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Spatial and temporal variations of spatial population accessibility to public hospitals: a case study of rural–urban comparison

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Quantification and assessment of nationwide population access to health-care services is a critical undertaking for improving population health and optimizing the performance of national health systems. Rural–urban unbalance of population access to health-care services is widely involved in most of the nations. This unbalance is also potentially affected by varied weather and road conditions. This study investigates the rural and urban performances of public health system by quantifying the spatiotemporal variations of accessibility and assessing the impacts of potential factors. Australian health-care system is used as a case study for the rural–urban comparison of population accessibility. A nationwide travel time-based modified kernel density two-step floating catchment area (MKD2SFCA) model is utilized to compute accessibility of travel time within 30, 60, 120, and 240 min to all public hospitals, hospitals that provide emergency care, and hospitals that provide surgery service, respectively. Results show that accessibility is varied both temporally and spatially, and the rural–urban unbalance is distinct for different types of hospitals. In Australia, from the perspective of spatial distributions of health-care resources, spatial accessibility to all public hospitals in remote and very remote areas is not lower (and may even higher) than that in major cities, but the accessibility to hospitals that provide emergency and surgery services is much higher in major cities than other areas. From the angle of temporal variation of accessibility to public hospitals, reduction of traffic speed is 1.00–3.57% due to precipitation and heavy rain, but it leads to 18–23% and 31–50% of reduction of accessibility in hot-spot and cold-spot regions, respectively, and the impact is severe in New South Wales, Queensland, and Northern Territory during wet seasons. Spatiotemporal analysis for the variations of accessibility can provide quantitative and accurate evidence for geographically local and dynamic strategies of allocation decision-making of medical resources and optimizing health-care systems both locally and nationally.

Keywords: accessibility; spatial and temporal variations; public hospitals; emergency and surgery service; MKD2SFCA model

1. Introduction

Nationwide measurement of population access to health-care services and the assessment of its quality and difference can provide accurate and reasonable evidence for the improvement

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of local population health and the performance of health systems (Barber et al. 2017). Universal health coverage (UHC) is an important issue for all nations to achieve equitable and sustainable development of health systems so that all residents and communities have access to quality health-care services (UN, General Assembly 2015). Australian health-care system is highly valued and considered as a model of transparent and public, easy access, and quality and comprehensive health-care services. The spending of health care accounts for about 3.7% of annual gross domestic product or nearly 2542 Australian dollars per person (AIHW 2015). Australian health system contains diverse public and private hospitals and their care services including preventive health services, primary and community health services, and spatialized services for all residents across the nation (AIHW 2011; AIHW 2016b). While the internal unbalance of population access to health-care services exists in the health systems of all nations, especially in Australia with a vast territory, due to various factors: varied locations of residents, distinct geographical conditions, the spatial variations of road network and traffic conditions, seasonal variation of weather conditions, uneven distributions of population, and the allocation of hospital resources such as general practitioners, medical specialists, and available beds (Smith et al. 2017; Makanga et al. 2017; Cheng et al. 2016; Arcury et al. 2005; Wang and Luo 2005; Guagliardo 2004). Most of the previous studies concern the geographical access to health-care services from the scale of a city or region to learn the performance of local health system (Cheng et al. 2016; Luo and Wang 2003; Shah, Bell, and Wilson 2016), but only a few researches accurately quantify the access to hospitals in a vast territory nation (Brabyn and Skelly 2002; Sanmartin et al. 2004; Schoen et al. 2004). Access to health-care services within a nation is much more sophisticated, potentially unbalance, uncertain, and distinct spatially and temporally than citywide conditions. In addition, compared with the researches in cities, current studies lack the information and assessment about the geographic distribution of health-care services, especially specialty services in rural regions and remote areas (Guagliardo 2004; Jütting 2004; McGrail and Humphreys 2009; Shah, Milosavljevic, and Bath 2017). Thus, accurately quantifying local access to health-care services across a nation is a critical undertaking to have comprehensive understanding of a complex nationwide health system.

