METHODOLOGIC ISSUES

Quantifying the effect of a community-based injury prevention program in Queensland using a generalized estimating equation approach

Emily Yorkston, Catherine Turner, Philip J Schluter, Rod McClure

Injury Prevention 2007;**13**:191–196. doi: 10.1136/ip.2006.014225

See end of article for authors' affiliations

Correspondence to: E Yorkston, School of Nursing, University of Queensland, Level 1 Edith Cavell Building, Royal Brisbane and Women's Hospital, Herston Road, Herston, Qld 4029, Australia; e.yorkston@uq.edu.au

Accepted 5 March 2007

Objective: To develop a generalized estimating equation (GEE) model of childhood injury rates to quantify the effectiveness of a community-based injury prevention program implemented in 2 communities in Australia, in order to contribute to the discussion of community-based injury prevention program evaluation.
Design: An ecological study was conducted comparing injury rates in two intervention communities in rural and remote Queensland, Australia, with those of 16 control regions. A model of childhood injury was built using hospitalization injury rate data from 1 July 1991 to 30 June 2005 and 16 social variables. The model was built using GEE analysis and was used to estimate parameters and to test the effectiveness of the intervention.
Results: When social variables were controlled for, the intervention was associated with a decrease of 0.09 injuries/10 000 children aged 0–4 years (95% CI −0.29 to 0.11) in logarithmically transformed injury rates; however, this decrease was not significant ($p = 0.36$).
Conclusions: The evaluation methods proposed in this study provide a way of determining the effectiveness of a community-based injury prevention program while considering the effect of baseline differences and secular changes in social variables.

Epidemiology has evolved in conjunction with the study of infectious diseases.[1] Examining ecologic factors was crucial to controlling infectious diseases. In developed countries, infectious disease-related morbidity and mortality have decreased concomitantly with an increase in the burden of chronic diseases, including injuries. Consequently, there has been diminished emphasis on ecologic risk factors for disease and increased focus on the contribution of individual risk factors.[2 3] Contemporary epidemiology recognizes the role of macrolevel physical and social determinants in injury aetiology, and the ecologic approach has become more common.[4 5] The ecologic approach underpins the community-based model of injury prevention.[6]

The rationale for community-based injury prevention programs is drawn from the social science theories of community development and community participation. The community-based approach recognizes that "behaviors occur in multiple contexts, from microsystems to macrosystems and even ecosystems that individuals do not enter have a profound effect on their behavior".[7] In essence, the model adopts an ecologic approach, where the potential to change an individual's risk behavior is considered within a social and cultural context.[8]

Despite global implementation of the community-based model, particularly by the World Health Organization Safe Communities program, few evaluations demonstrate the effectiveness of the model in reducing injuries.[9 10] Evaluations are limited by inadequate evaluation time frames, the absence or inappropriate selection of community controls, and failure to match the evaluation approach with the ecologic nature of the community-based model.[11] Evaluations may also be limited by the analytic techniques used. Many studies have used linear regression or similar techniques, which do not accommodate the effect of clustering. A further restriction of community-based injury prevention programs is their limited statistical power.

Individuals are nested within communities and tend to be similar to each other, rather than to individuals within other communities.[12] Unless within-cluster correlation is statistically accounted for, the SEs of parameter estimates of the model will be underestimated, exaggerating the significance of the estimates.[13 14]

The number of intervention and control communities in a prevention program, the number of people within those communities, and the variability of the outcome measure are crucial determinants of the study's power to detect statistically significant program-related changes in outcome.[15] The number of communities constrains the sample size because of the effect of the within-cluster correlation coefficient.[14] Increasing the sample size per community confers a smaller increase in statistical power than that achieved by increasing the number of participating communities. Inclusion of additional intervention communities, however, does not assist in estimating the counterfactual injury rates in the study community, and may often not be feasible for ethical, logistic or financial reasons. The most practical option for improving power is to increase the number of control communities.

Generalized estimating equation (GEE) analysis is an analytic technique for longitudinal data that accommodates within-cluster correlation and enables analyses of multiple control communities, by adding a correlation matrix to a base regression model. The matrix estimates the within-community correlations between measures at different time points over the study period.[16] GEE analysis has been successfully used in evaluations of community-based substance misuse prevention programs,[13] and may be useful to redress some limitations of community-based injury prevention program evaluation.

