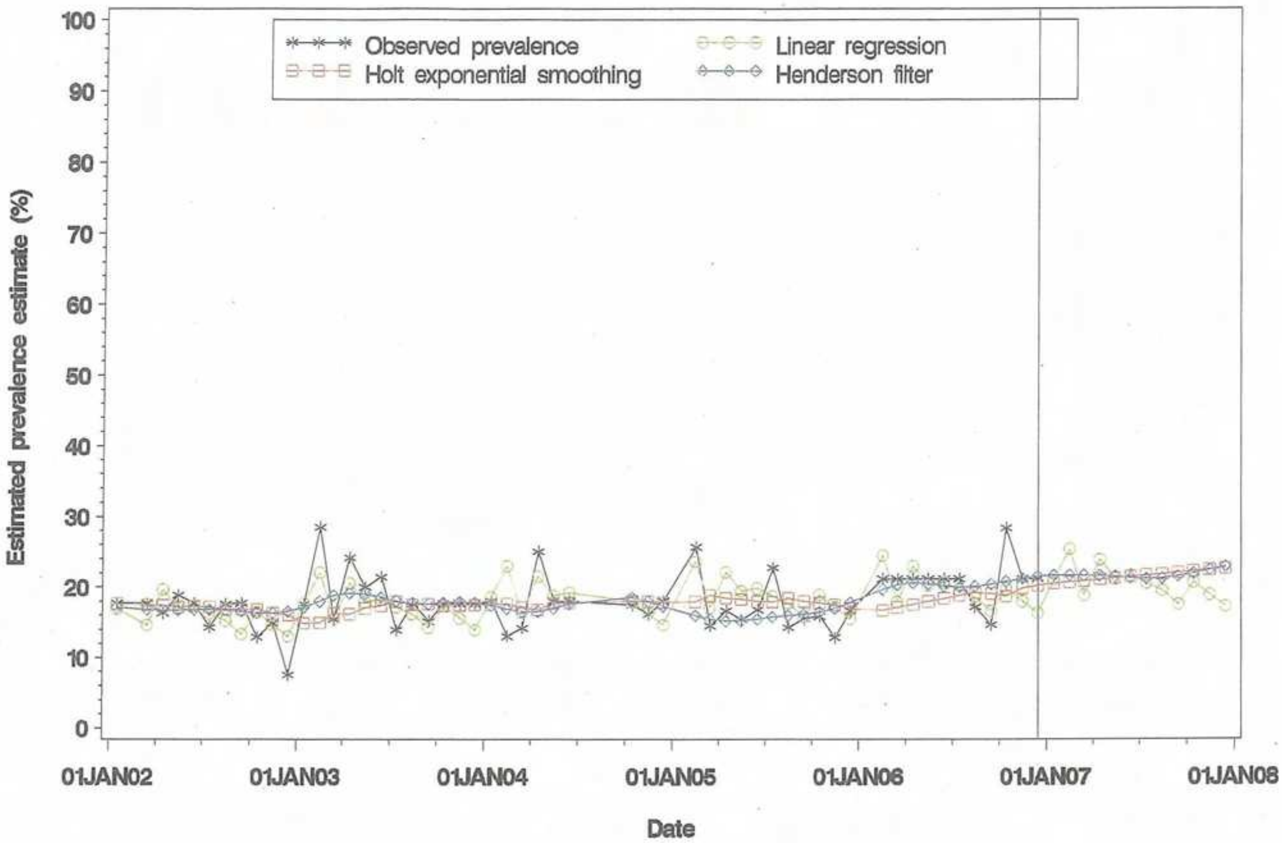
Comparison of different prediction methods

Obesity, persons aged 16 years or over

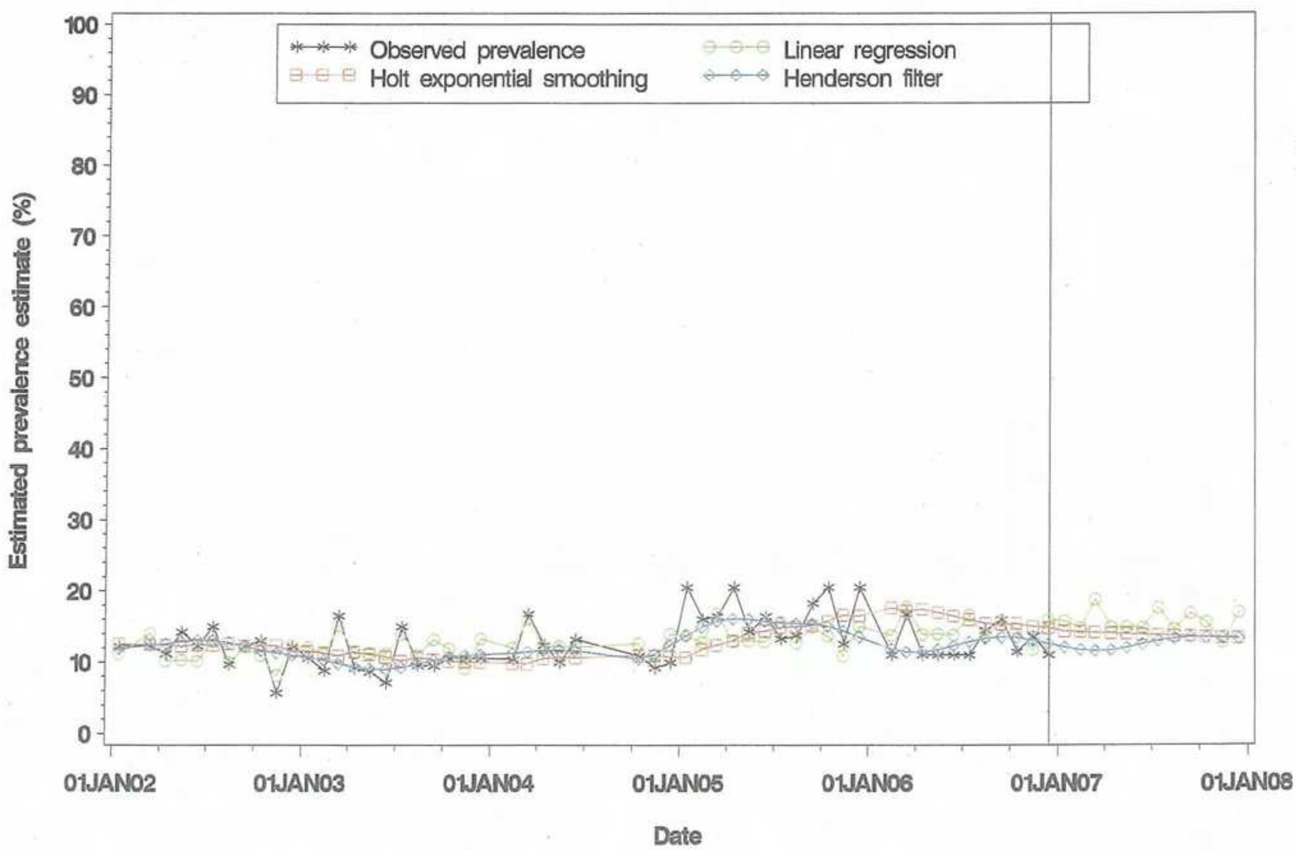
Sydney West AHS, 2002—2006



Comparison of different prediction methods

Obesity, persons aged 16 years or over

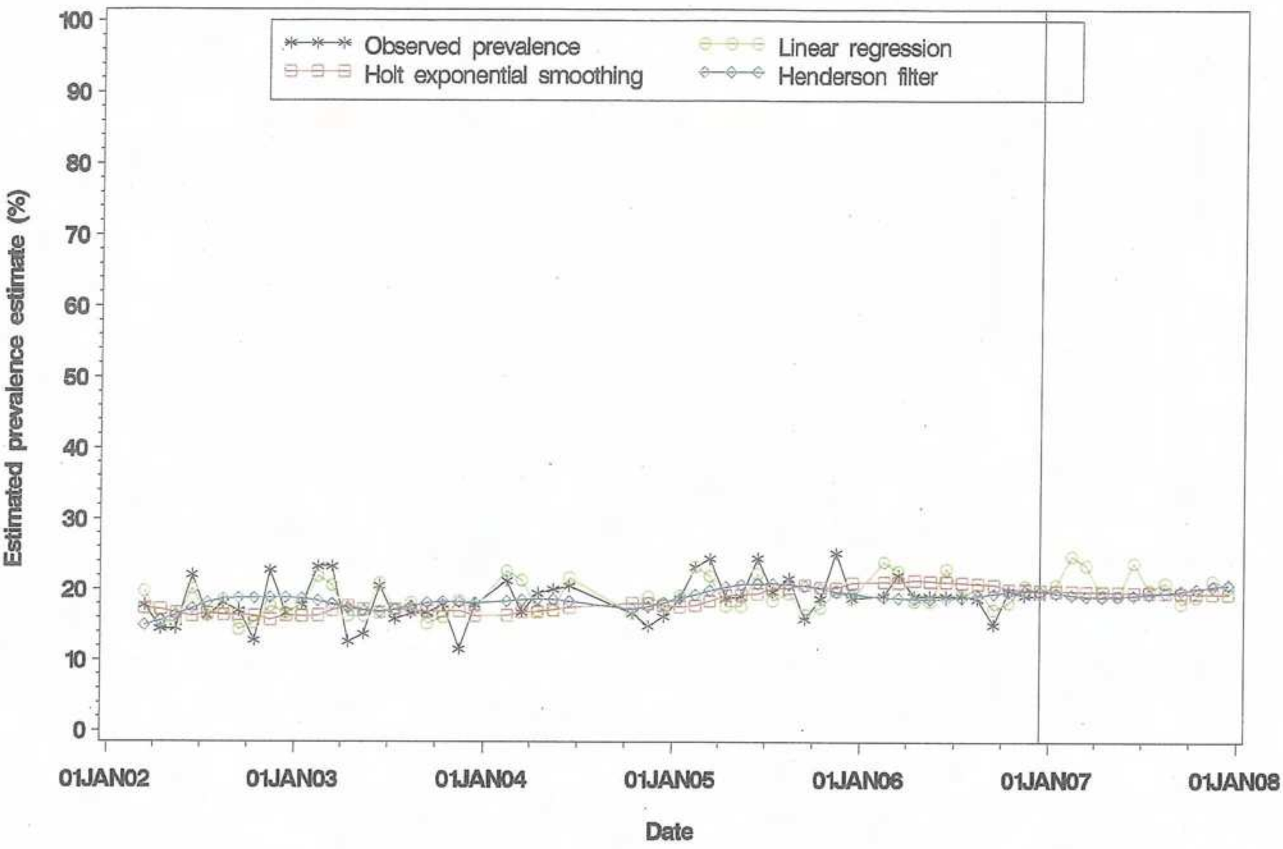
Northern Sydney & Central Coast AHS, 2002—2006