Spatial or geographical accessibility refers to the ease and resources with which residents in a region can access facilities and services (Hewko, Smoyer-Tomic, and Hodgson 2002). It provides essential quantitative information of the spatial and social inequalities in the access for the decision-making of planning, maintenance, and optimization of facilities (Apparicio et al. 2008). These inequalities potentially lead to both positive health conditions such as quality health-care services and easy access to recreational facilities in some regions and negative ones with waste and pollution-related facilities and infrastructures in other areas (Wang and Luo 2005; Witten, Exeter, and Field 2003; Song et al. 2015; Wu et al. 2017; Wu et al. 2016). Spatial accessibility is a commonly measured indicator based on the travel distance or time to the facilities from demands (Luo and Wang 2003). In terms of the travel distance or time-based calculation, the measurements of spatial accessibility can be divided into two categories. The first one is calculating distance or time, and a series of indicators are utilized such as the distance or time between a demand and its closest facility or a given number of closest facilities, the average distance or time between a demand, and all facilities or a given number of facilities, etc. (Apparicio et al. 2008; Apparicio, Cloutier, and Shearmur 2007; Smith et al. 2017). Another category of measurements is to compute the number of facilities or facility–demand ratio within a certain administrative unit, time, or distance threshold (Apparicio et al. 2008; Luo and Wang 2003; Jamtsho, Corner, and Dewan 2015; Love and Lindquist 1995). The latter one has improvements to quantify spatial accessibility by incorporating the medical staff or beds to population ratios with the relative geographical relations in capturing the population access to hospitals (Love and Lindquist 1995). For instance, doctor-population ratio (DPR) is applied in analyzing the spatial layout and distributions of high-level medical resources in Shenzhen, China (Cheng et al. 2016), and bed-population ratio (BPR) together with distinct critical distances from inhabitants to hospitals is used to study the accessibility of cardiovascular diseases to hospitals in Kentucky, USA (Hare and Barcus 2007).

The DPR or BPR-oriented spatial accessibility to hospitals is generally analyzed using floating catchment area (FCA) models (Luo and Wang 2003; Jamtsho, Corner, and Dewan 2015). Compared with traditional gravity model, FCA models are specialized variants and have improvement since they are intuitively interpretable for the facility–demand relations, and use spatially varied population catchment areas for service centers (McGrail and Humphreys 2014; Delamater 2013; Wan, Zou, and Sternberg 2012). To further describe the spatial competing relationships between population and hospitals that local residents compete for the finite health-care resources in the nearby hospitals, and hospitals share the necessities of surrounding residents, a two-step floating catchment area (2SFCA) model is proposed by repeating FCA process twice for both facilities and demands (Radke and Lan 2000). 2SFCA model is a primary measurement of spatial accessibility to health-care services due to its incorporation of population demands, hospital resources, and the travel cost calculated as geographical distance or travel time (Cheng et al. 2016; Luo and Wang 2003). Two concerns need to be determined to analyze spatial accessibility using 2SFCA model and its revised or improved versions. The first one is to outline the catchment areas of population. Catchment areas are commonly outlined by the concentric circles within a given travel time or distance including Manhattan distance, Euclidean distance, and the travel distance in the road network (Apparicio et al. 2008; Luo and Qi 2009; McGrail 2012). The nearest administrative or geographical neighbors within a clustering region also could be utilized to define catchment areas (Jamtsho, Corner, and Dewan 2015). Second, a proper distance decay function should be determined to descript relative distance weights of distance impendence parameters related to residents, resources of hospitals, and DPR or BPR. Since few studies investigate the impact of distance decay function on spatial accessibility, the choice of distance decay function depends on the case and expert experience (Jamtsho, Corner, and Dewan 2015). The commonly used distance decay functions include inverse power, linear, exponential, Gaussian, and their revisions (Apparicio et al. 2008; Cheng et al. 2016; Langford, Fry, and Higgs 2012; Bauer et al. 2017; Jamtsho, Corner, and Dewan 2015; Fransen et al. 2015; Pan et al. 2015; Kwan 1998). A proper distance decay function can benefit the determination of critical weighted distance of both demands of residents and resources of hospitals. For instance, an enhanced 2SFCA (E2SFCA) model is proposed to apply different constant weights to the accessibility within discrete zones of the catchment areas of residents and hospitals (Luo and Qi 2009), and kernel density 2SFCA (KD2SFCA) utilized a continuous function of decay distance for weighting parameters (McGrail 2012; Polzin, Borges, and Coelho 2014).