Abbreviations: ARIA, Accessibility/Remoteness Index of Australia; GEE, generalized estimating equation; MSE, mean squared error

Table 1 Demographic characteristics of the intervention and control communities

Characteristic	Intervention community 1	Intervention community 2
Region	North–west	Mackay
ARIA+ score*	11.47	2.23
ARIA+ classification*	Remote	Inner regional
Population size	20 648	78 352
Median age (years)	30	34
Proportion male	0.53	0.49
Proportion indigenous	0.13	0.04

*Accessibility/Remoteness Index of Australia (ARIA+) scores are the standard classification for rurality and remoteness in Australia.[18]

We aimed to develop a GEE model of childhood injury rates to quantify the effectiveness of a community-based injury prevention program implemented in two communities.

METHODS

Study design

Evaluation of a community-based injury prevention program was undertaken. The prevention programs were implemented in two intervention communities in rural and remote Queensland. Intervention communities were selected by program funders because of their high childhood injury rates. Table 1 summarizes the properties of the intervention communities. The program aimed to reduce injury-associated falls, burns/scalds, poisonings and drowning-related mortality in 0–4-year olds over a 4-year period. Programs were conducted according to the World Health Organization Safe Communities criteria.[17] The programs were initiated in February 2003, and concluded in February 2007. Approval was granted by the relevant University of Queensland Ethics Committee.

Data sources and variable construction

Injury outcome data

The model used hospitalization injury rate data from 1 July 1991 to 30 June 2005. The numerator comprised all 0–4-year-old patients admitted to hospital with an external cause of injury. Injuries were coded using the International classification of disease, clinical modifications criteria, revisions ICD 9-CM and ICD 10-CM.[19 20] Data were extracted from the Queensland Health Admitted Patients Data Collection and Queensland Morbidity and Mortality System databases, and were supplied at Healthwiz area level. Healthwiz areas are groupings of "statistical local areas" with populations of approximately 10 000 people.[21] We further aggregated Healthwiz areas to form 18 regions congruent with the Australian Standard Geographical Classifications used by the Australian Bureau of Statistics.[21] The intervention communities corresponded to 2 of the 18 regions, and the remaining 16 regions were deemed control regions.

The denominator population was all 0–4-year olds living in Queensland between 1991 and 2004. Data were drawn from the Australian Census of Population and Housing. Data were available for census years only (1991, 1996 and 2001); therefore, the denominator in non-census years was estimated using linear interpolation. Data for financial years 2002–2004 were extrapolated from 2001 census data using a linear assumption. Data were aggregated into the 18 regions for which numerator data were available. Figure 1 shows the patterns of all childhood injuries in intervention and control communities for 1991–2004.

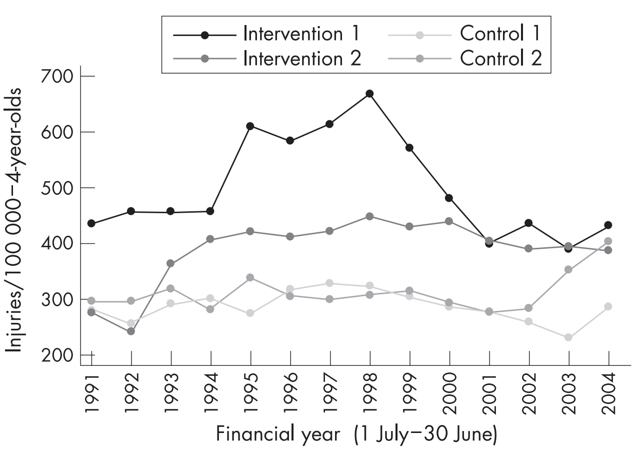

Figure 1 Childhood injury rates in intervention and control communities, 1991–2004.

Social variables

Social variables were constructed using 1991, 1996 and 2001 census data. Sixteen variables whose association with general health outcomes has been described as important in the scientific literature were derived from the census data (table 2). Fourteen variables were expressed as regional proportions. Two categorical social variables were constructed: income and socioeconomic status. Linear interpolation and extrapolation were necessary.