Comparison of different prediction methods

Obesity, persons aged 16 years or over

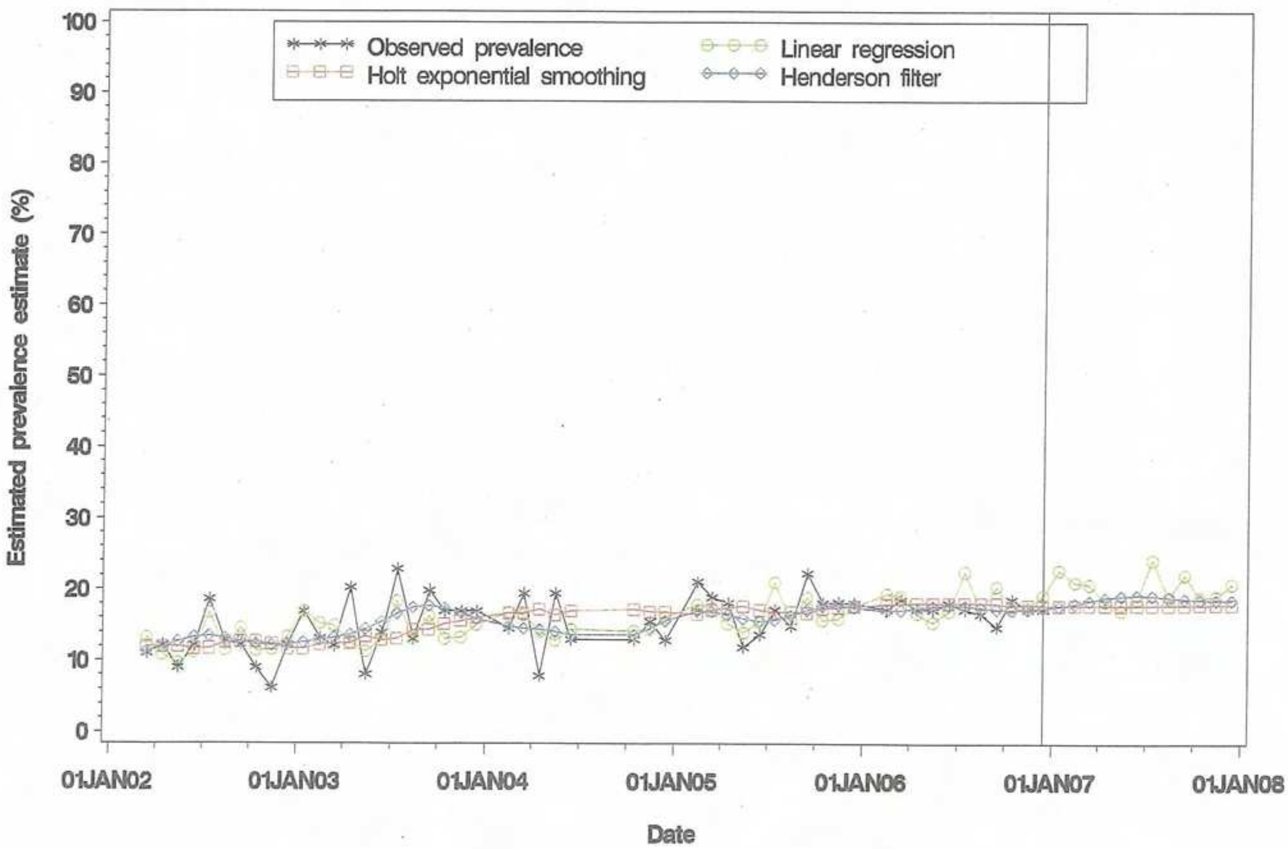
Hunter & New England AHS, 2002–2006



Comparison of different prediction methods

Obesity, persons aged 16 years or over

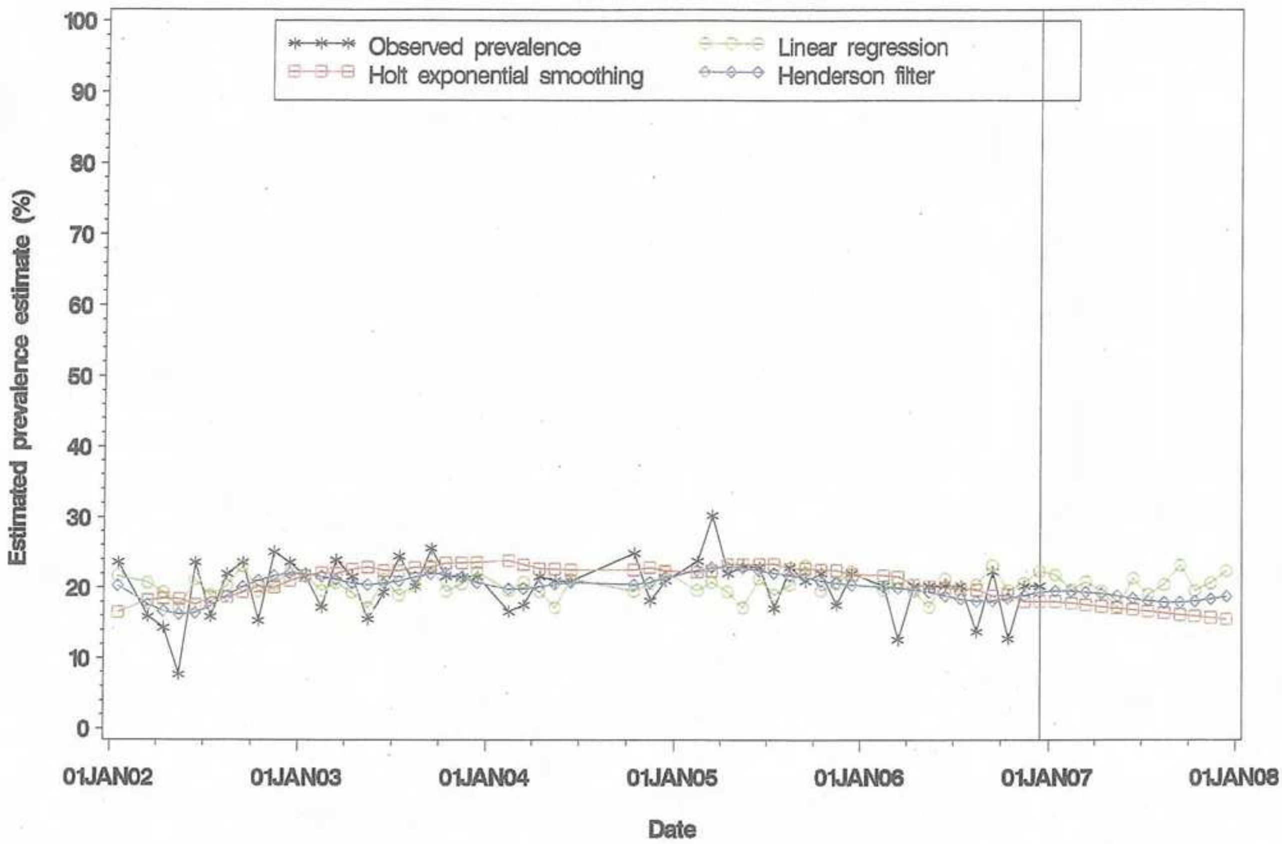
North Coast AHS, 2002–2006



Comparison of different prediction methods

Obesity, persons aged 16 years or over

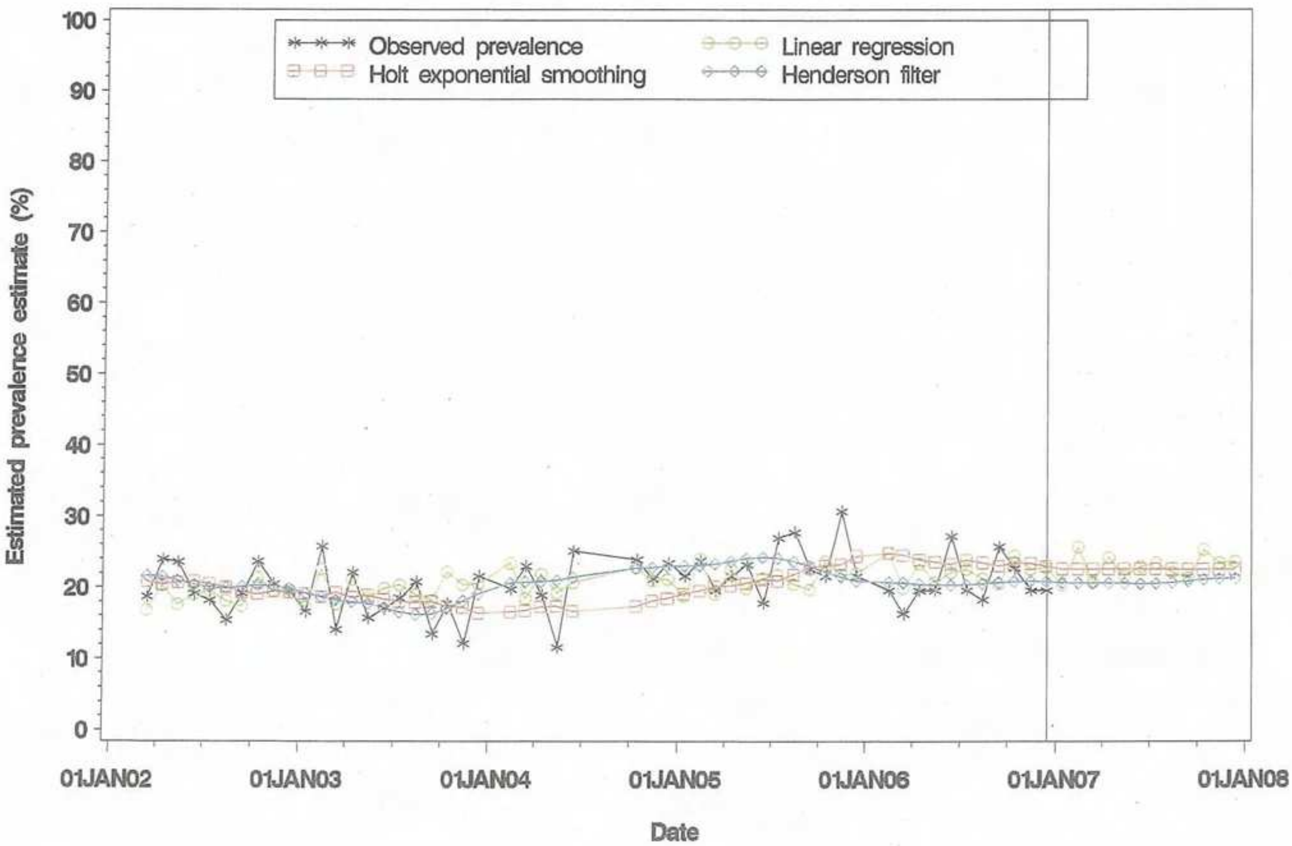
Greater Southern AHS, 2002–2006



Comparison of different prediction methods

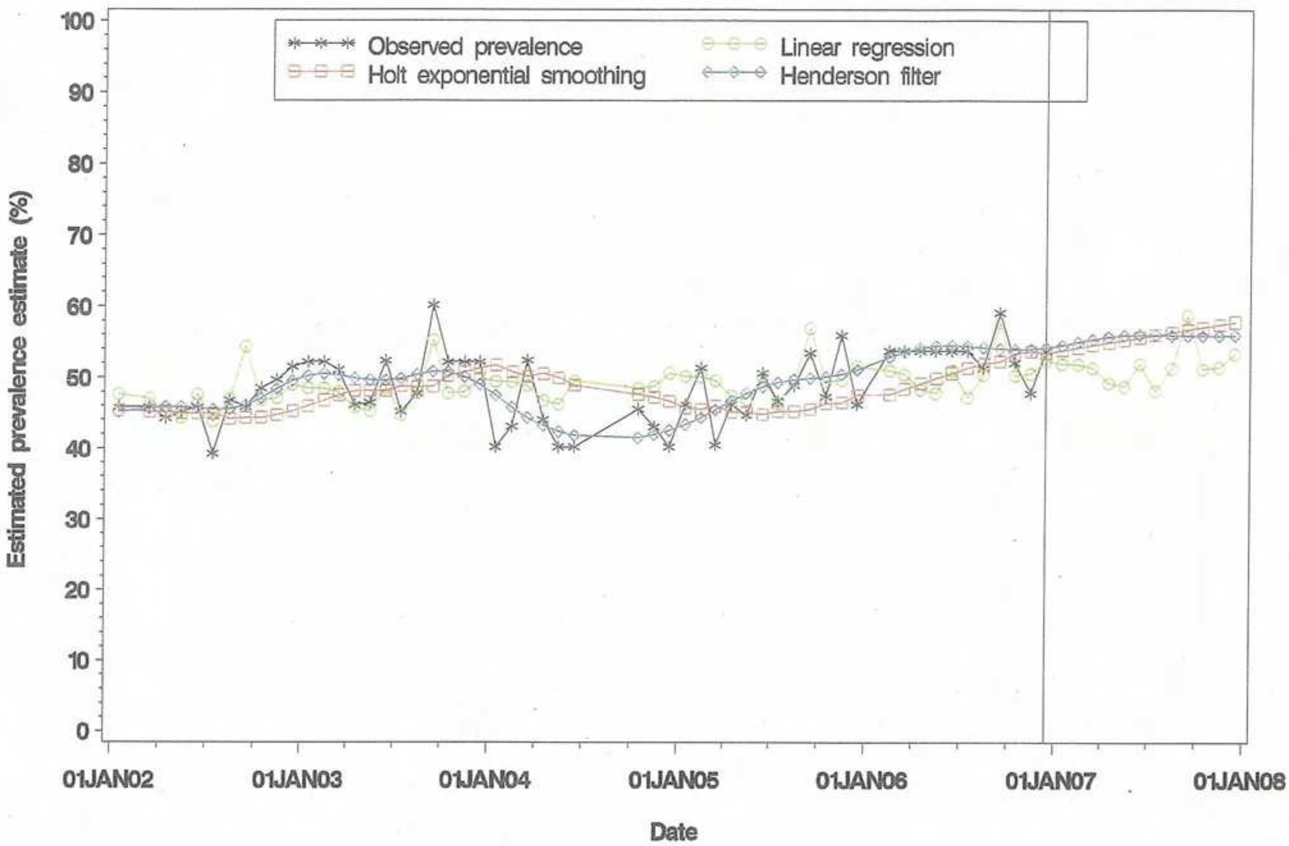
Obesity, persons aged 16 years or over

Greater Western AHS, 2002–2006



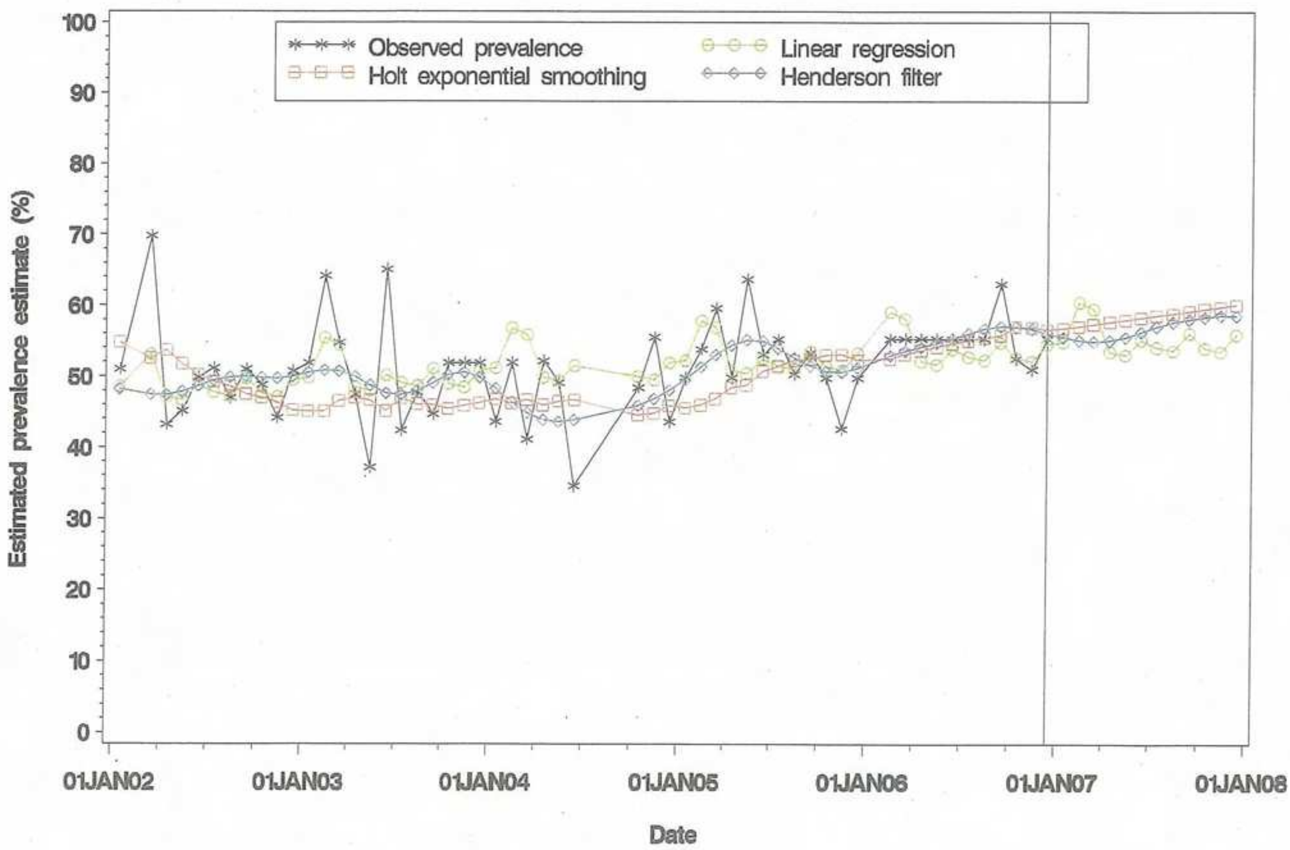
Comparison of different prediction methods

Recommended fruit consumption, persons aged 16 years or over
Sydney South West AHS, 2002–2006



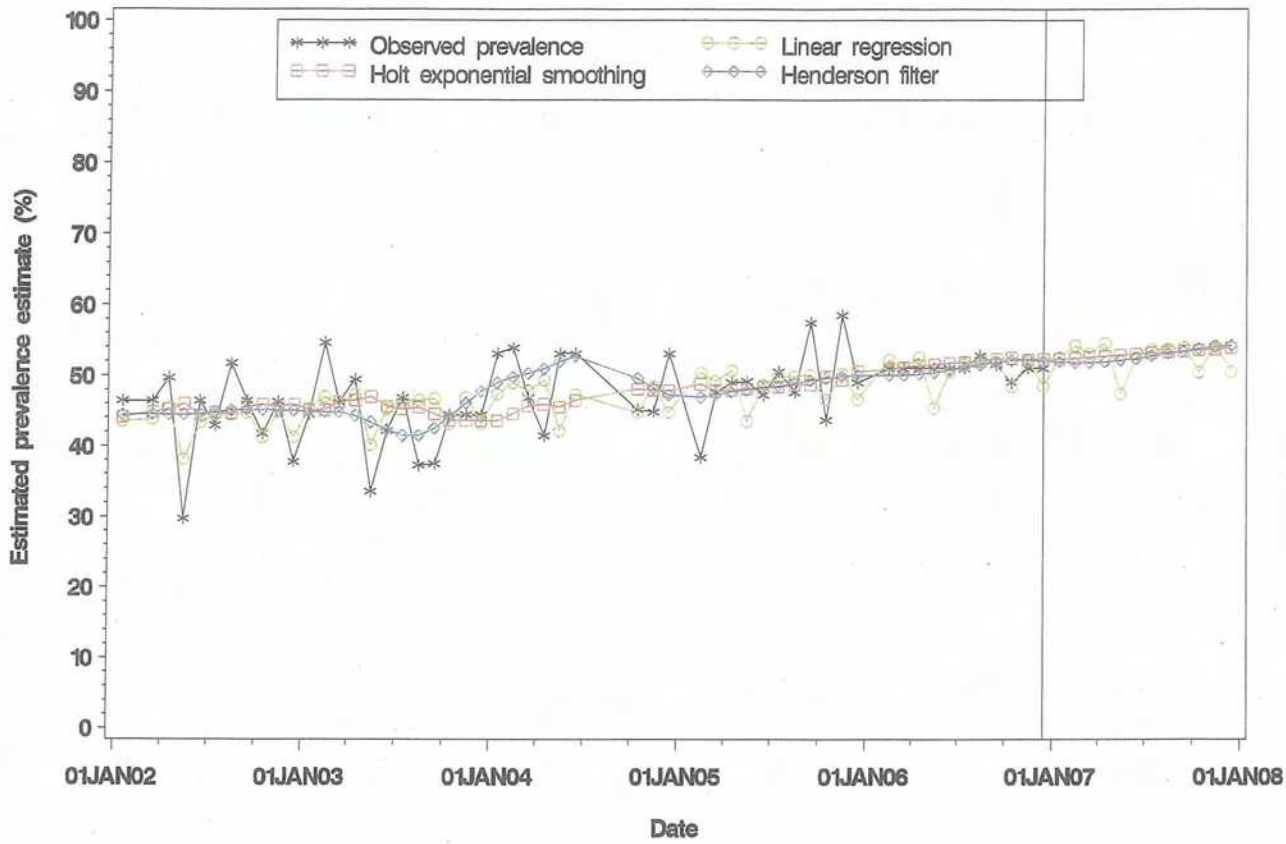
Comparison of different prediction methods

Recommended fruit consumption, persons aged 16 years or over
South Eastern Sydney & Illawarra AHS, 2002–2006



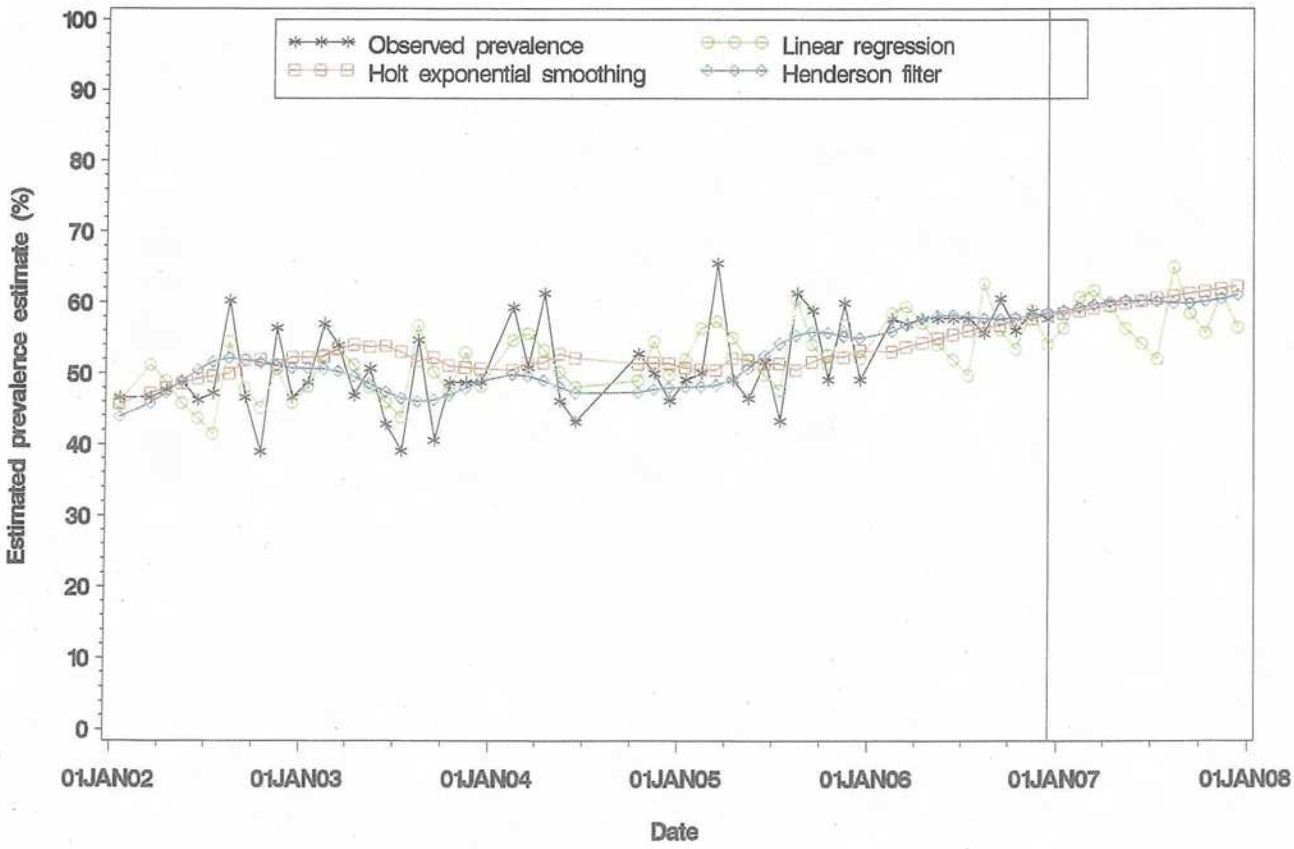
Comparison of different prediction methods

Recommended fruit consumption, persons aged 16 years or over
Sydney West AHS, 2002—2006



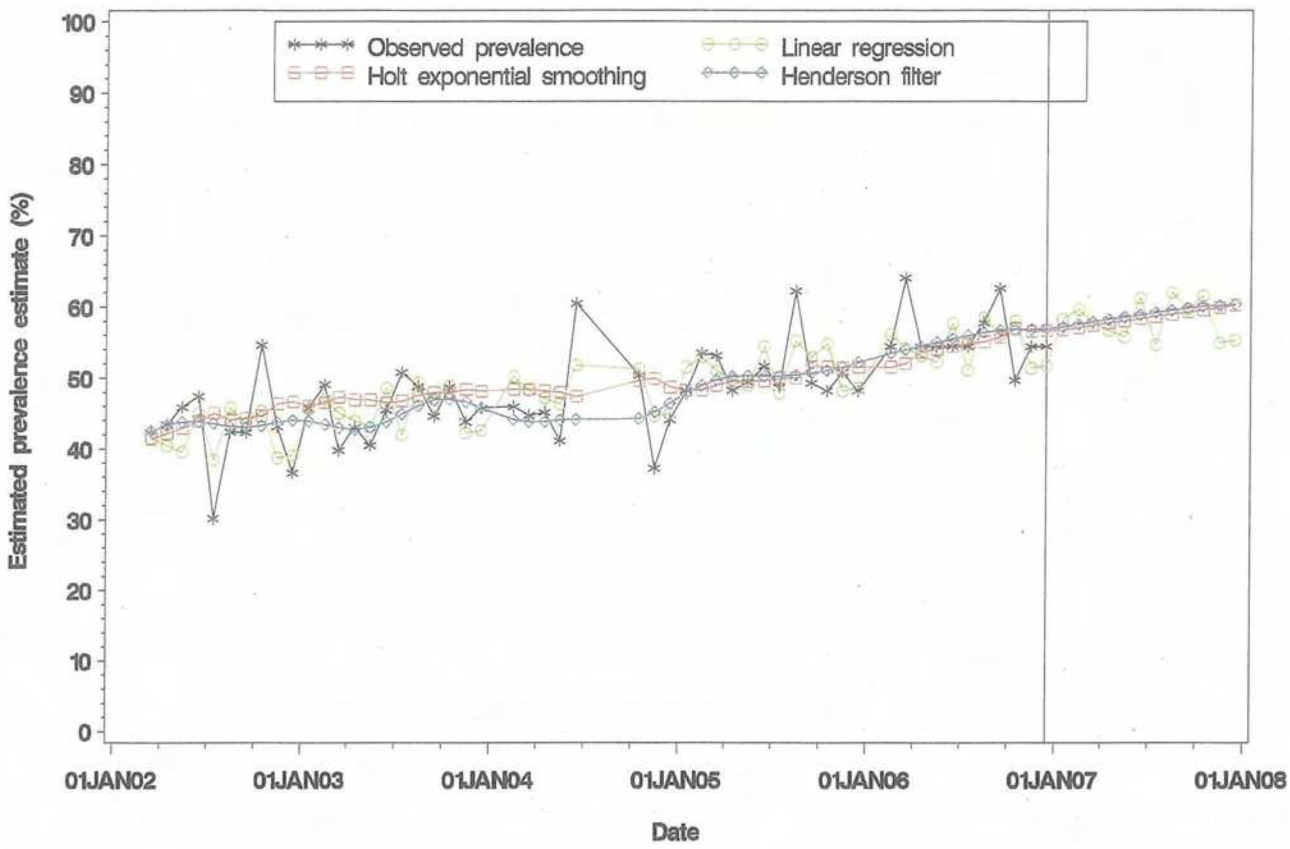
Comparison of different prediction methods

Recommended fruit consumption, persons aged 16 years or over
Northern Sydney & Central Coast AHS, 2002—2006



