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Original Research

Spatial variation in cancer incidence and survival over time across Queensland, Australia☆

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ABSTRACT

Interpreting changes over time in small-area variation in cancer survival, in light of changes in cancer incidence, aids understanding progress in cancer control, yet few space–time analyses have considered both measures. Bayesian space–time hierarchical models were applied to Queensland Cancer Registry data to examine geographical changes in cancer incidence and relative survival over time for the five most common cancers (colorectal, melanoma, lung, breast, prostate) diagnosed during 1997–2004 and 2005–2012 across 516 Queensland residential small-areas. Large variation in both cancer incidence and survival was observed. Survival improvements were fairly consistent across the state, although small for lung cancer. Incidence changes varied by location and cancer type, ranging from lung and colorectal cancers remaining relatively constant over time, to prostate cancer dramatically increasing across the entire state. Reducing disparities in cancer-related outcomes remains a health priority, and space–time modelling of different measures provides an important mechanism by which to monitor progress.

1. Introduction

With an estimated 14.1 million cancer cases diagnosed globally in 2012 (Ferlay et al., 2013), the impact of cancer is felt worldwide. With wide variation in cancer incidence and survival not only between countries (Ferlay et al., 2013; Allemani et al., 2015), but also within countries (Siegel et al., 2016; Australian Institute of Health and Welfare, 2014), there are important disparities depending on where people live.

Quantifying and understanding the extent of small-area variation in cancer incidence and survival is becoming increasingly important, with government and other policy makers needing to make evidence-based decisions on resource allocation and planning interventions to address any known disparities. Consistent with this, an increasing number of small-area cancer atlases have been published, including those in Australia (Public Health Information Development Unit, 2012; Cramb et al., 2011; Bois et al., 2007), USA (National Cancer Institute, 2015) and the UK (Quinn et al., 2005).

There is great variation in the statistical approaches used in these atlases. These methods range from direct estimation of area-specific age-standardised incidence rates (Public Health Information Development Unit, 2012) through to modelling approaches incorporating smoothing such as Poisson kriging (Goovaerts, 2005), empirical

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Bayes (Benach et al., 2001) or fully Bayesian methods (Bois et al., 2007). While each method has various benefits and disadvantages, some form of smoothing is often preferred to reduce spurious variation associated with very small area-specific counts (Best et al., 2005).

We have previously demonstrated the extent of small area variation in incidence and survival across the state of Queensland, Australia for around 20 of the most commonly diagnosed cancers (Cramb et al., 2011). This cancer atlas highlighted the extent of the geographical variability in incidence across Queensland, and how the survival outcomes were poorer in many of the more remote areas of the state.

However, it was unclear how these geographical patterns in cancer incidence and survival have changed over time. Since the ability to understand whether the spatial patterns are changing over time and in what direction is critical to guide efforts to reduce existing disparities, we have examined how the geographical variation in cancer incidence and survival in Queensland has changed over time for the five most commonly diagnosed cancers.

2. Methods

Ethical approval to conduct this study was obtained from the Darling Downs Hospital and Health Service Human Research Ethics Committee (HREC/15/QTDD/57).

2.1. Data and analysis

De-identified data on all cases of colorectal (ICD-O-3 (Fritz et al., 2000) C18-C20, C218), lung (ICD-O-3 C33-C34), melanoma (ICD-O-3 C44 M872-M879), breast (ICD-O-3 C50) and prostate (ICD-O-3 C61) diagnosed in Queensland during 1997–2012 was obtained from the population-based Queensland Cancer Registry (QCR). All non-keratinocytic cancers diagnosed are notifiable by law.

The patient's address at diagnosis was geocoded within the QCR, and assigned to one of 516 residential Statistical Area 2s (SA2s) based on the 2011 Australian Statistical Geography Standard (ASGS) boundaries (Australian Bureau of Statistics, 2011). SA2s with an average population below 5 during 1997–2012 were considered to be non-residential and were excluded ($n = 10$). In 2011, the median population of a residential SA2 was 7996 (range: 7–29,641). Cases with insufficient information to determine the SA2 at diagnosis were excluded.

The study cohort included those diagnosed with an invasive cancer and aged 15–89 years at diagnosis. Cases diagnosed through death or autopsy were excluded. Year of diagnosis was split into two diagnostic time periods: 1997–2004 and 2005–2012.

The QCR routinely conducts data linkage with the Australian National Death Index to determine the survival status of all cancer patients. Survival time (in days) was provided by the QCR, with follow-up of all patients to 2013. For the survival analyses, cases were censored at the earliest of five years from diagnosis or the specified censoring date, which was 31 December 2005 for the 1997–2004 cohort and 31 December 2013 for the 2005–2012 cohort.

As is the case for most population-based cancer survival studies, we used relative survival to estimate net survival. Since it compares the cohort mortality against the population mortality, relative survival has the advantage over cause-specific survival in not requiring cause of death information (Sarfati et al., 2010).

To calculate the SA2-specific population mortality rates, unit record death data were obtained from the Australian Bureau of Statistics (ABS) (for deaths from 1997 to 2005) (Australian Bureau of Statistics 2007) and the Australian Coordinating Registry (2006–2013) (Australian Coordinating Registry, 2014). Corresponding population data for each SA2, 5-year age group and sex was obtained from the Australian Bureau of Statistics (ABS) for 1997–2013. Concordance files provided by the ABS were used to adjust all the geographical information to the 2011 ASGS SA2 boundaries. To account for the low numbers of deaths in some SA2, single year age, sex and year categories, a smoothing process was used to increase the stability of the expected mortality. Briefly, population and mortality data for each SA2 were aggregated into strata comprising three time periods (1997–2002, 2003–2008, 2009–2013), by 5-year age group (to 90 + years) and sex. Neighbouring SA2s were identified based mainly on shared boundaries, although islands included nearby mainland areas. "Smoothed" population mortality rate estimates for specific SA2s by strata group were then calculated by combining the SA2-specific mortality and population with the corresponding data from all neighbouring areas. These smoothed estimates were then expanded so the same mortality rate was assigned to each single year age, single calendar year, sex and SA2 within any given 5-year age group, 5-year or 6-year calendar time period, sex and SA2. These smoothed estimates were used in both the non-Bayesian and Bayesian relative survival models.

2.2. Incidence models

To examine changes in cancer incidence over time, a Bayesian space–time model based on that introduced by Bernardinelli et al.(1995) was used. A Poisson distribution:

$$O_{ij} \sim \text{Poisson}\left(\theta_{ij} E_{ij}\right)$$

forms the foundation of this model, where O_{ij} are the observed new cancer cases in $i = 1,2,\ldots,516$ areas and $j = 1,2$ time periods (representing 1997–2004 and 2005–2012), θ_{ij} is the corresponding modelled standardised incidence ratio (SIR) and E_{ij} represents the age- and sex-standardised expected counts. The log of the modelled SIR can then be written as:

$$\log\left(\theta_{ij}\right) = \alpha + \lambda\delta_j + s_i\delta_j + u_i + v_i$$

and each of these parameters were given prior distributions. The intercept term α and coefficients λ for the jth time period indicator δ have vague normal priors, u_i (structured spatial variation) and s_i (the differential trend) are assumed to follow an intrinsic conditional autogressive (CAR) prior with neighbours assigned based largely on geographically adjacent boundaries (since islands included the closest mainland areas as neighbours), and v_i represents unstructured spatial variation, with a vague normal distribution for each of i areas. Additional details on the prior distributions are provided in Supplementary Table S1.