Developing a model of childhood injury rates

All analysis and modelling used Stata V8.0, and $\alpha = 0.05$ was used to define statistical significance. The model was built using GEE analysis[22] and was used to estimate parameters and to test for intervention effectiveness. Correlation between yearly observations was examined by region, and an appropriate correlation structure (exchangeable) was specified. The Huber–White sandwich variance estimation technique was used to calculate SEs and CIs.[23 24] Regression diagnostics and residual checks were undertaken to identify violations of model assumptions. Transformation of injury rate data was necessary to ensure that residuals met the normal assumption. Linear and higher-order time variables were related to regional injury rates and tested. Time was taken as years since baseline (1991). A measure of regional rurality (Accessibility/Remoteness Index of Australia (ARIA$^+$) score) was included in the base model of childhood injury rates, along with time.[25] ARIA$^+$ scores were continuous and ranged from 0 to 15, with higher scores indicative of greater remoteness.[18] Each social variable and time interaction was separately added to the baseline model. Only variables significant in crude analyses were considered for the full multivariate model. Both backward elimination and forward selection of the variables identified in the crude analysis (each using an entry and exit significance level of 5%) were used to derive the most parsimonious multivariate model. To improve model convergence, stability and interpretation, colinearity between related variables was assessed using a correlation matrix and examining the magnitude of correlation coefficients between variables. Decisions to remove collinear variables were based on the variability (mean squared error (MSE)) explained by each factor. Interactions that literature identified as important (eg, interaction between indigenous status and remoteness) were also assessed for significance. The effect of the community-based injury prevention programs was tested by including a binary variable "intervention", where a value of 0 was assigned to the control communities and the study communities in the non-intervention years, and a value

Table 2 Construction of social variables

Variable label	Variable composition
Age	$= \left(\dfrac{\text{People} \geqslant 65\ \text{years}_{\text{region}}}{\text{Total population}_{\text{region}}} \right)$
Sex	$= \left(\dfrac{\text{Males}_{\text{region}}}{\text{Total population}_{\text{region}}} \right)$
Indigenous	$= \left(\dfrac{(\text{Aboriginal+TSI+both people})_{\text{region}}}{\text{Total population}_{\text{region}}} \right)$
Birthplace	$= \left(\dfrac{\text{Australian born people}_{\text{region}}}{\text{Total population}_{\text{region}}} \right)$
Marital status	$= \left(\dfrac{\text{Married people}_{\text{region}}}{\text{Total population}_{\text{region}}} \right)$
Language	$= \left(\dfrac{\text{English-speaking only people}_{\text{region}}}{\text{Total population}_{\text{region}}} \right)$
Religion	$= \left(\dfrac{\text{Non religious people}_{\text{region}}}{\text{Total population}_{\text{region}}} \right)$
Education	$= \left(\dfrac{\text{Postgraduate+Bachelor+Advanced Diploma/Diploma}_{\text{region}}}{\text{Total population}_{\text{region}}} \right)$
Unemployment	$= \left(\dfrac{\text{Unemployed people}_{\text{region}}}{\text{Total labour force}_{\text{region}}} \right)$
Occupation	$= \left(\dfrac{\text{People professional occupation}_{\text{region}}}{\text{Total population}_{\text{region}}} \right)$
Families with children	$= \left(\dfrac{\text{Couple families with} \geqslant 1\ \text{child}_{\text{region}}}{\text{Total population}_{\text{region}}} \right)$
Single-parent families	$= \left(\dfrac{\text{Sole parent families}_{\text{region}}}{\text{Total population}_{\text{region}}} \right)$
Unoccupied dwellings	$= \left(\dfrac{\text{Occupied dwellings}_{\text{region}}}{\text{Total dwellings}_{\text{region}}} \right)$
Housing tenure	$= \left(\dfrac{\text{Fully owned dwellings}_{\text{region}}}{\text{Total dwellings}_{\text{region}}} \right)$

of 1 was assigned to study communities for the post-implementation years.

RESULTS

Baseline model

First- and second-order time variables and rurality (ARIA$^+$ scores) were significantly related to childhood injury rates; however, residual checks revealed important skewness (0.92) which subsequent logarithmic transformation removed. Pursuant GEE modeling was undertaken on logarithmically transformed injury rate data. Figure 2 shows the transformed injury rates over time by region. The exchangeable matrix more closely resembled the estimated values of the unstructured matrix and had the lowest MSE (0.0450) compared with the AR^1 matrix (MSE = 0.0453), and was used for the remaining analyses.