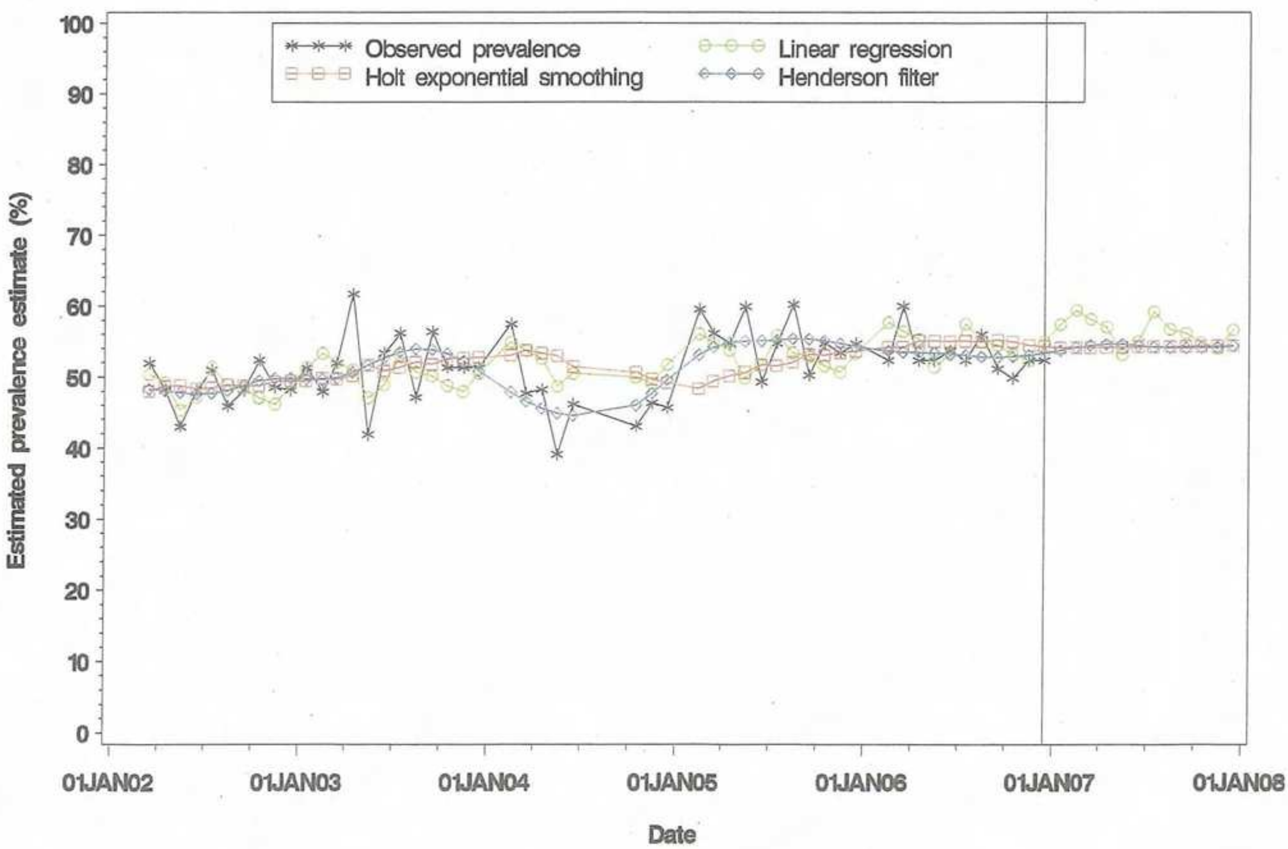
Comparison of different prediction methods

Recommended fruit consumption, persons aged 16 years or over
Hunter & New England AHS, 2002–2006



Comparison of different prediction methods

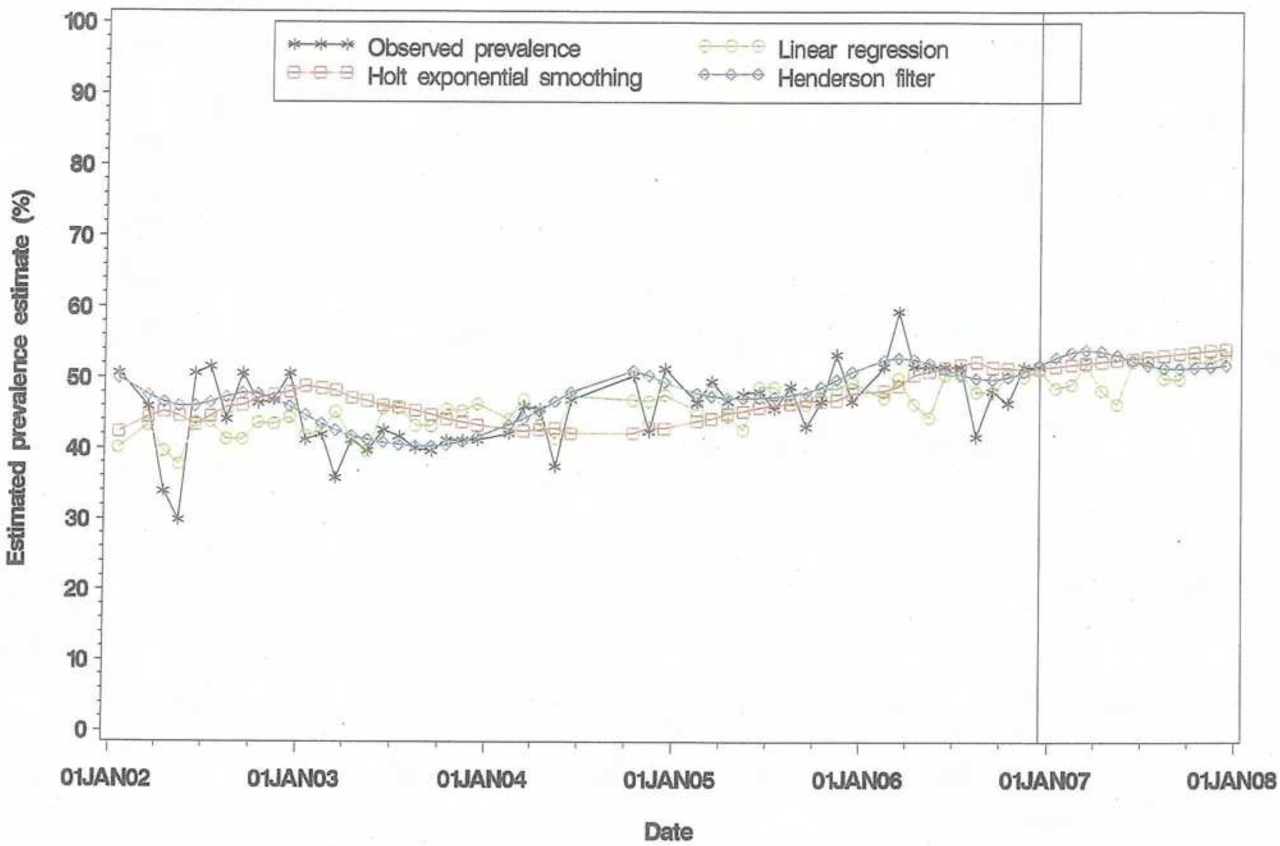
Recommended fruit consumption, persons aged 16 years or over
North Coast AHS, 2002–2006



Comparison of different prediction methods

Recommended fruit consumption, persons aged 16 years or over

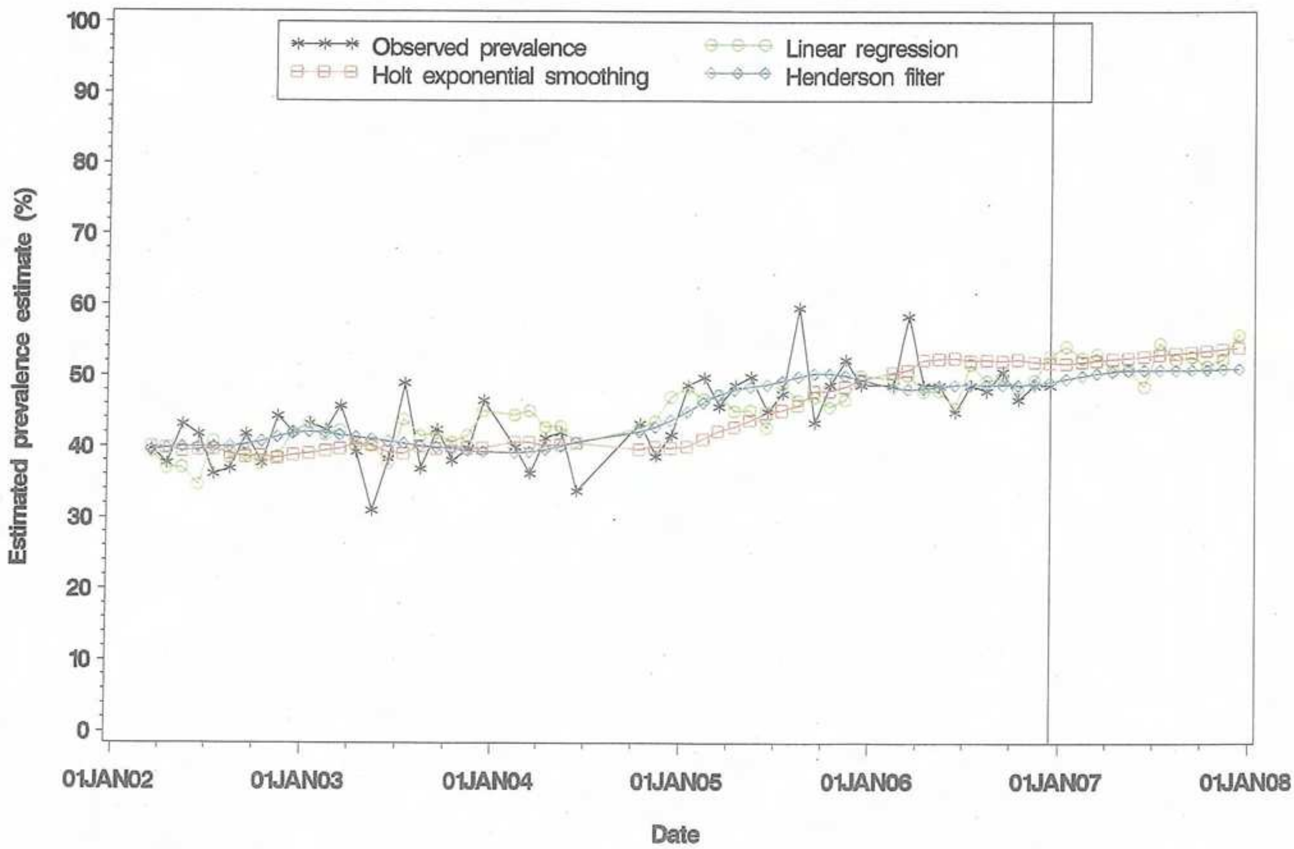
Greater Southern AHS, 2002–2006



Comparison of different prediction methods

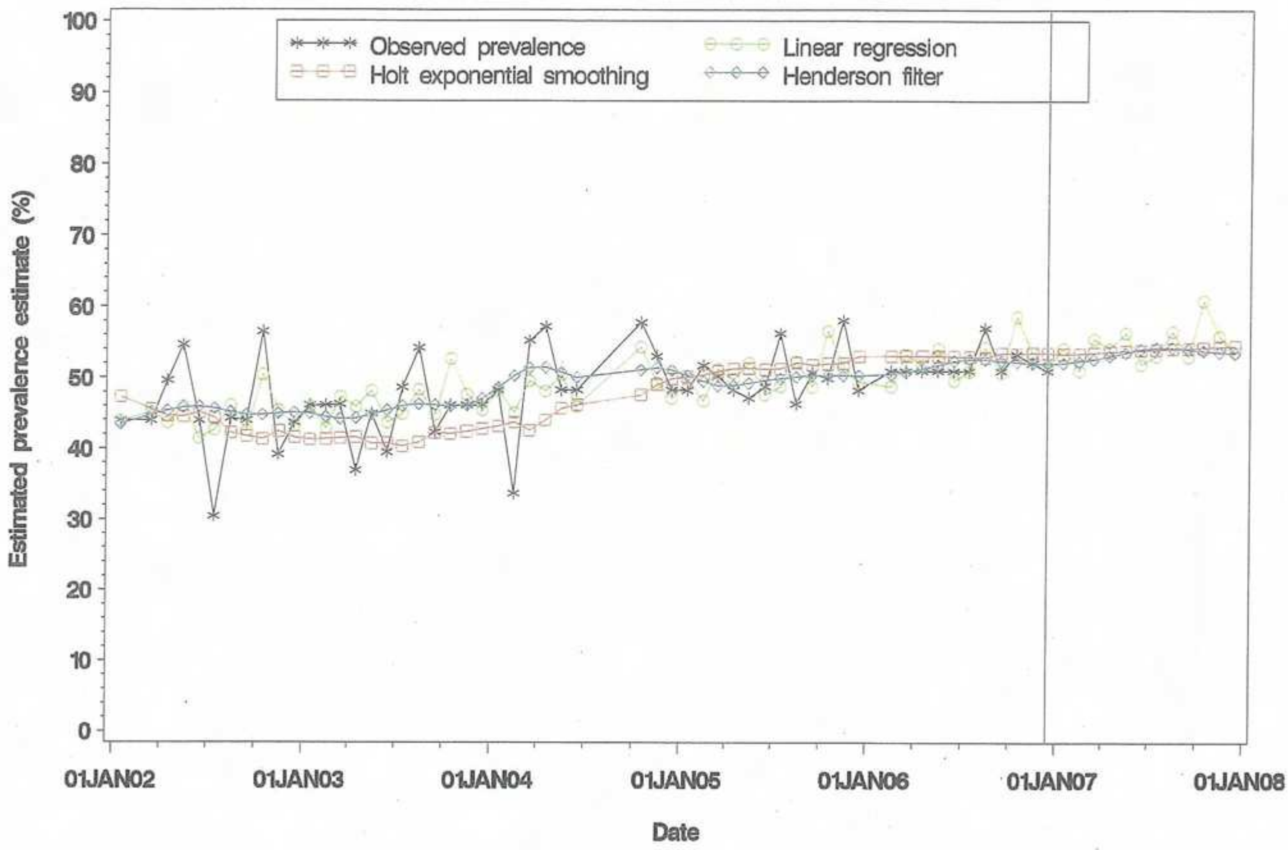
Recommended fruit consumption, persons aged 16 years or over

Greater Western AHS, 2002–2006



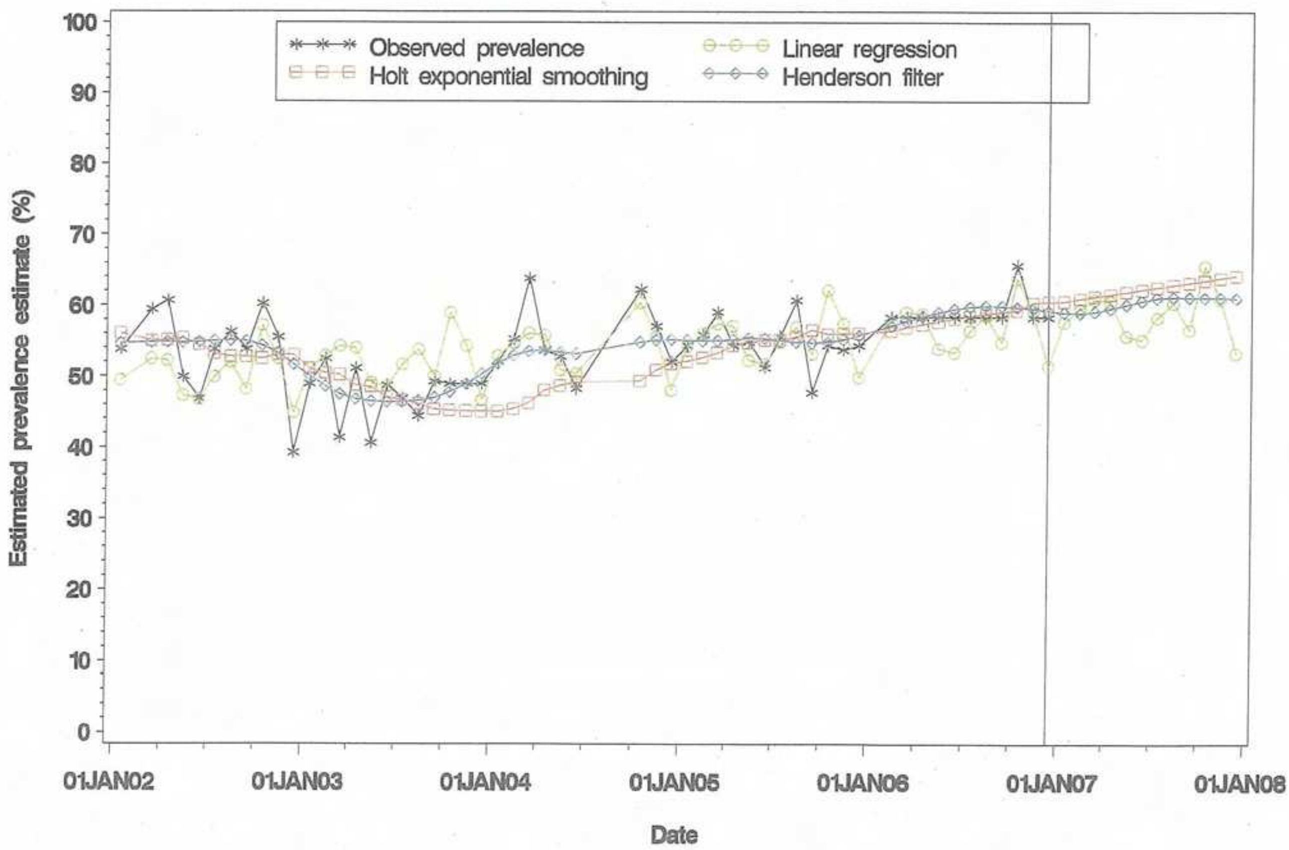
Comparison of different prediction methods

Adequate physical activity, persons aged 16 years or over
Sydney South West AHS, 2002–2006



Comparison of different prediction methods

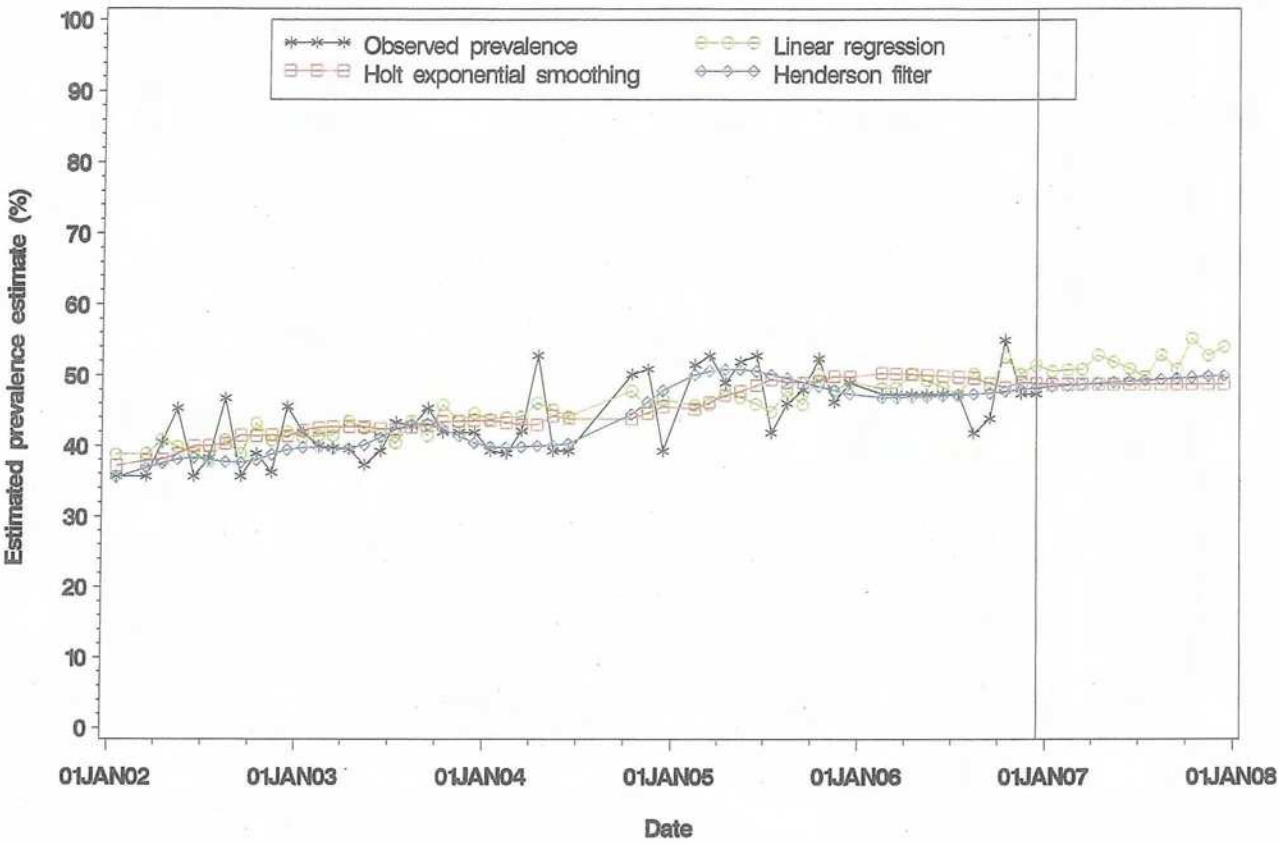
Adequate physical activity, persons aged 16 years or over
South Eastern Sydney & Illawarra AHS, 2002–2006