Crude analyses

In crude analyses, five social variables were found to be significantly related to childhood injury and were hence candidates for the multivariate model development (table 3).

Multivariate analyses

Two variables were found to be significant in crude analyses (marital status and single-parent status), with $r = -0.41$. Single-parent status was removed because it explained less of the variability in injuries than marital status. The remaining four significant variables and their time interactions (eight

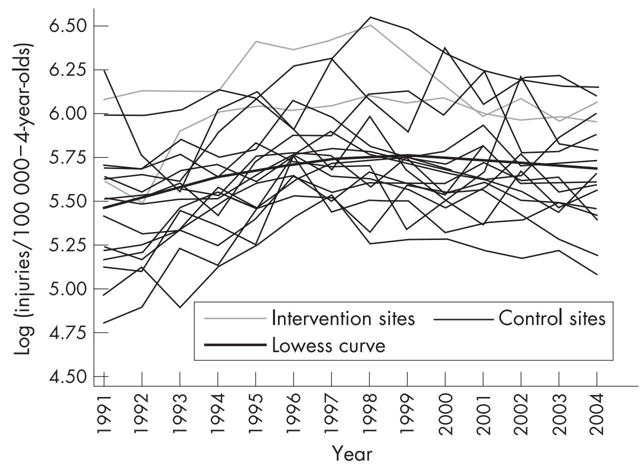

Figure 2 Spaghetti plot of logarithmically transformed childhood injury rate data over time, together with Lowess curve.

variables) were investigated. Both backward elimination and forward selection strategies yielded the same most parsimonious model (table 4). Serial correlation between successive yearly observations for each site was estimated at r = 0.43. In this model, distribution of the residuals of the logarithmically transformed childhood injury rates was not significantly different from the normal. There was a moderately strong interaction between indigenous status and $ARIA^+$ score (r = 0.77); however, this was not significantly associated with childhood injury rates at the univariate level (p = 0.06), nor did it alter the magnitude or direction of association of other variables, and hence was removed from the backward elimination model.

Intervention effectiveness test

The intervention was associated with an estimated reduction of 0.09 injuries/10 000 children aged 0–4 years (95% CI −0.29 to 0.11) in logarithmically transformed injury rates; however, it was not significant (p = 0.36).

DISCUSSION

This study demonstrates that the consideration of the effect of changes in social variables can be integrated into program evaluation, and that social variables can be controlled when testing the effectiveness of community-based injury prevention programs. The modeling processes presented are not in themselves new; however, their application to community-based injury prevention program evaluation is considered to be so.

The model indicated that the effects of the prevention program were not significantly associated with childhood injuries. The lack of measured effect may be due to implementation of an ineffective prevention program, or the relatively short time frame of post-intervention data collection. The program encouraged individual behavior modifications that invoke changes to outcome measures—a process that requires considerable time.[26] The lack of observed changes may be due to an insufficient evaluation time frame.

This evaluation used injury hospitalizations as its outcome measure. Despite their convenience for use in program evaluation, injury rates are subject to measurement errors and response biases, and are influenced by variations in hospitalization and admission policies. These deficiencies have led to the suggestion that other outcome measures, such as

Table 3 Crude relationship among social variables, time and logarithmically transformed childhood injury rates, adjusted for time components and rurality