Comparison of different prediction methods

Adequate physical activity, persons aged 16 years or over

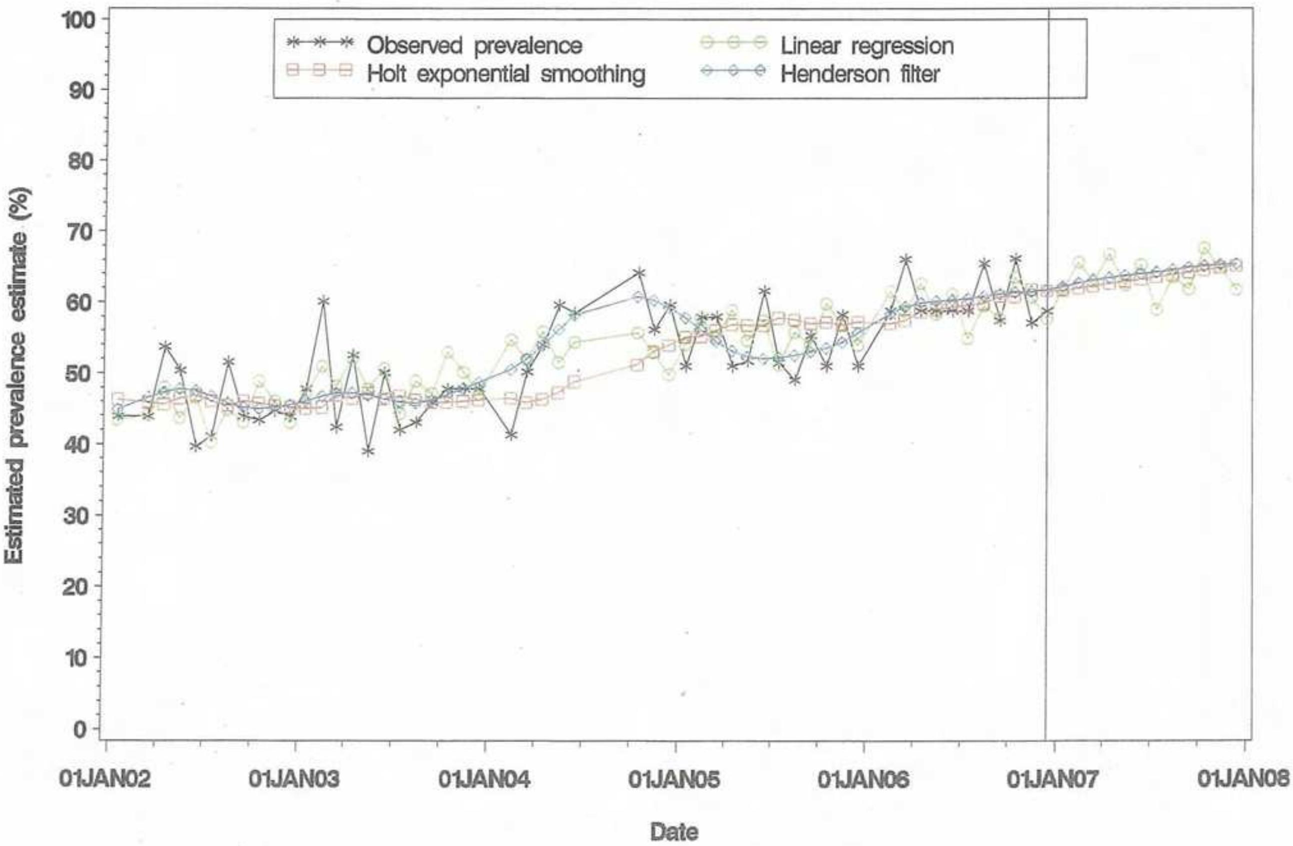
Sydney West AHS, 2002—2006



Comparison of different prediction methods

Adequate physical activity, persons aged 16 years or over

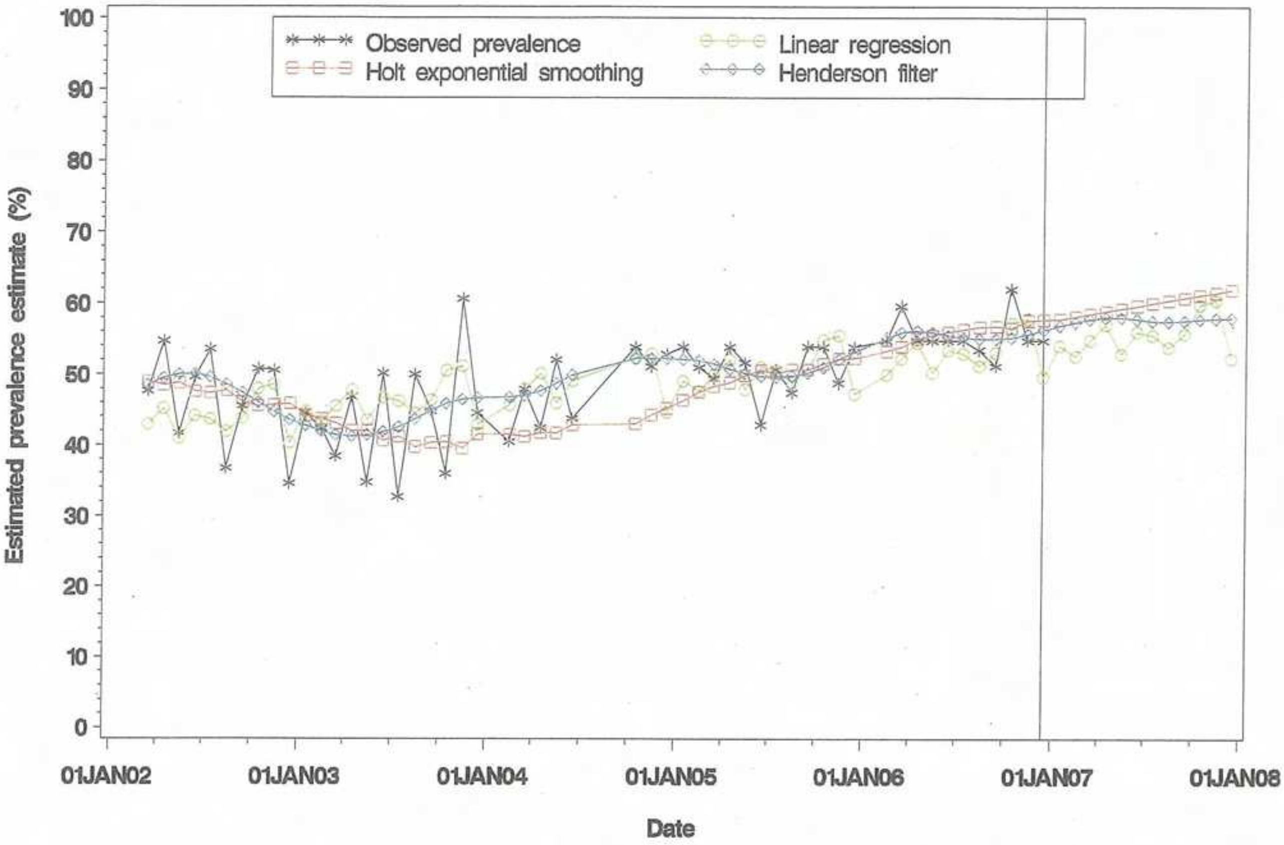
Northern Sydney & Central Coast AHS, 2002—2006



Comparison of different prediction methods

Adequate physical activity, persons aged 16 years or over

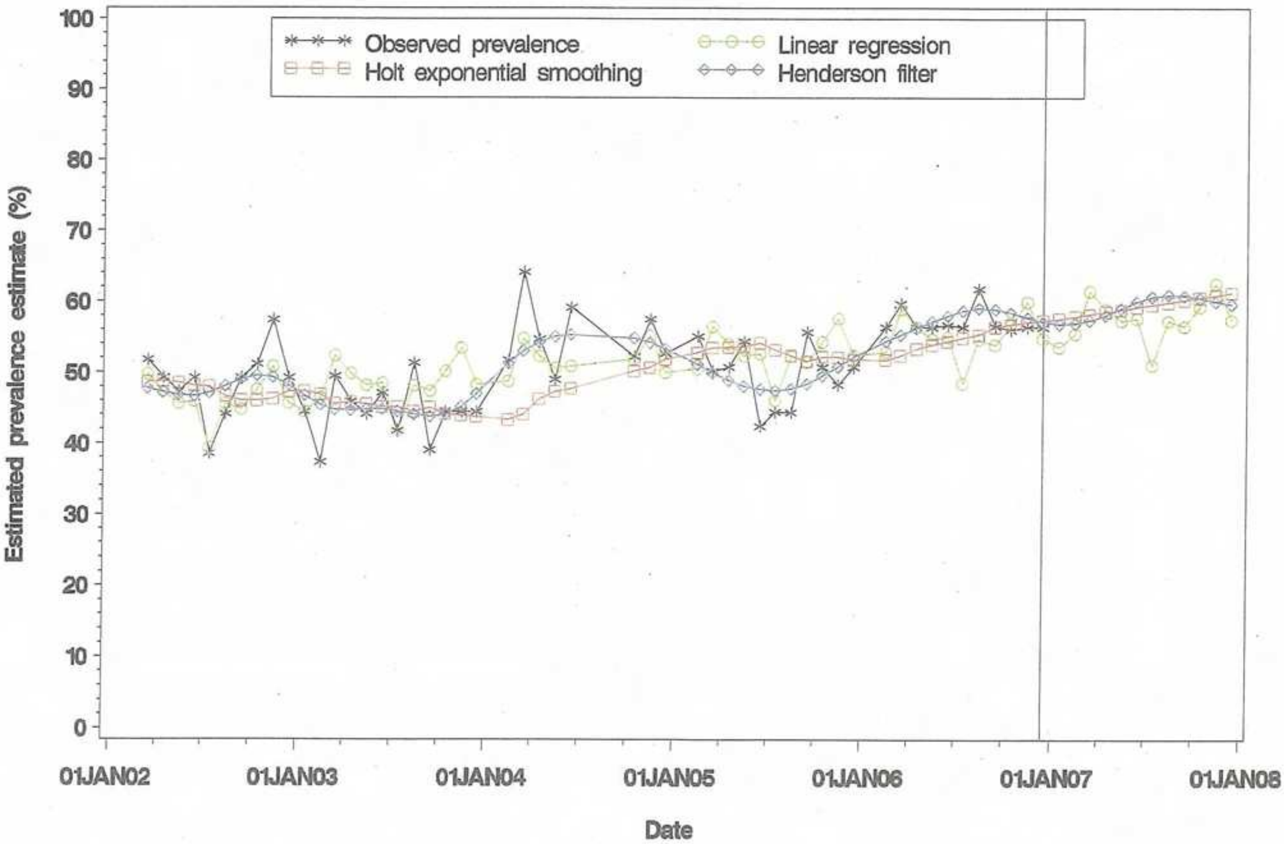
Hunter & New England AHS, 2002–2006



Comparison of different prediction methods

Adequate physical activity, persons aged 16 years or over

North Coast AHS, 2002–2006



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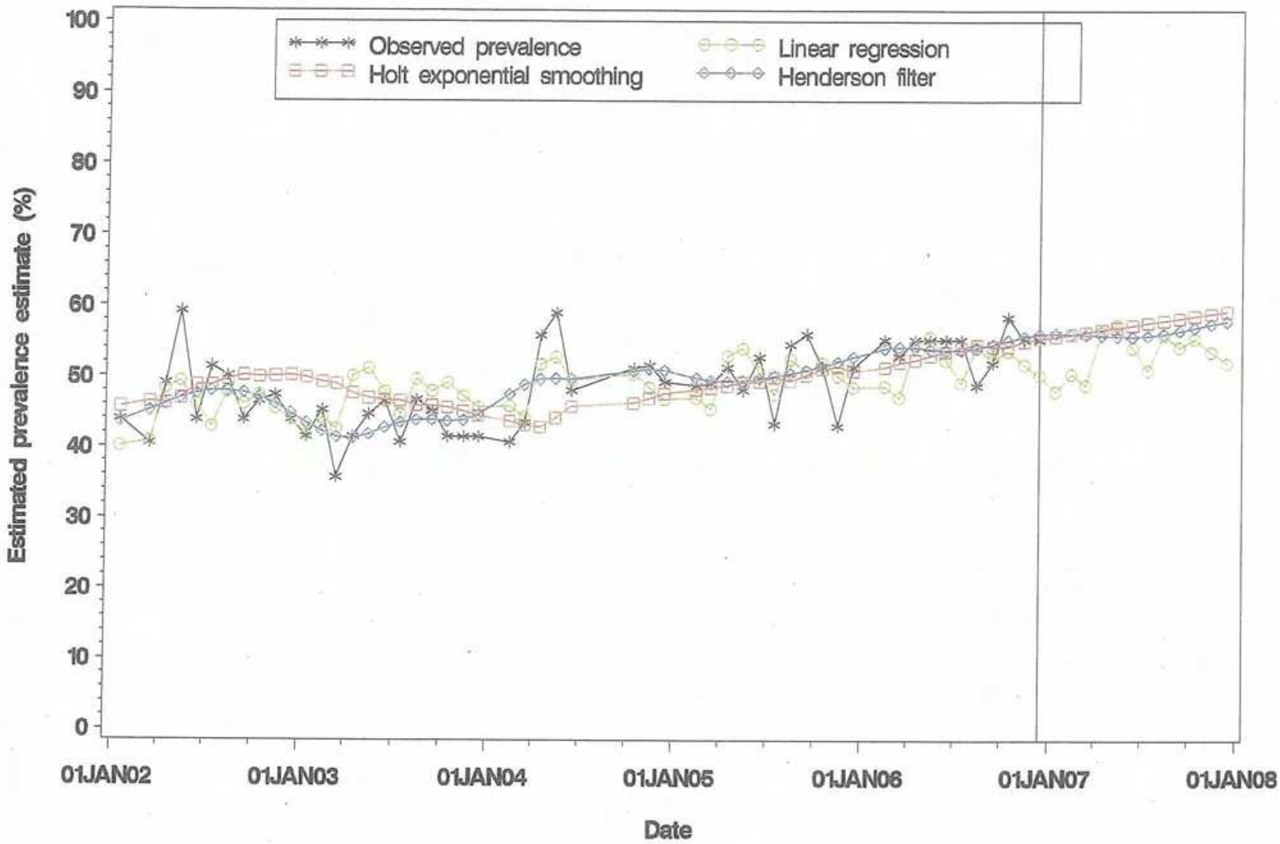
Adequate physical activity, persons aged 16 years or over

Greater Southern AHS, 2002–2006



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Adequate physical activity, persons aged 16 years or over

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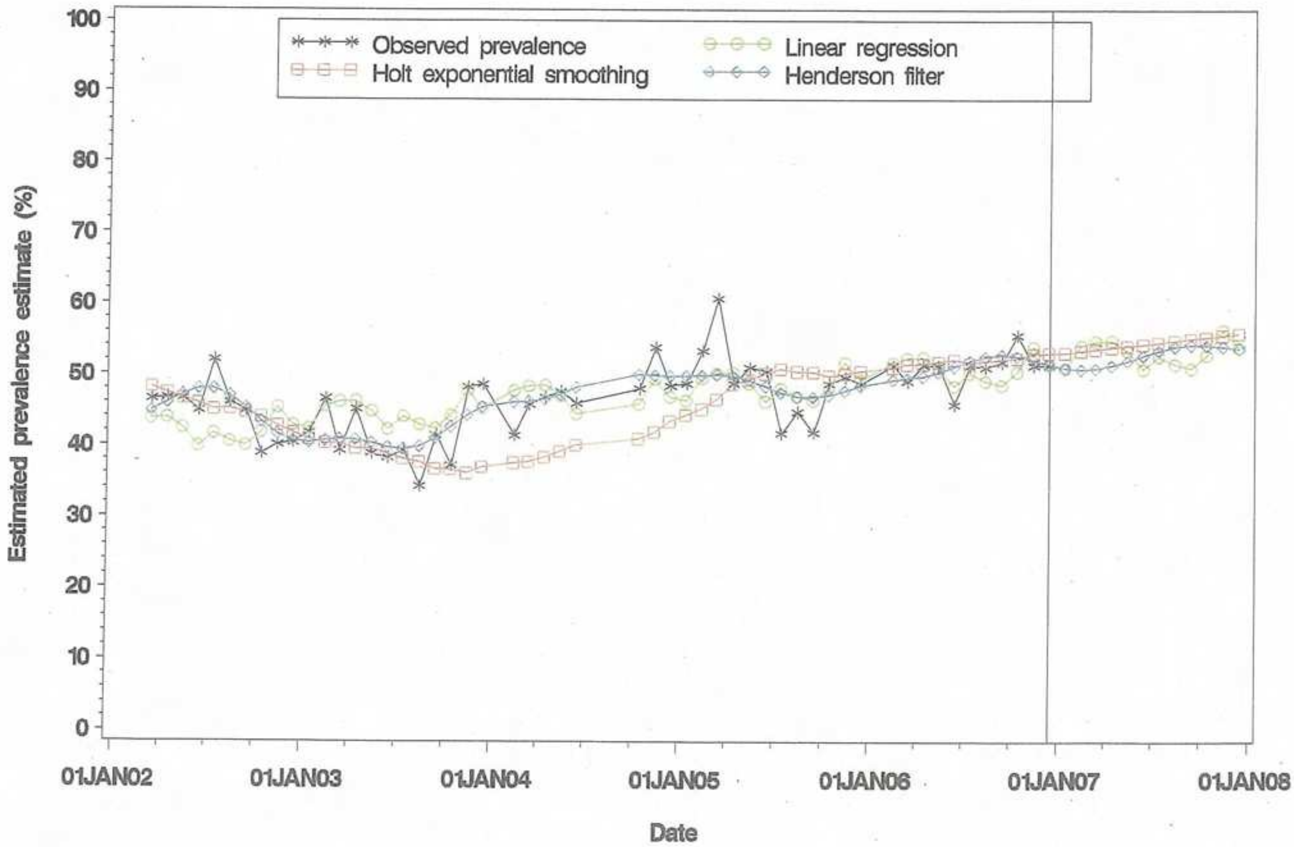
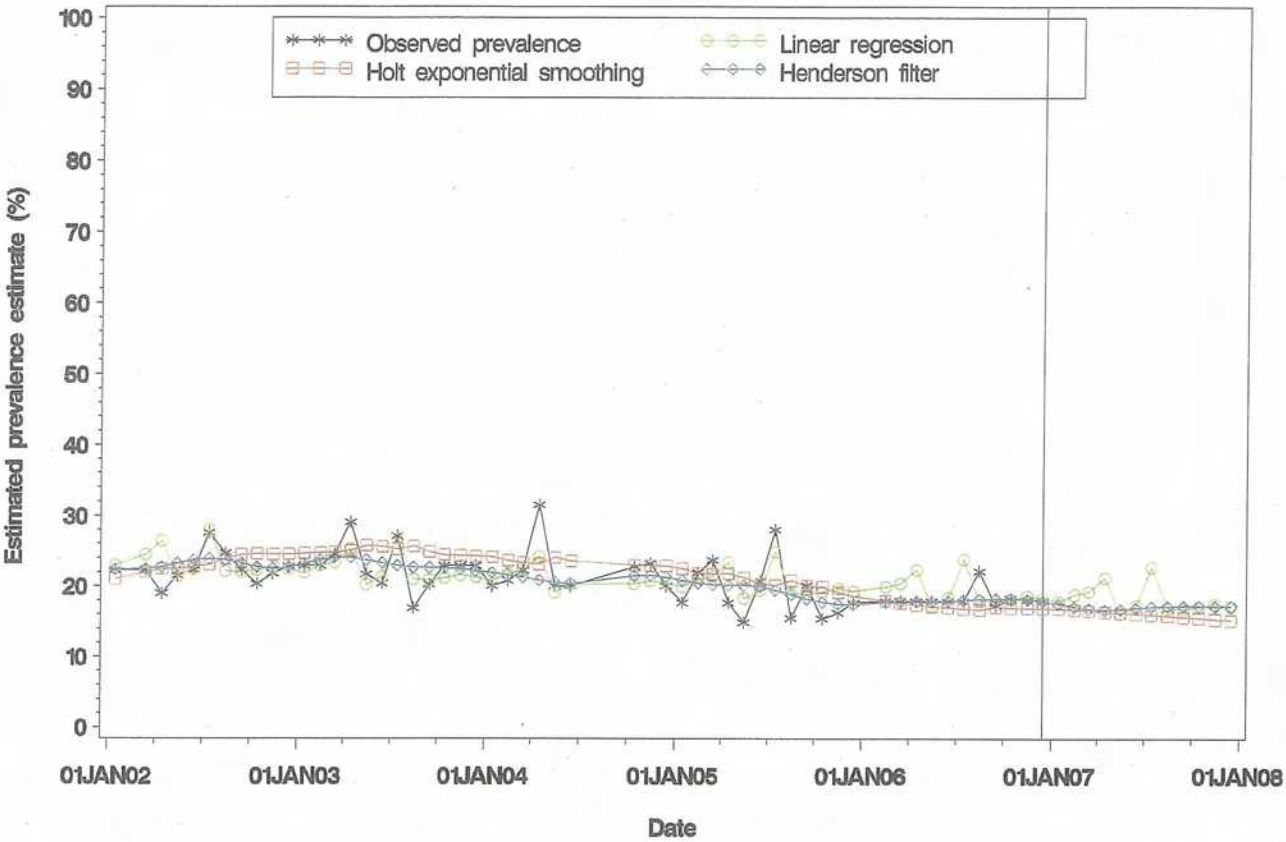