Variable	Coefficient (95% CI)	p Value
Age	−0.20 (−2.64 to 2.24)	0.87
Age×time	−0.04 (−0.18 to 0.11)	0.63
Birth place	1.41 (−0.17 to 3.00)	0.08
Birth place×time	−0.04 (−0.15 to 0.06)	0.42
Unoccupied dwellings	−1.49 (−3.68 to 0.69)	0.18
Unoccupied dwellings×time	−0.16 (−0.37 to 0.05)	0.15
Education	1.77 (−0.32 to 3.86)	0.10
Education×time	0.13 (0.01 to 0.25)	0.03
Family with children	0.54 (−1.24 to 2.33)	0.55
Family with children×time	−0.06 (−0.22 to 0.10)	0.48
Single-parent family	−3.21 (−9.35 to 2.93)	0.31
Single-parent family×time	−0.61 (−1.00 to −0.24)	0.003
Indigenous	−1.96 (−4.12 to 0.19)	0.07
Indigenous×time	−0.23 (−0.43 to −0.04)	0.02
English language	1.58 (−0.64 to 3.80)	0.16
English language×time	0.07 (−0.13 to 0.28)	0.49
Marital status	2.62 (1.22 to 4.03)	<0.001
Marital status×time	0.01 (−0.26 to 0.28)	0.95
Occupation	1.01 (−1.22 to 3.26)	0.37
Occupation×time	0.03 (0.16 to 0.21)	0.77
Religion	3.30 (0.21, 6.39)	0.04
Religion×time	0.14 (−0.08 to 0.36)	0.22
Housing tenure	1.16 (−0.40 to 2.73)	0.15
Housing tenure×time	0.09 (−0.85 to 0.24)	0.20
Male sex	3.21 (−5.50 to 11.92)	0.47
Male sex×time	−0.10 (−0.65 to 0.45)	0.72
Unemployment	0.60 (−2.02 to 3.23)	0.65
Unemployment×time	−0.09 (−0.30 to 0.11)	0.37
Median income	−9.8E-5 (−6.6E-4 to 4.8E-4)	0.74
Median income×time	2.0E-5 (−2.2E-5 to 6.3E-5)	0.34
Income category	−0.03 (−0.09 to 0.02)	0.24
Income category×time	4.9E-3 (−2.1E-3 to 0.01)	0.17

Table 4 Predictor variables of the generalized estimating equation model of logarithmically transformed childhood injury rates for 18 regions of Queensland

Variable	Coefficient (95% CI)	p Value
Time	0.12 (0.10 to 0.14)	<0.001
Time^2	−5.5E-3 (−7.0E-3 to −4.0E-3)	<0.001
ARIA$^+$ score	0.06 (0.04 to 0.08)	<0.001
Marital status	2.69 (1.13 to 4.25)	0.001
Indigenous	−1.86 (−2.96 to −0.77)	0.001
Indigenous×time	−0.24 (−0.39 to −0.09)	0.002
Intervention	−0.09 (−0.29 to 0.11)	0.36

ARIA, Accessibility/Remoteness Index of Australia.

community-level indicators, are more appropriate and sensitive outcome measures.[27 28]

There is some indication that the model could be improved if more specific data could be made available. The model found that childhood injuries increase by 2.69/10 000 children aged 0−4 years, as the proportion of married people increased. Other studies have reported lower injury rates for children who live with both biological parents.[29] It is possible that the positive association between childhood injury rates and the proportion of married couples demonstrated at the community level in this model may be because married couples are more likely to have more children.

This model describes a negative association between both the indigenous status and the indigenous status/time variable. Deaths from injury in indigenous Australians occur at 2.8 times the rate in non-indigenous Australians,[30] hence the negative association described in this model was unanticipated. A possible explanation may be that the predominant causes of injury-related mortality in indigenous Australians are transport accidents and suicide, which are not typical causes of death for 0−4-year olds. The direction of association may be different in this younger population. Secondly, the correlation between ARIA$^+$ score and indigenous status was high ($r = 0.77$), although not significant, in the final multivariate model. As a group, indigenous Australians are less likely to report childhood injuries, and as many indigenous Australians live in remote settings, their ability to access medical services may be reduced. Further investigation is hence warranted.

Factors such as social capital,[31] income inequality[32] and neighborhood physical environment[33] have important relationships with general health outcomes, including cancer, cardiovascular disease and intentional injuries. Such variables could not be derived for this study. The social variables were derived by aggregating individual-level census data and are therefore subject to the ecologic fallacy.[2] In addition, the social variables were constructed after an extensive literature review. It is possible that other variables may be more relevant to childhood injury, and may alter the model if included. Research on the ways to measure and collect data for these and other social variables is required.

The strength of this paper is not in providing a definitive list of social variables associated with childhood injuries, but in demonstrating that such associations exist and should be considered during community-based injury prevention evaluation. In this context, the proposed model has several advantages. Firstly, use of GEE analysis permits clustered data to be statistically accommodated.[16] Secondly, examination of the study variables at baseline as well as changes in these variables over time is possible. Theoretically, both the baseline level of social variables and the magnitude of their changes may be important for injury outcomes.