Comparison of different prediction methods

Current smoke, persons aged 16 years or over

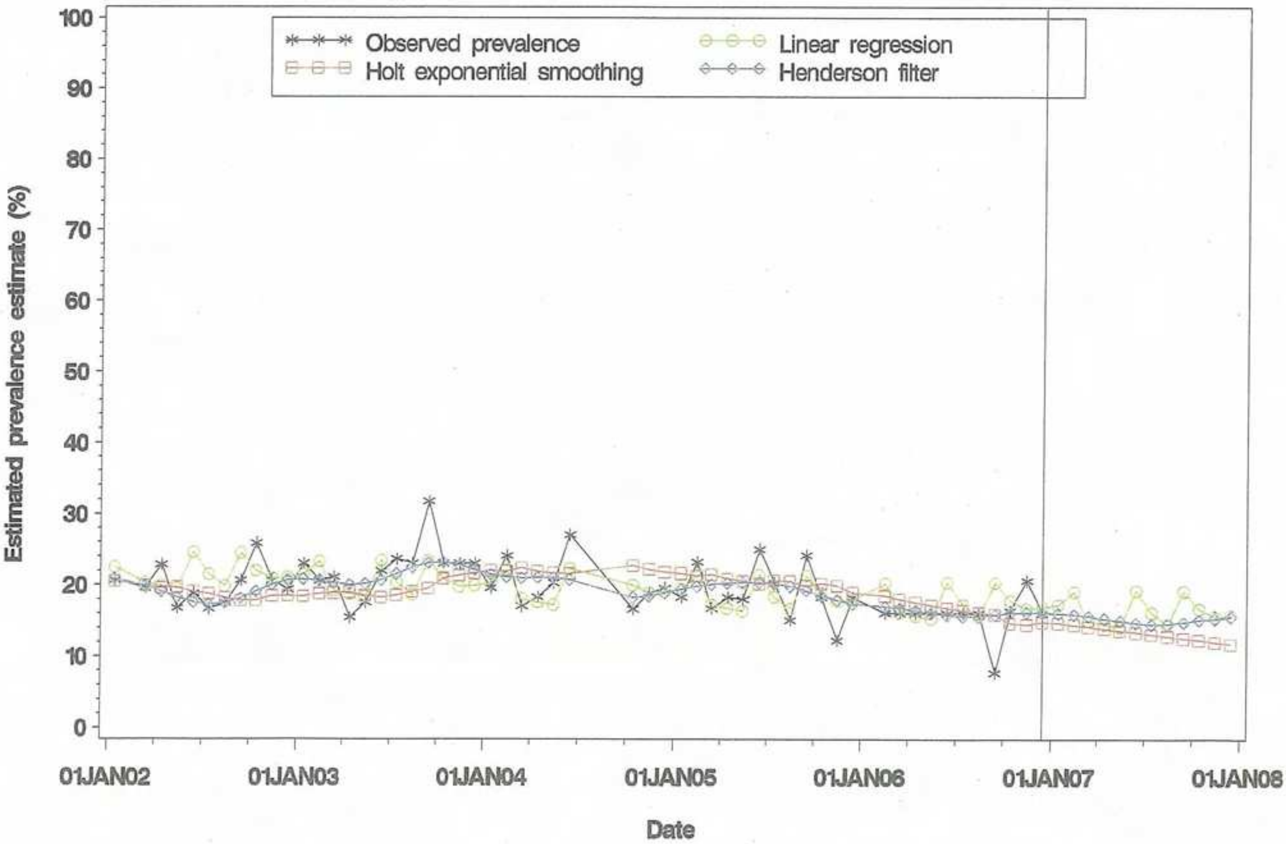
Sydney South West AHS, 2002–2006



Comparison of different prediction methods

Current smoke, persons aged 16 years or over

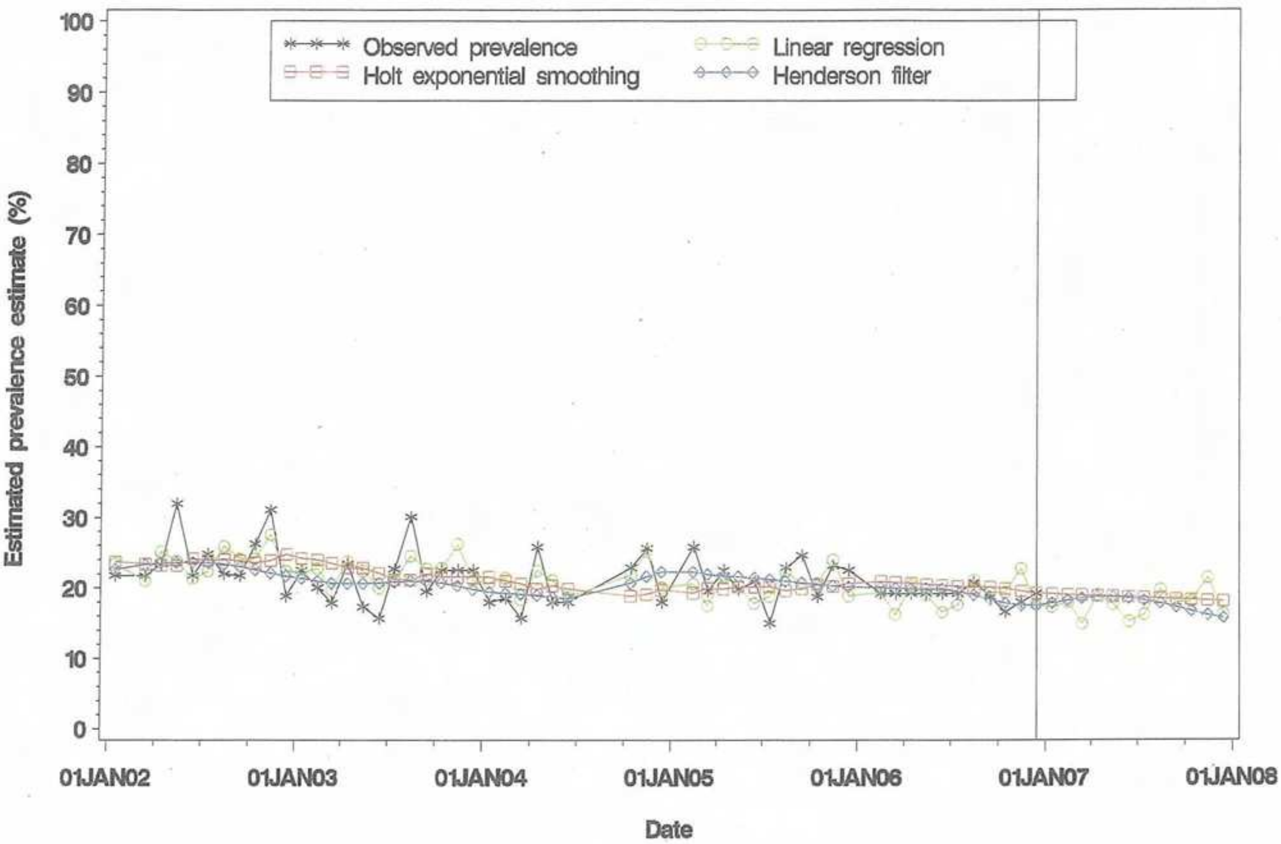
South Eastern Sydney & Illawarra AHS, 2002–2006



Comparison of different prediction methods

Current smoke, persons aged 16 years or over

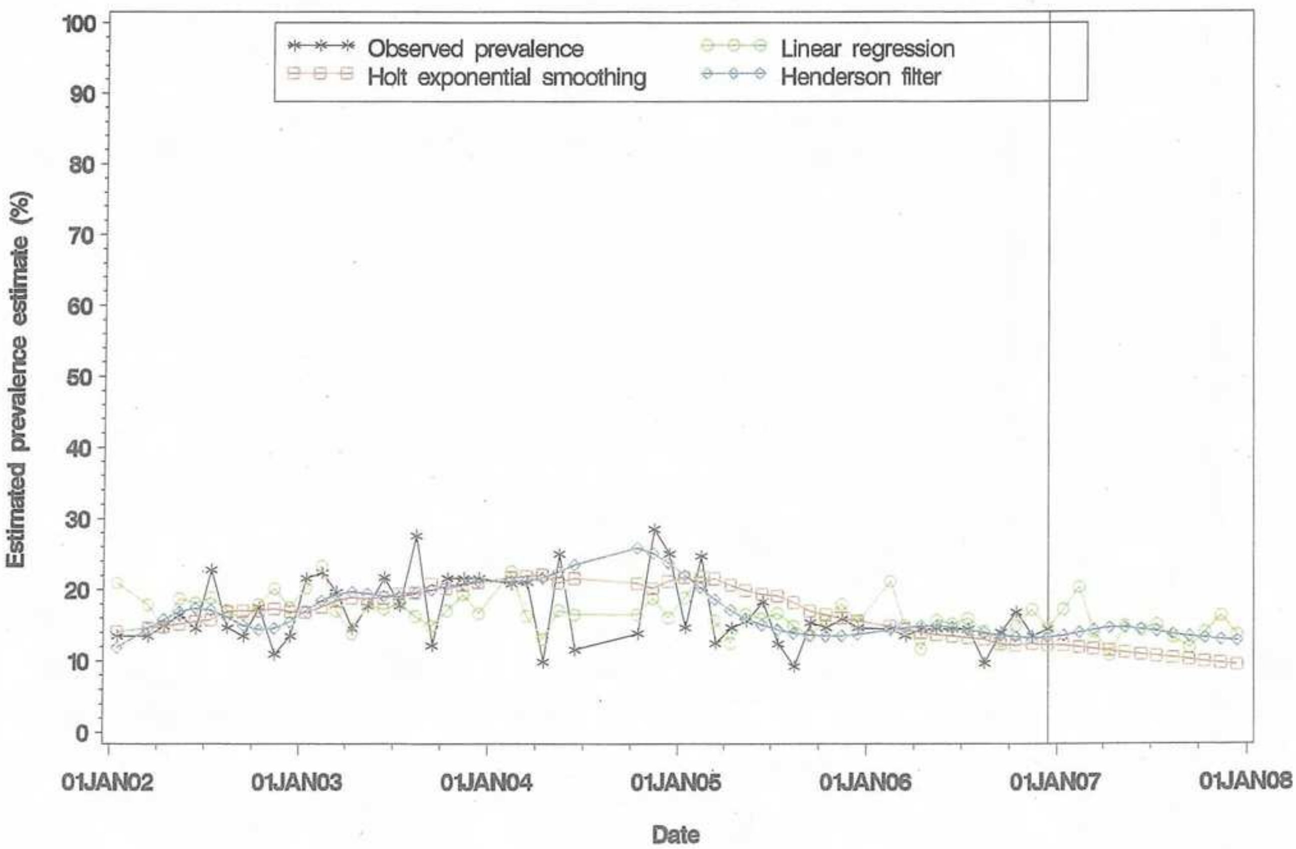
Sydney West AHS, 2002–2006



Comparison of different prediction methods

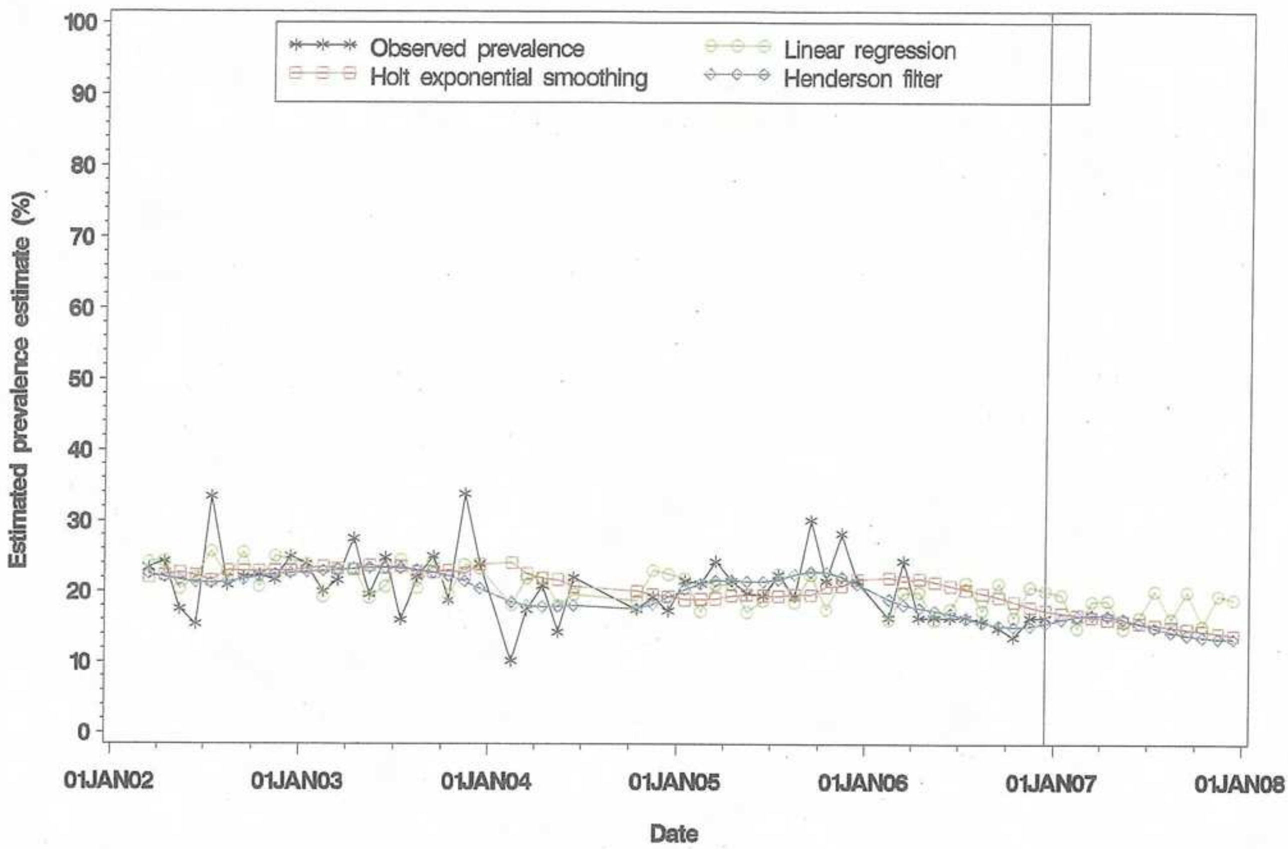
Current smoke, persons aged 16 years or over

Northern Sydney & Central Coast AHS, 2002–2006



Comparison of different prediction methods

Current smoke, persons aged 16 years or over
Hunter & New England AHS, 2002–2006



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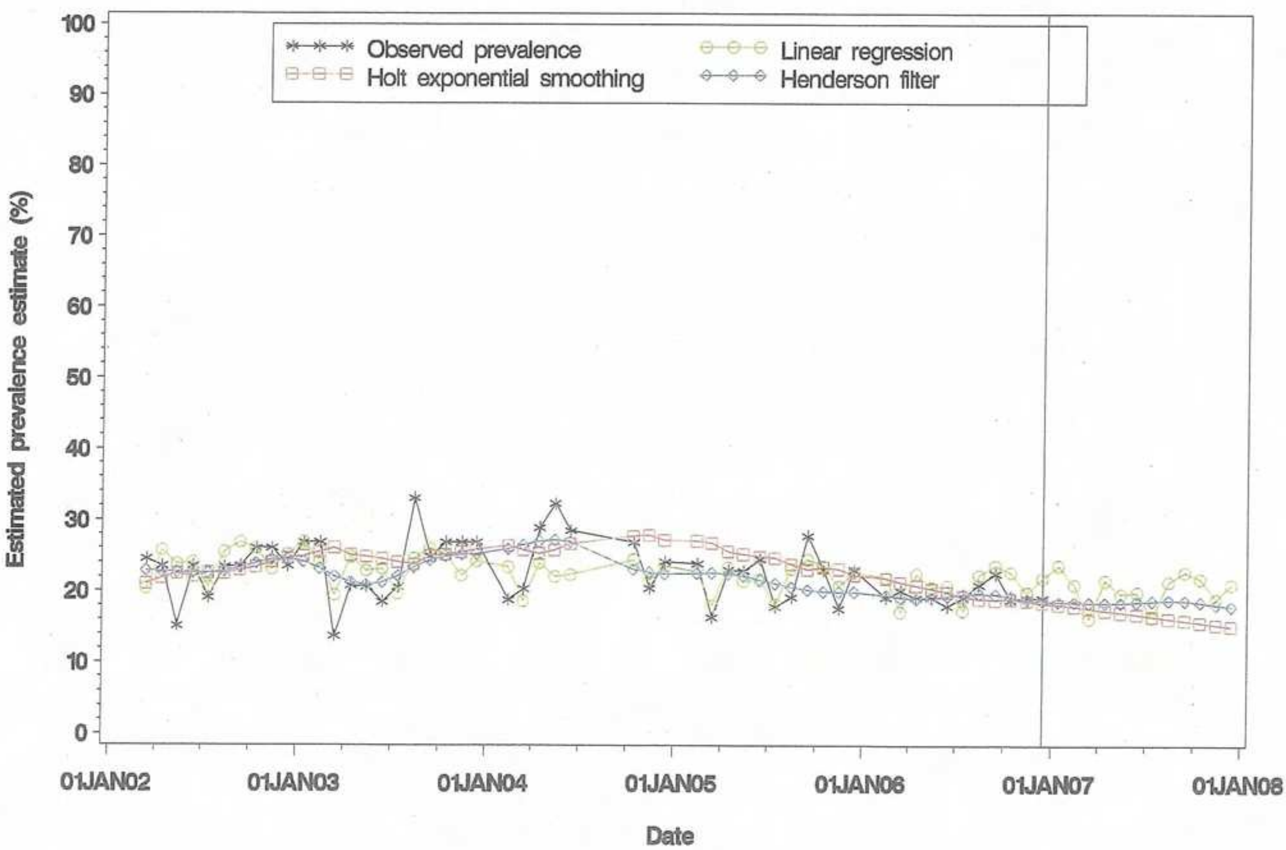
Current smoke, persons aged 16 years or over
North Coast AHS, 2002–2006



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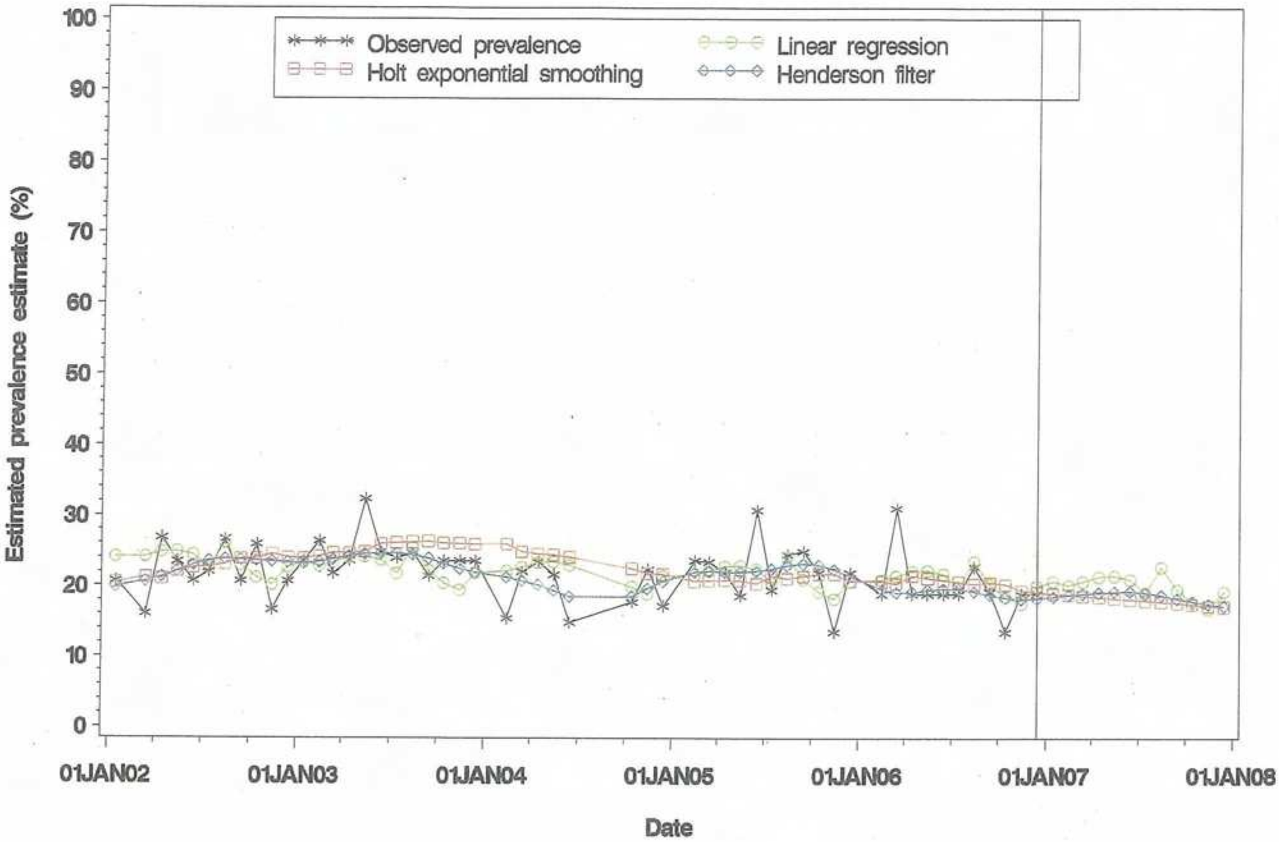

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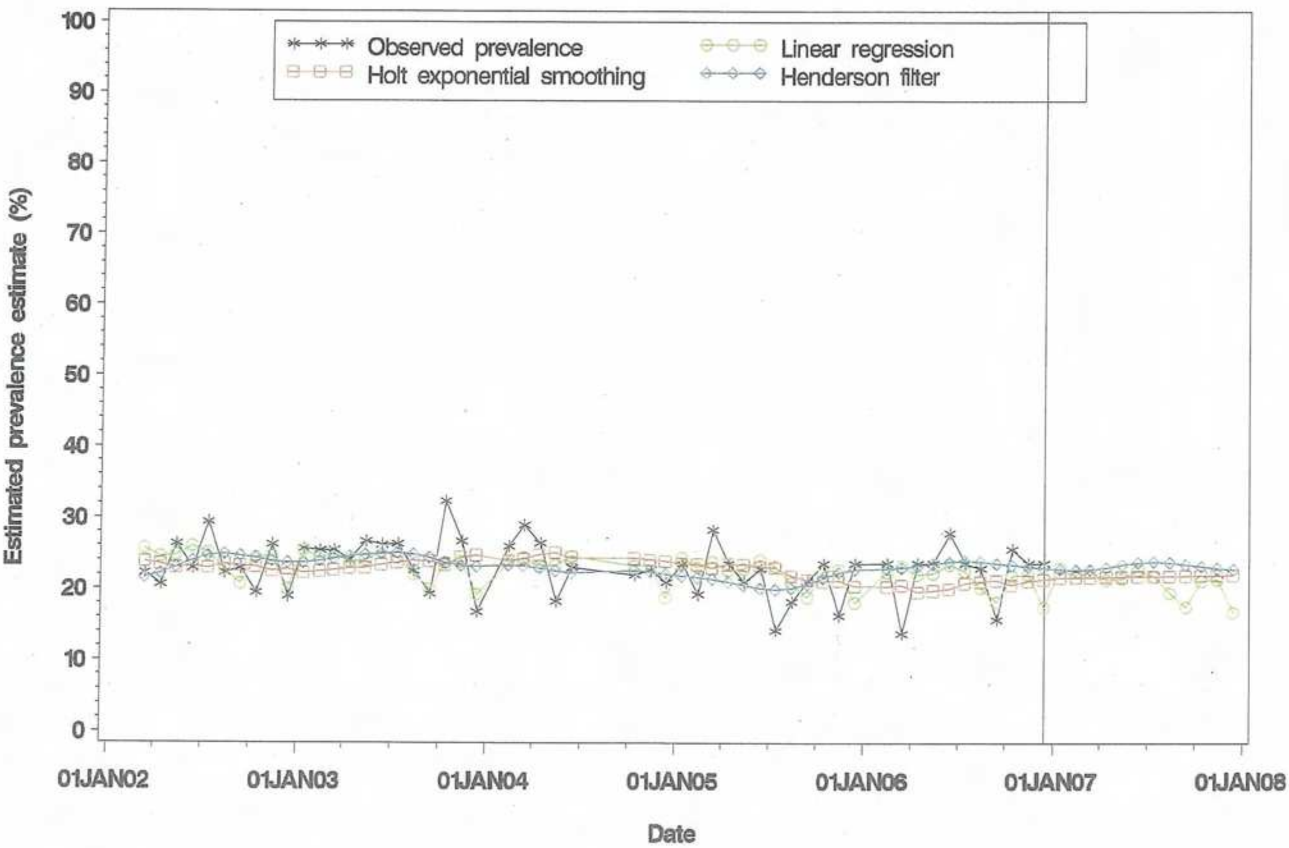
Current smoke, persons aged 16 years or over

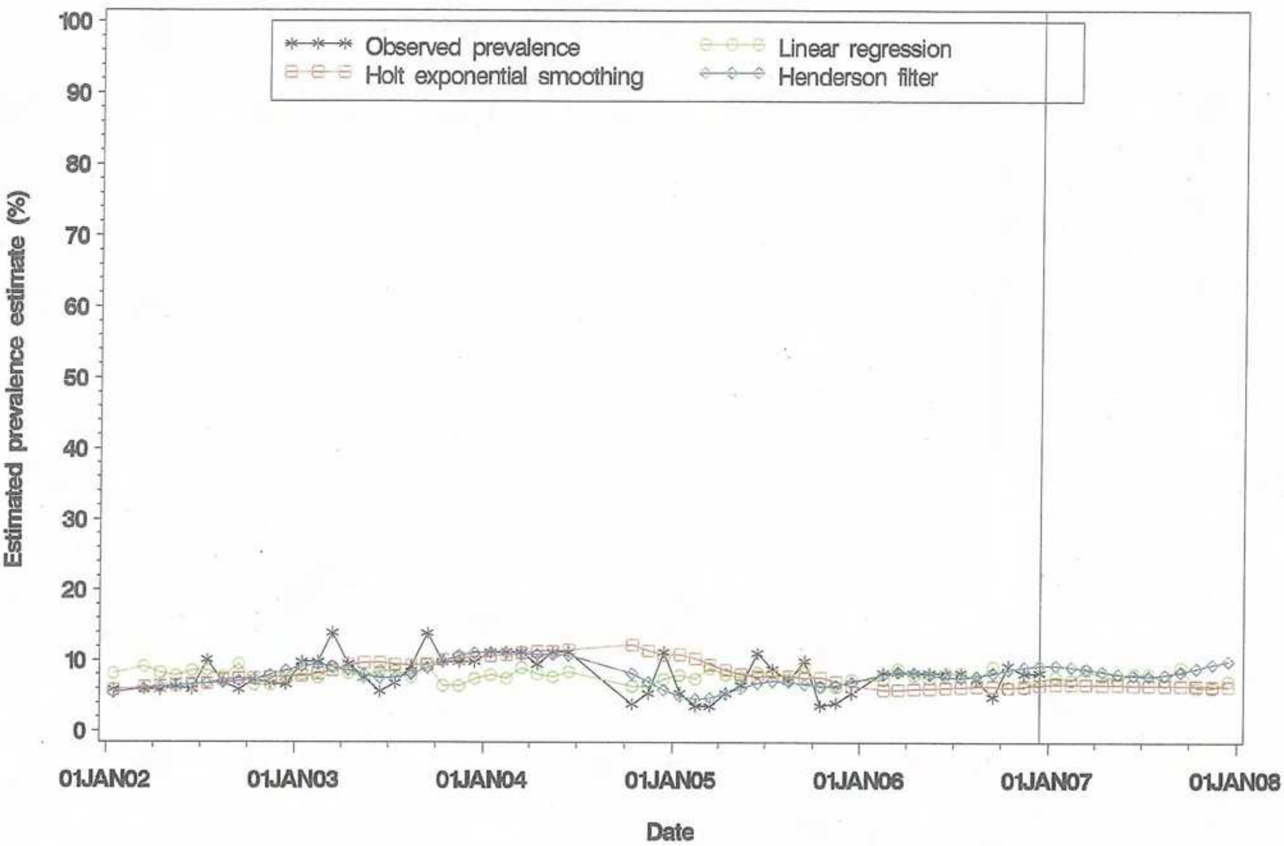
Greater Western AHS, 2002–2006



Comparison of different prediction methods

Recommended vegetable consumption, persons aged 16 years or over

Sydney South West AHS, 2002–2006



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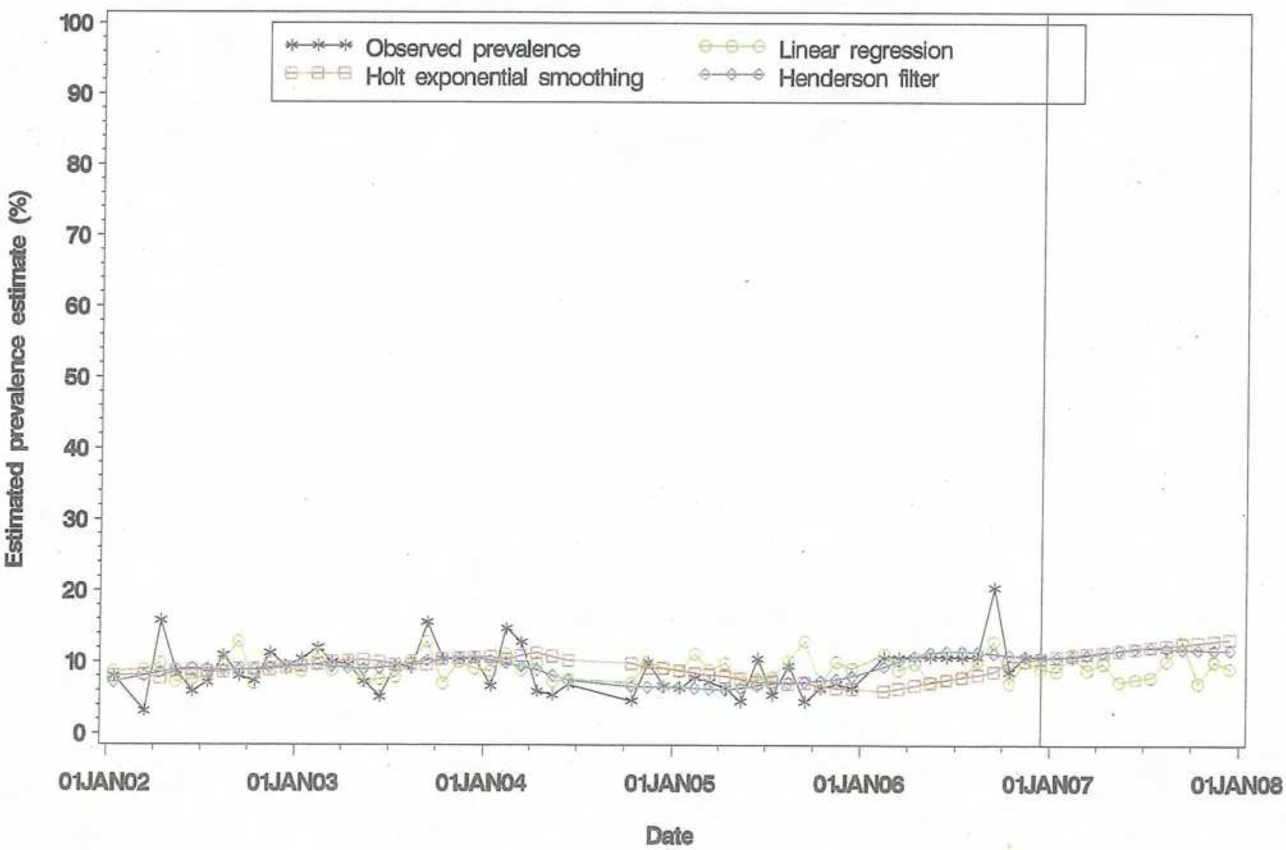
Recommended vegetable consumption, persons aged 16 years or over

South Eastern Sydney & Illawarra AHS, 2002–2006



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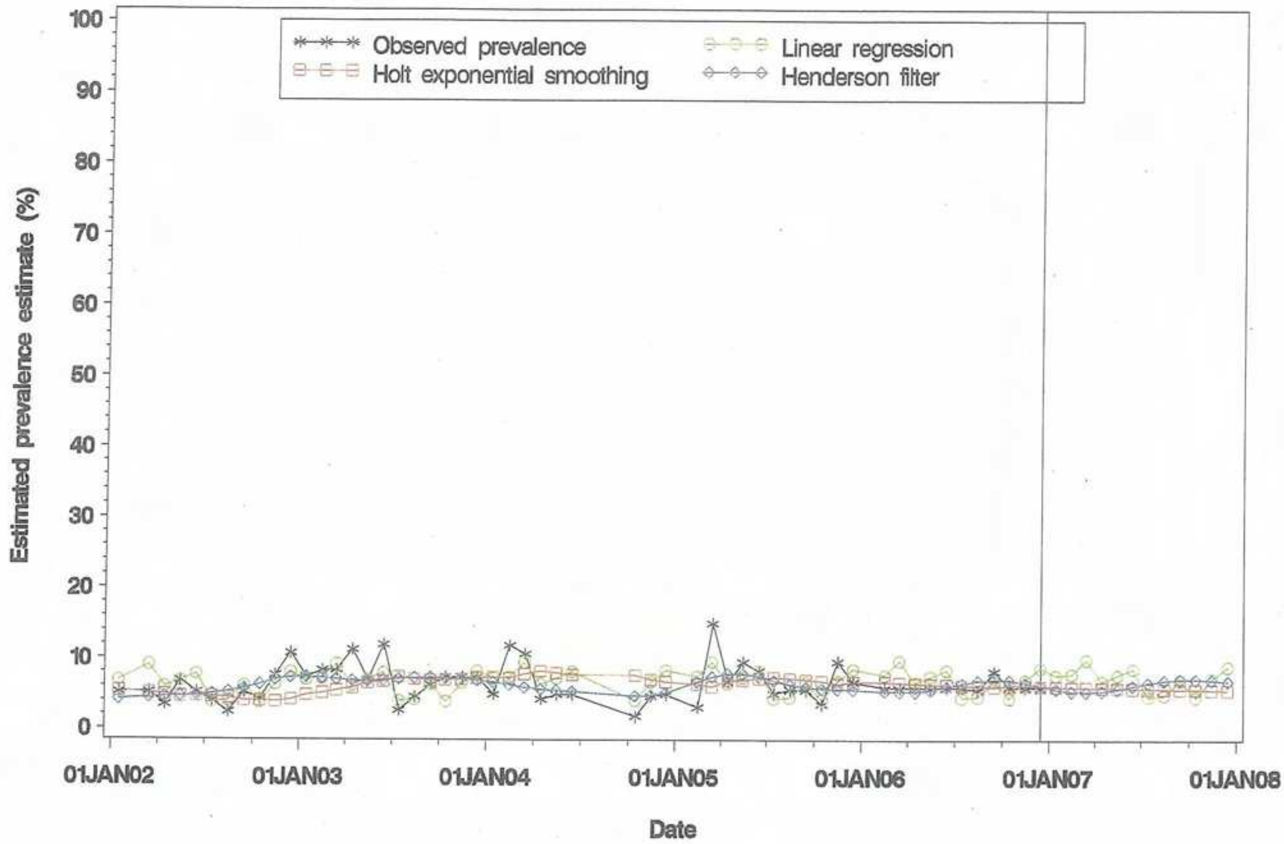

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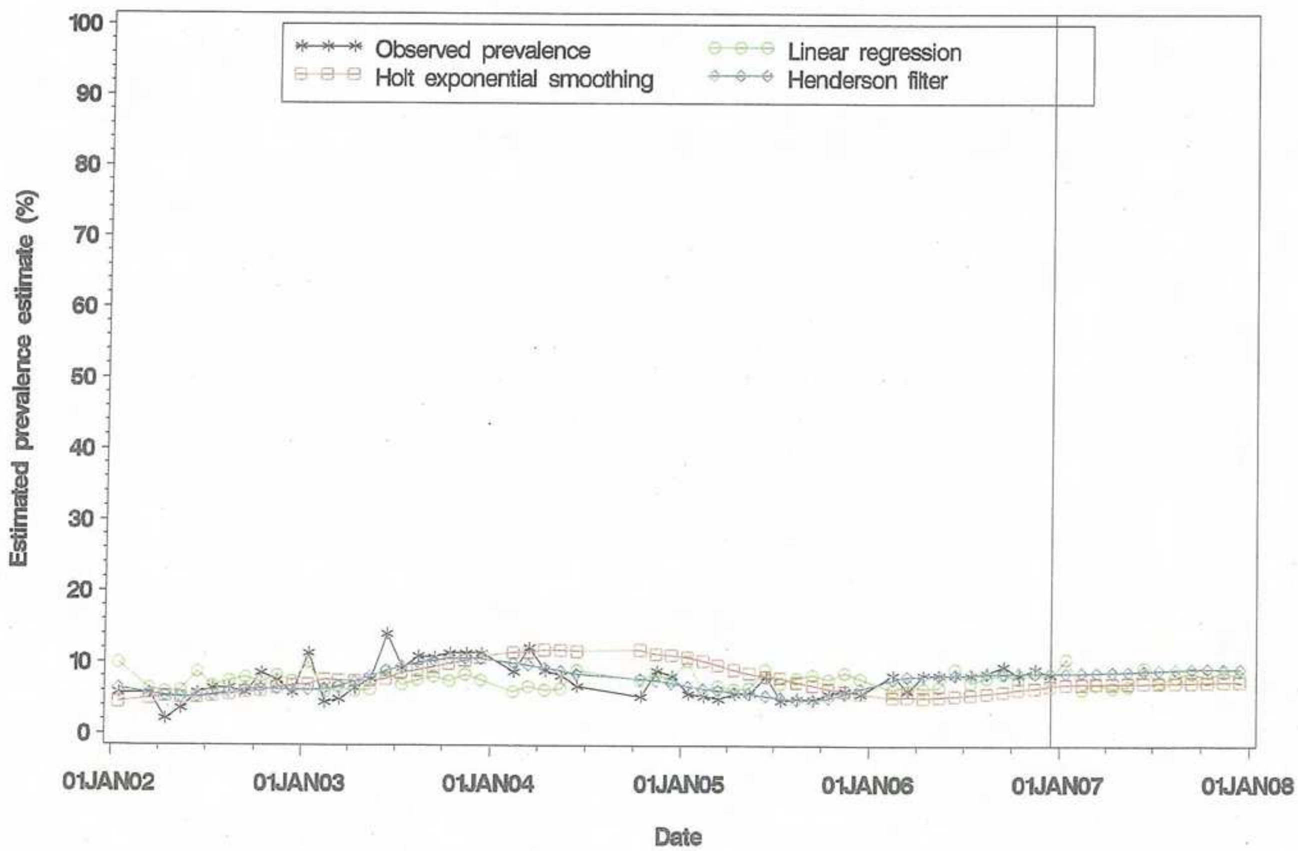