Although our GEE model had advantages over the traditional two-community trial in terms of increased statistical power, the issue of sample size remained problematic. Algebraically manipulating sample size formulae[34] and use of empirical estimates derived from this study, by post hoc calculations our study had 33% power to detect a significant change at the $\alpha = 5\%$ level. Increasing the post-evaluation period from 2 to 3 years would increase the power of the study to 37%. The mean difference in logarithmically transformed childhood injury rates would need to decrease from −0.09 to −0.17 before 80% power to detect a significant change at $\alpha = 5\%$ would be attained for the 18 regions, of which two were intervention communities.

GEE methods were chosen because of their versatility, interpretability, ability to adequately model longitudinal clustered data, and appropriateness for health research. Methods including mixed-effect modeling, time-lag models, autoregressive models, and hierarchical Bayesian models may be useful for longitudinal data analysis.[34–36] The hierarchical Bayesian approach may be particularly suitable, owing to its ability to model naturally occurring hierarchical structures and clusters, together with its capacity to easily incorporate pertinent auxiliary information into the analysis.[35] Using these methods to further explore the effect of community-based programs on injury outcomes when controlling for social variables is warranted.

What this paper adds

This paper adds to the suite of methods currently available for the evaluation of community-based injury prevention programs. The proposed methods can increase the evidence base to support the effectiveness of the community-based model of prevention.

Policy implications

Enhancing the quality of community-based program evaluation methods means that policies implemented for prevention of chronic diseases and injury can be based on stronger evidence.

CONCLUSIONS

While methodologically limited, the model demonstrates that social variables are significantly associated with childhood injury rates, but are not adequately controlled for using the control community method of program evaluation. This study demonstrates the need to develop robust evaluation measures for social variables to further quantify their role in community-based prevention. The evaluation methods illustrated in this study provide an exemplar of a method to account for the effect of baseline differences and secular changes in social variables when considering the effectiveness of community-based injury prevention programs.

ACKNOWLEDGEMENTS

This research was undertaken with the support of a PhD scholarship from Injury Prevention and Control Australia (Pty) as part of an evaluation undertaken for Queensland Health and the Department of Emergency Services.

Authors' affiliations

Emily Yorkston, Catherine Turner, School of Nursing, University of Queensland, Brisbane, Queensland, Australia

Philip J Schluter, Faculty of Health and Environmental Sciences, Auckland University of Technology, Auckland, New Zealand

Rod McClure, School of Medicine, Griffith University, Meadowbrook, Queensland, Australia

Competing interests: None.