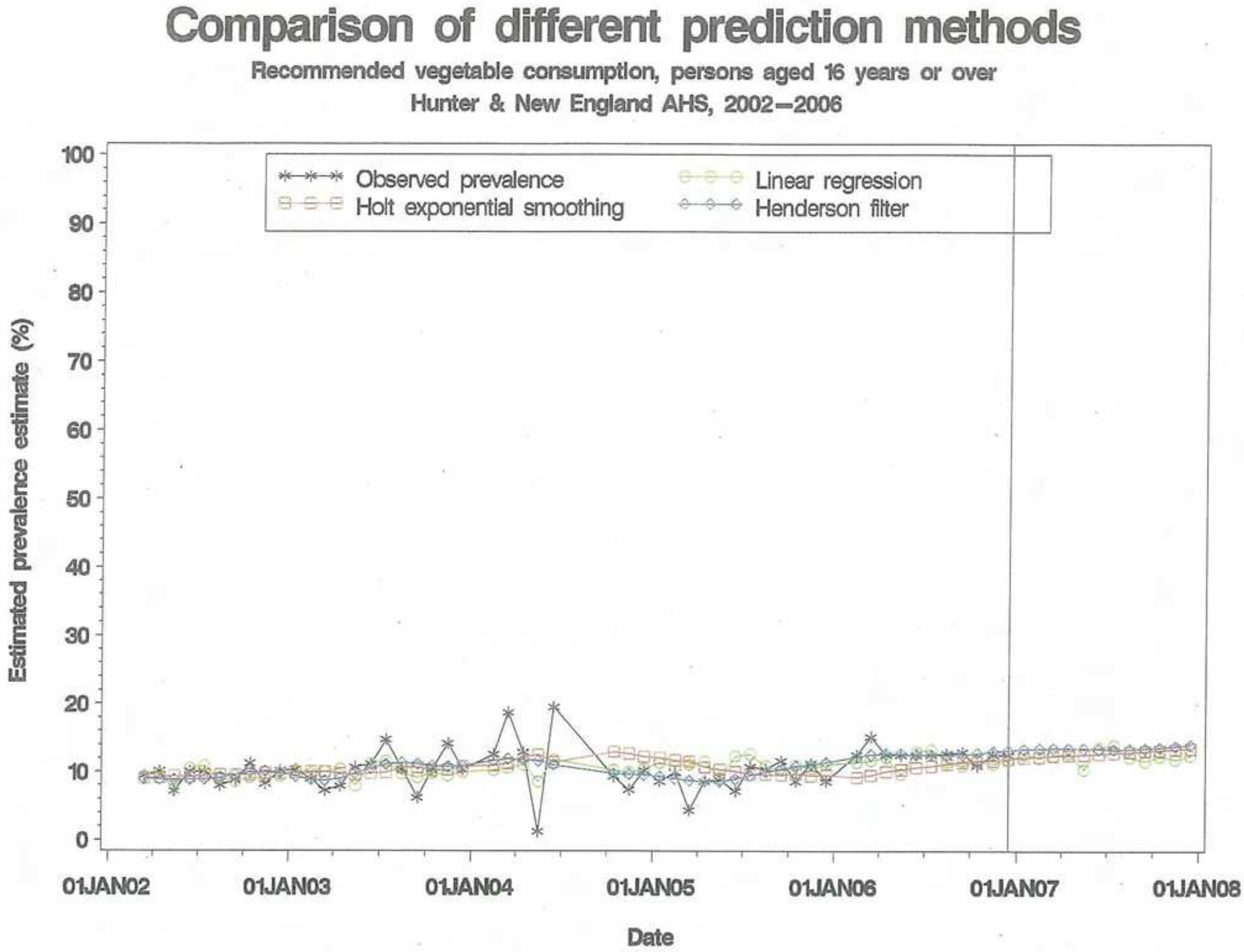

Comparison of different prediction methods
Recommended vegetable consumption, persons aged 16 years or over
Hunter & New England AHS, 2002–2006
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Linear regression
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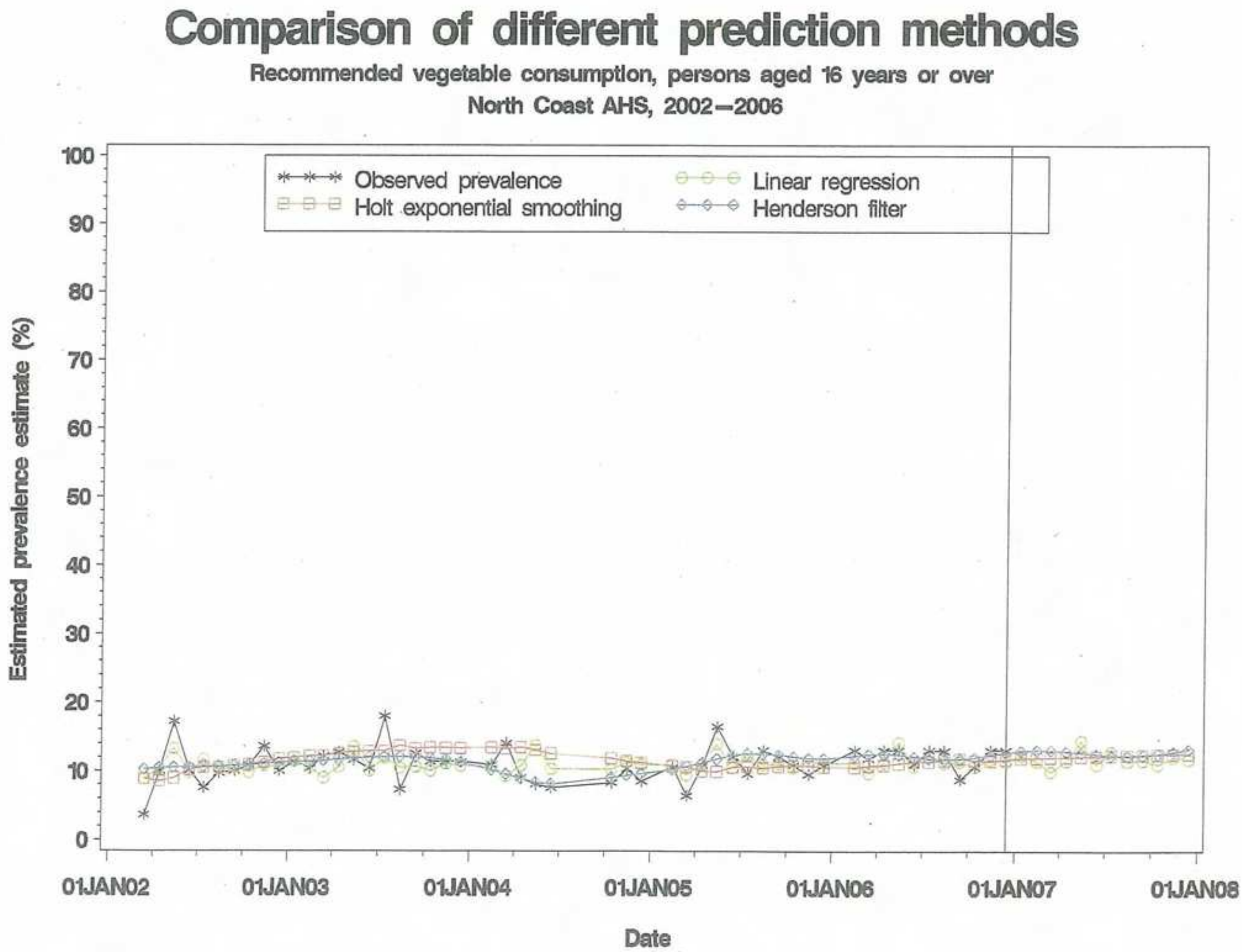
Date



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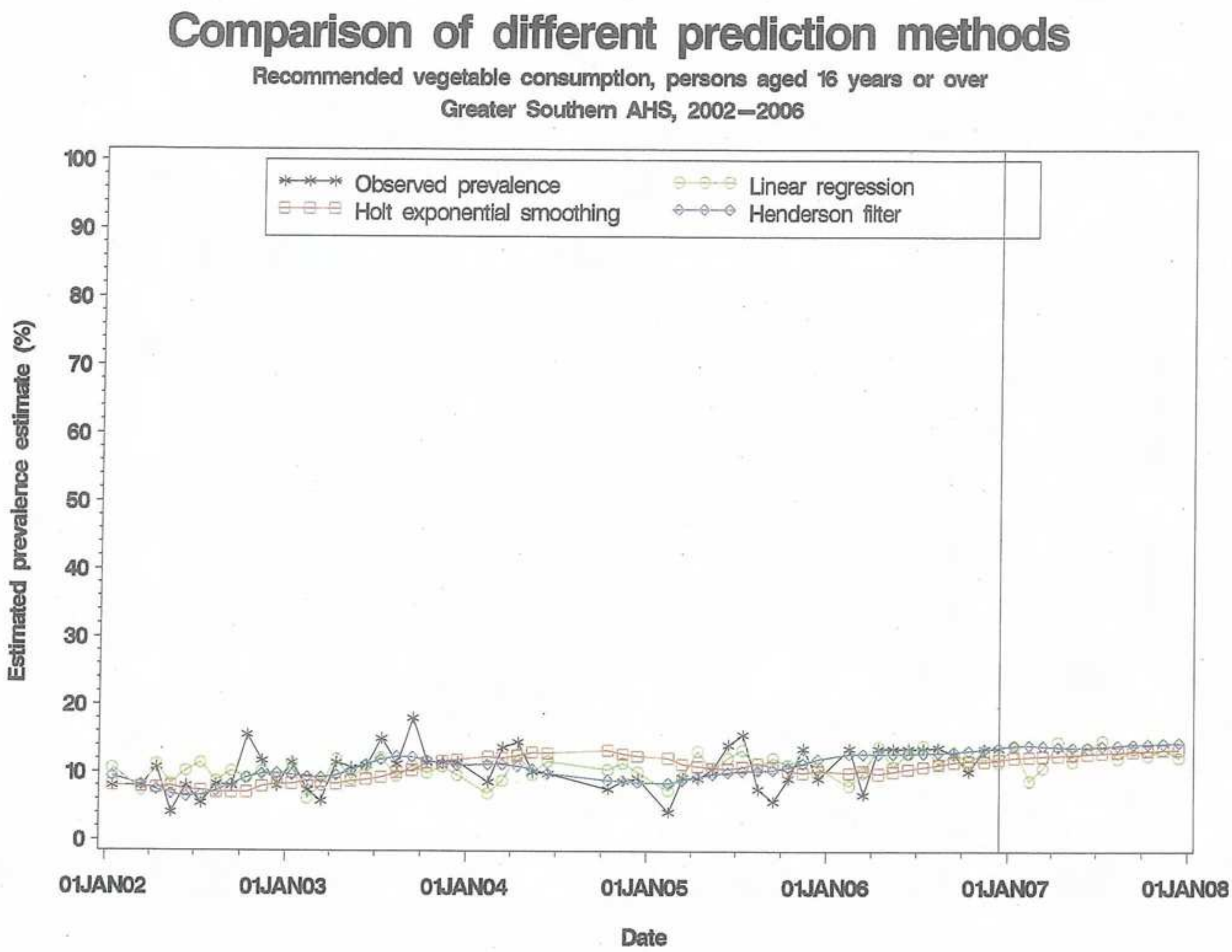
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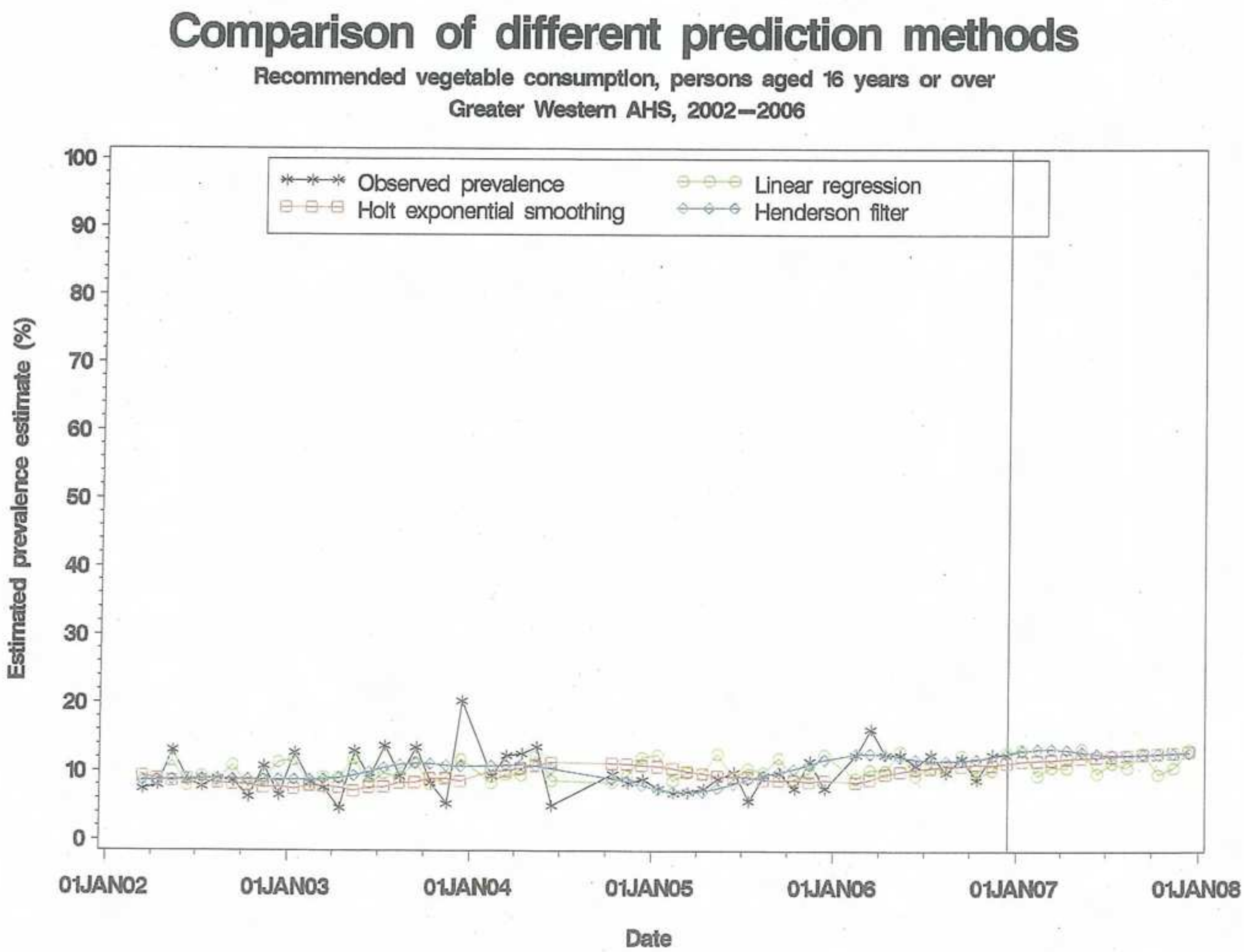
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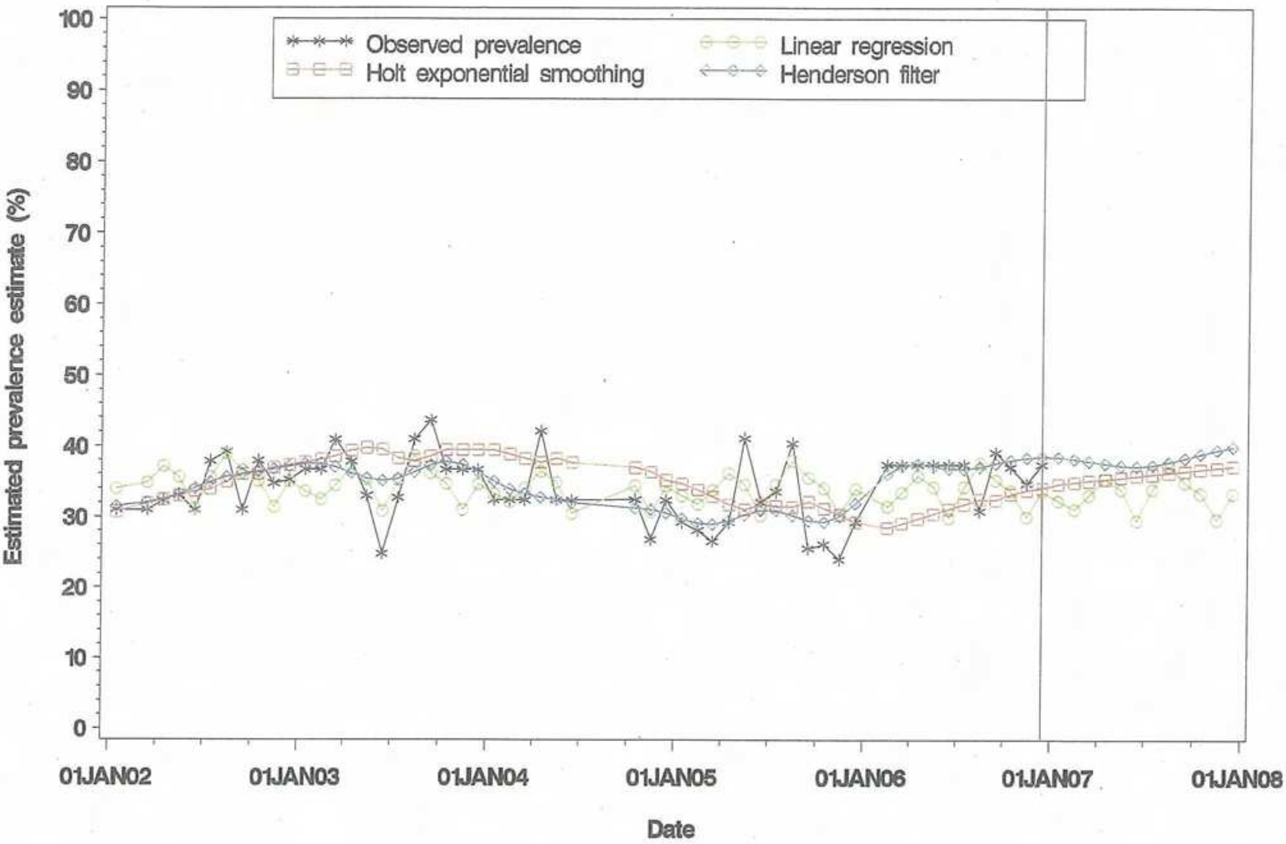
Comparison of different prediction methods