REFERENCES

1 **Szreter S**. The population health approach in historical perspective. *Am J Public Health* 2003;**93**:421–31.
2 **Diez-Roux AV**. Bringing context back into epidemiology: variables and fallacies in multilevel analysis. *Am J Public Health* 1998;**88**:216–22.
3 Mohan D, Tiwari G, eds. *Injury prevention and control*. London: Taylor and Francis, 2000.
4 **Moller J**. Community-based interventions: an emerging dimension of injury control models. *Health Promot J Australia* 1991;**1**:51–4.
5 **Spinks A**, McClure R, Nixon J, *et al*. The ''WHO Safe Communities'' model for the prevention of injuries in whole populations. *Cochrane Database Syst Rev* 2005;(2):CD004445.
6 **Nilsen P**. What makes community-based injury prevention work? In search of evidence of effectiveness. *Inj Prev* 2004;**10**:268–74.
7 **Shinn M**. Ecological assessment: introduction to the special issue. *Am J Community Psychol* 1996;**24**:1–3.
8 **Goodman RM**, Wandersman A, Chinman M, *et al*. An ecological assessment of community-based interventions for prevention and health promotion: approaches to measuring community coalitions. *Am J Community Psychol* 1996;**24**:33–61.
9 **Hofler M**. The Bradford Hill considerations on causality: a counterfactual perspective. *Emerg Themes Epidemiol* 2005a;**2**:11.
10 **Newman SC**. Commonalities in the classical, collapsibility and counterfactual concepts of confounding. *J Clin Epidemiol* 2004;**57**:325–9.
11 **Nilsen P**. Evaluation of community-based injury prevention programs: methodological issues and challenges. *Int J Injury Control Saf Promot* 2005;**12**:143–56.
12 **Murray DM**, Varnell SP, Blitstein JL. Design and analysis of group-randomised trials: a review of recent methodological developments. *Am J Public Health* 2004;**94**:423–32.
13 **Norton EC**, Bieler GS, Ennett ST, *et al*. Analysis of prevention program effectiveness with clustered data using generalised estimating equations. *J Consult Clin Psychol* 1996;**64**:919–26.
14 **Siddiqui O**, Hedeker D, Flay BR, *et al*. Intraclass correlation estimates in a school-based smoking prevention study: outcome and mediating variables, by sex and ethnicity. *Am J Epidemiol* 1996;**144**:425–33.
15 **Livert D**, Rindskopf D, Saxe L, *et al*. Using multilevel modeling in the evaluation of community-based treatment programs. *Multivariate Behav Res* 2001;**36**:155–84.
16 **Twisk JW**, Smidt N, de Vente W. Applied analysis of recurrent events: a practical overview. *J Epidemiol Commun Health* 2005;**59**:706–10.
17 **World Health Organization**. Manifesto for Safe Communities. Safety—a universal concern and responsibility for all. *First world conference on accident and injury prevention*. Geneva: Switzerland, 1989.
18 **National Key Centre for Social Applications of Geographic Information Systems (GISCA)**. Accessibility/Remoteness Index of Australia (ARIA). 2002. http://www.gisca.adelaide.edu.au/web_aria/aria/aria.html (accessed 29 Mar 2007).
19 **American Medical Association**. *International classification of diseases, 9th revision. Clinical modification: ICD-9-M*. Chicago: AMA, 1999.
20 **World Health Organisation**. *ICD-10: international statistical classification of diseases and related health problems*. Geneva: WHO, 1994.
21 **Australian Bureau of Statistics**. *Australian Standard Geographical Classification (ASGC) 2005*. Canberra: Australian Bureau of Statistics, 2005.
22 **Liang K-Y**, Zeger SL. Longitudinal data analysis using generalised linear models. *Biometrika* 1986;**73**:13–22.
23 **Huber PJ**. The behaviour of the maximum likelihood estimator under non-standard conditions. In: Le Cam LM, Neyman J, eds. *The 5th Berkeley symposium on mathematical statistics and probability*, 1967. Berkeley, California: University of California, 1967:361–79.
24 **White H**. Maximum likelihood estimation of mis-specified models. *Econometrics* 1982;**50**:1–25.
25 **Loos C**, Oldenburg B, O'Hara L. Planning of a community-based approach to injury control and safety promotion in a rural community. *Aust J Rural Health* 2001;**9**:222–8.
26 **Damashek A**, Peterson L. Unintentional injury prevention efforts for young children: levels, methods, types and targets. *J Dev Behav Pediatr* 2002;**23**:443–56.
27 **Cheadle A**, Sterling TD, Schmid TL, *et al*. Promising indicators for evaluating cardiovascular health-promotion programs. *Health Educ Res* 2000;**15**:109–16.
28 **Cheadle A**, Wagner E, Koepsell T, *et al*. Environmental indicators: a tool for evaluating community-based health promotion programs. *Am J Prev Med* 1992;**8**:345–50.
29 **Sellstrom E**, Guldbrandsson K, Bremberg S, *et al*. Association between childhood community safety interventions and hospital injury records: a multilevel study. *J Epidemiol Community Health* 2003;**57**:724–9.
30 **Helps YLM**, Harrison JE. *Reported injury mortality of Aboriginal and Torres Strait Islander peoples in Australia, 1997–2000*. Canberra: Australian Institute of Health and Welfare, 2004.
31 **Putnam R**. Bowling alone: America's declining social capital. *J Democracy* 1995;**6**:65–78.
32 **Kennedy BP**, Kawachi I, Glass R, *et al*. Income distribution, socioeconomic status and self rated health in the United States: multilevel analysis. *BMJ* 1998;**317**:917–22.
33 **Cohen DA**, Mason K, Bedimo A, *et al*. Neighbourhood physical conditions and health. *Am J Public Health* 2003;**93**:467–71.
34 **Twisk JWR**. *Applied longitudinal data analysis for epidemiology: a practical guide*. New York: Cambridge, 2003.
35 **Congdon P**. *Bayesian statistical modelling*. Chichester: Wiley, 2002.
36 **Diggle PJ**, Heagerty P, Lain K-Y, *et al*. *Analysis of longitudinal data*, 2nd edn. Oxford: Oxford University Press, 2003.