3 or more servings of vegetables per day, persons aged 16 years or over

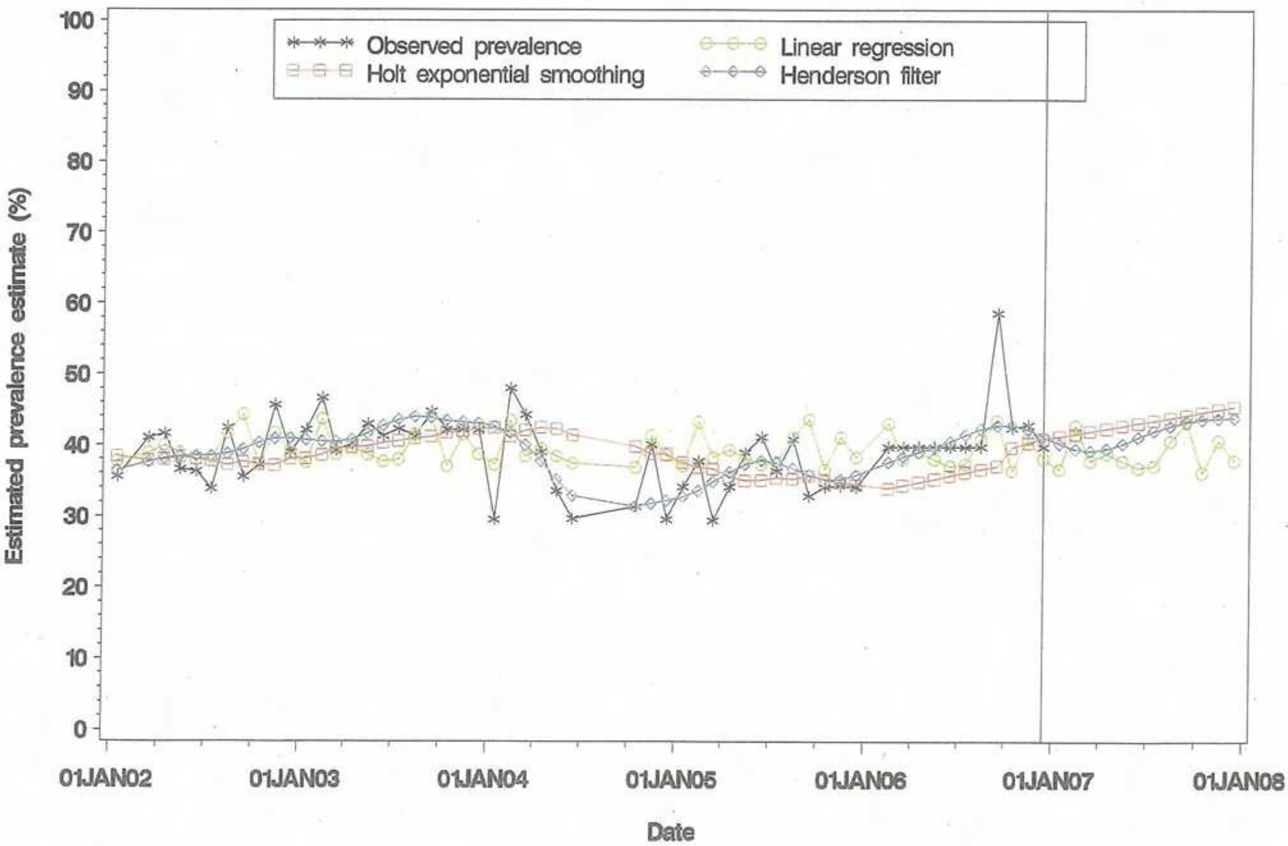
Sydney South West AHS, 2002–2006



Comparison of different prediction methods

3 or more servings of vegetables per day, persons aged 16 years or over

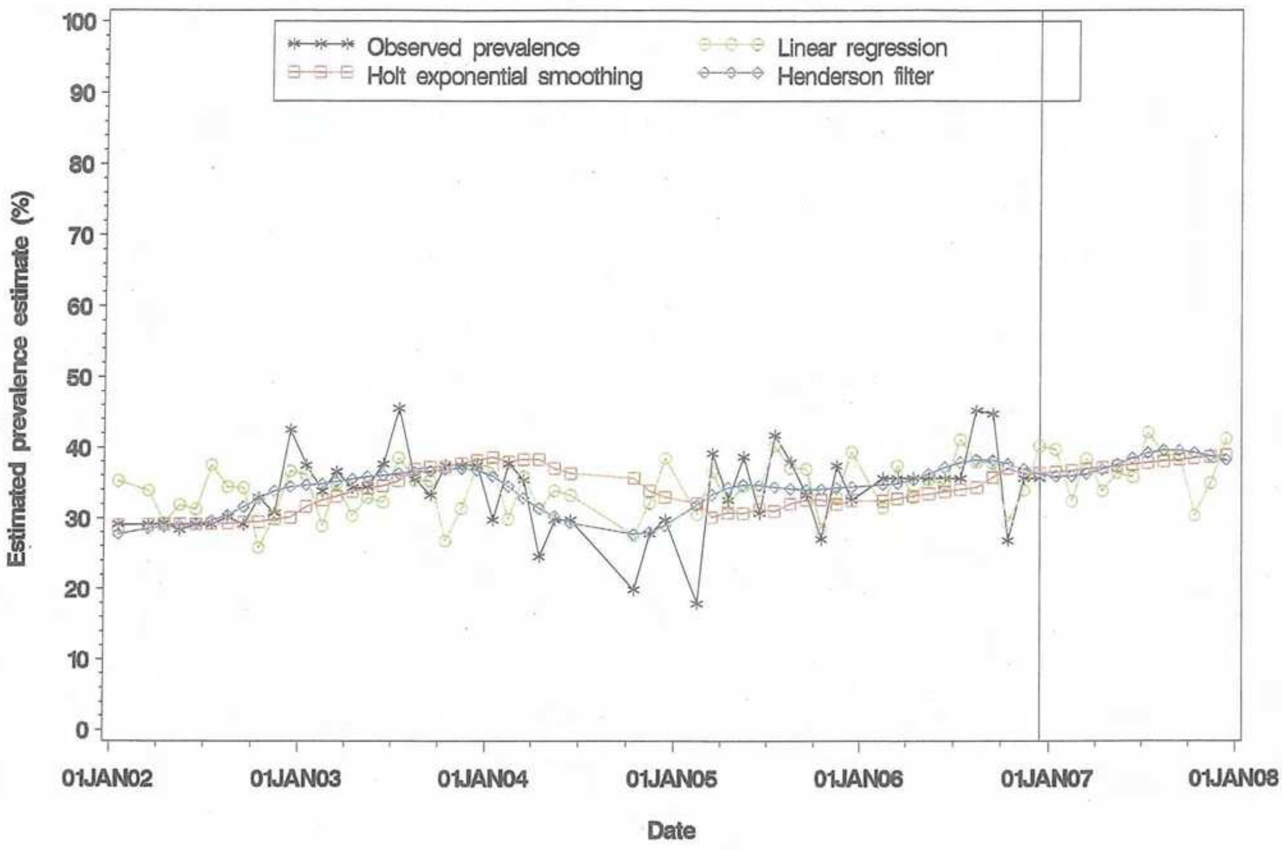
South Eastern Sydney & Illawarra AHS, 2002–2006



Comparison of different prediction methods

3 or more servings of vegetables per day, persons aged 16 years or over

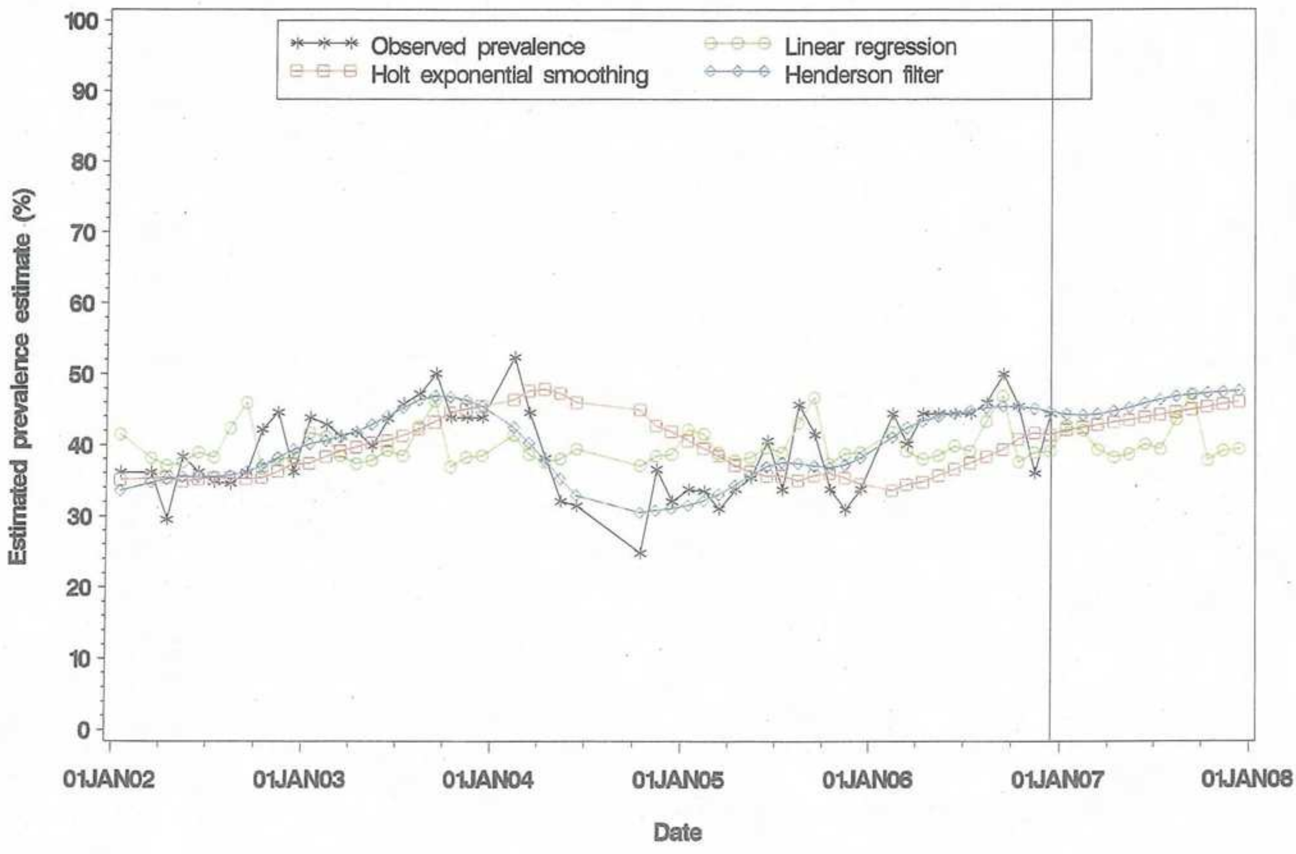
Sydney West AHS, 2002–2006

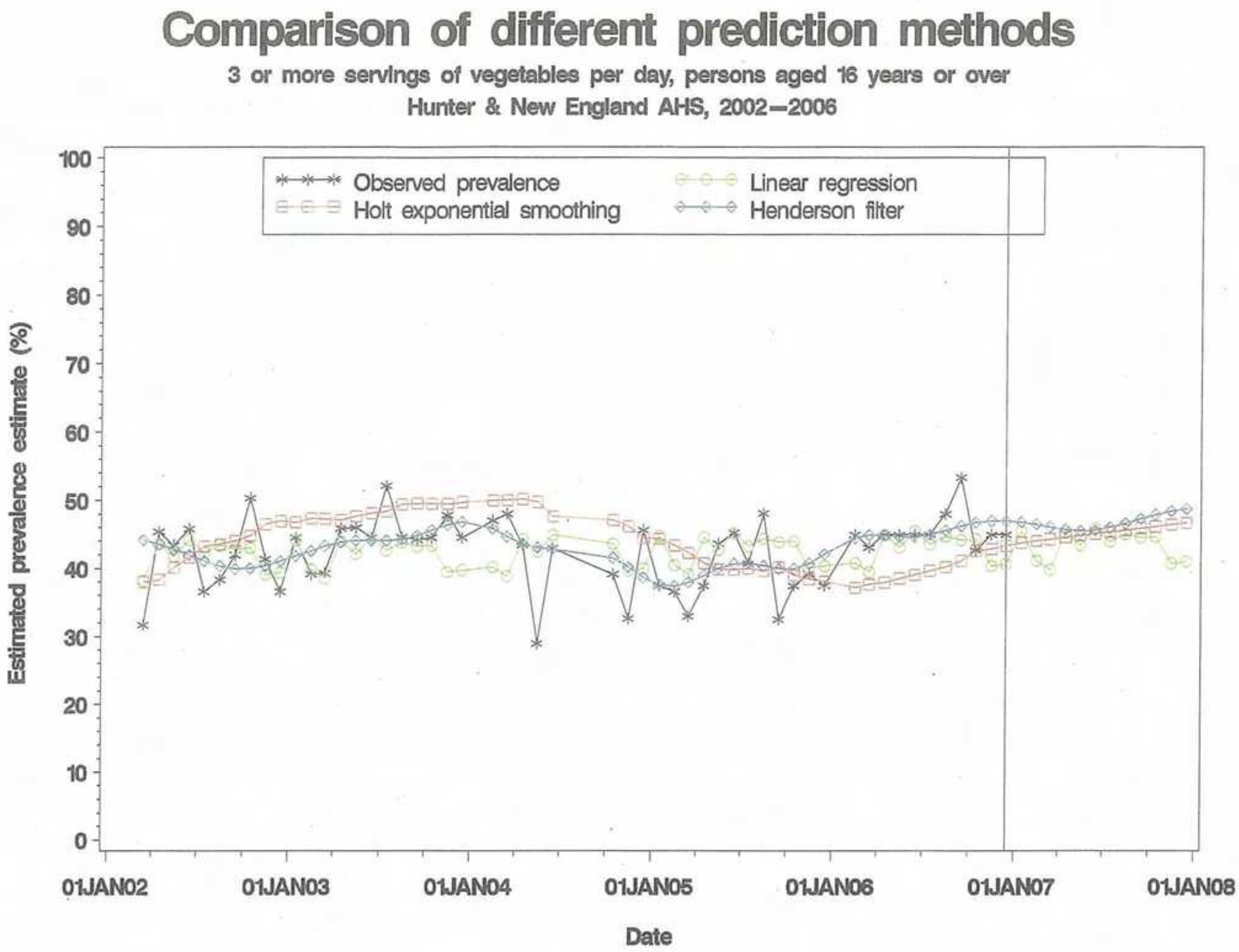


Comparison of different prediction methods

3 or more servings of vegetables per day, persons aged 16 years or over

Northern Sydney & Central Coast AHS, 2002–2006




Comparison of different prediction methods
3 or more servings of vegetables per day, persons aged 16 years or over
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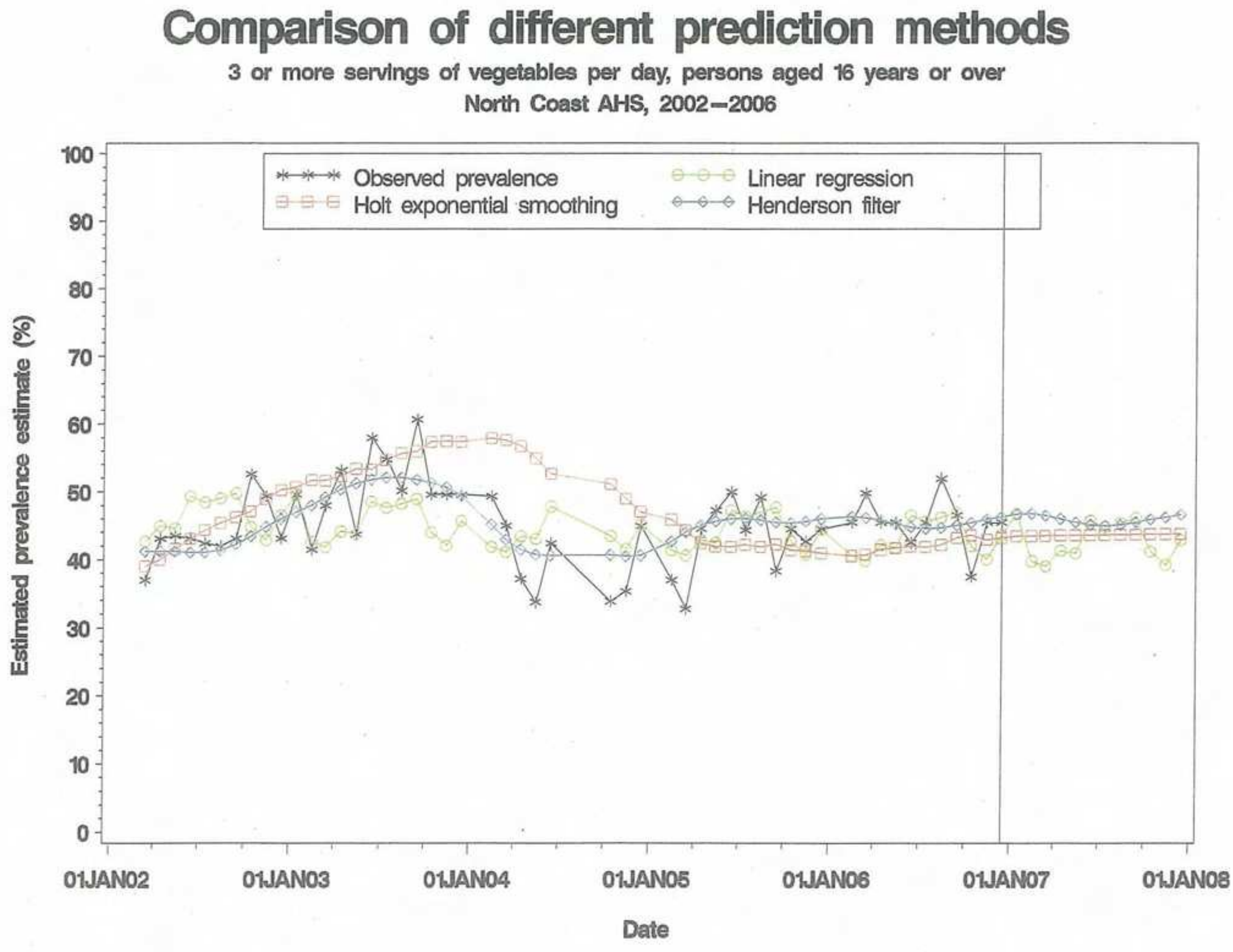
Comparison of different prediction methods
3 or more servings of vegetables per day, persons aged 16 years or over
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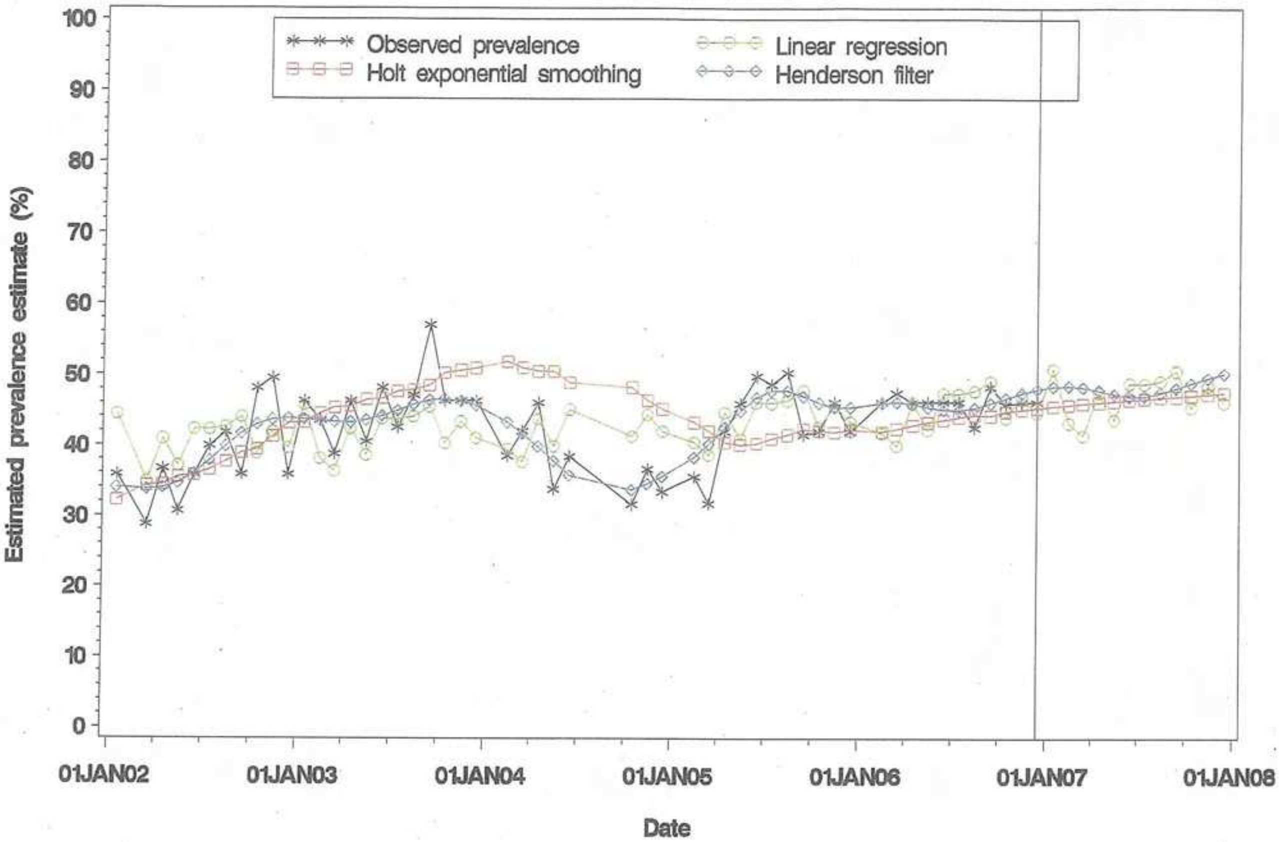
Greater Southern AHS, 2002–2006



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