In recent studies, the 2SFCA series of models are further improved to deal with the overestimation of spatial accessibility. 2SFCA, E2SFCA, and KD2SFCA models tend to overestimate the accessibility in the catchment areas where hospitals are densely distributed (Chu et al. 2016). The three-step FCA model is proposed to introduce competition among health-care resources of hospitals to minimize variability in spatial accessibility under the assumption that the demands of residents are affected by the availability of health-care resources in other neighboring hospitals (Chu et al. 2016; Wan, Zou, and Sternberg 2012; Shah, Milosavljevic, and Bath 2017). All the above FCA models contain an underlying assumption that hospitals are optimally allocated to meet the requirements of the population within the health system, but truly optimal allocations are extremely unlikely in real-world health-care systems, leading to an overestimation of spatial accessibility throughout the system (Delamater 2013; Jamtsho, Corner, and Dewan 2015). To address this issue, a modified 2SFCA (M2SCFA) model is proposed based on 2SFCA and permits suboptimal allocations of health-care resources of hospitals in the health system (Delamater 2013). Due to the integration of the accessibility to hospitals and availability of health-care resources, and progressively decreased total opportunities available for the population access to hospitals with the increased distance from residents to hospitals, M2SCFA model makes more sense in the real-world health systems and is much more reliable for measuring spatial accessibility to health-care services than previous models (Delamater 2013; Jamtsho, Corner, and Dewan 2015). Especially, it has advantages over quantitative assessment and comparison of large spatial scale health systems in a state or nation, and is accurate in evaluating the overall impacts of local variations in the whole health system (Delamater 2013; Jamtsho, Corner, and Dewan 2015).

This paper aims to investigate the spatial and temporal variations of population accessibility to public hospitals in Australia. In this paper, three aspects are involved in accessibility calculation: health-care resources in hospitals, demands of health care, and the travel time of residents to hospitals. The number of beds is used as a proxy variable of health-care resources in all public hospitals across Australia since medical staff and available beds are two primary indicators of health-care resources as mentioned above, but data of medical staff is not available in this study. Spatial accessibility of all public hospitals is studied, and accessibility of the hospitals that provide emergency care and those providing surgery service is also studied. Public hospitals are the objective in this study and private hospitals are not concerned because public hospitals are mainstream in Australian health-care system, which are more concerned by authorities in their decision-making, and public and private hospitals provide different services. In the 2011–2012 financial year, public hospitals and available beds are 1.27 times and 2.33 times the numbers of private hospitals, and public hospitals provide most emergency (94%) and outpatient (97%) services, but private hospitals are primarily serving hospitalizations (AIHW 2014a). Population-weighted centroids (PWCs) and the total population within local government areas (LGAs) are computed with high spatial resolution population data to reflect the demands of health-care resources. Then the nationwide travel time-based spatial accessibility is measured using a modified kernel density 2SFCA (MKD2SFCA) model by incorporating the M2SCFA model and a continuous kernel density function of decay distance for weighting distance impendence functions. Precipitation is regarded as a primary variable affecting the travel speed in local road segments, influencing the spatial and temporal variations of travel time and population accessibility to public hospitals. Spatially local autocorrelation is performed to explore the spatial and temporal variations of the hot-spot and cold-spot regions of accessibility with local indicators of spatial association (LISA) (Anselin 1995), respectively. Variations of accessibility are investigated by the monthly summary of accessibility and its spatial clusters within different remoteness regions, states, and the selected cities.

2. Material and methods

2.1. Public hospitals data

Australian health system is an important exemplar for nationwide accurate study of the performance of health-care services due to continuous and relatively complete statistics, diverse hospitals and health-care resources, and the complex conditions of access to hospitals across a vast territory. Statistical information of 778 public hospitals, including 204 hospitals that provide emergency care and 246 hospitals providing surgery service, is collected by the Australian Institute of Health and Welfare (AIHW) across Australia in the 2012–2013 financial year (AIHW 2014c; AIHW 2014b). The numbers of beds in three types of hospitals are 58,311, 44,404, and 46,576, respectively. According to the statistical report from AIHW, the spatial distributions of public hospitals and their health-care resources are stable and have no great changes, where the total number of public hospitals is slightly decreased, and the bed numbers are increased by an average of 1.0% per year from 2011–2012 to 2015–2016 (AIHW 2017). Thus, the data of public hospitals in 2012–2013 is representative for assessing the spatial and temporal variations of accessibility to public hospitals. Public hospitals of different types are geocoded and mapped in Figure 1, where Figure 1a shows the distributions of hospitals and bed numbers across Australia, and the distributions in eight capital cities in the states or territories are mapped in Figure 1b–I. The capital cities are Sydney in New South Wales (NSW), Melbourne in Victoria (VIC), Brisbane in Queensland (QLD), Perth in Western Australia (WA), Adelaide in South Australia (SA), Canberra in Australian Capital Territory (ACT), Hobart in Tasmania (TAS), and Darwin in Northern Territory (NT).

2.2. *Variables affecting spatial accessibility*

The demands of residents are characterized by population located at PWCs of LGAs. Population is unlikely distributed homogeneously within a local administrative census unit, particularly in Australia. PWC can therefore more accurately represent the location of population in a LGA than the geometric centroid (Hwang and Rollow 2000). The spatial locations of PWCs are probably distinct and far from the geometric centroids of LGAs especially in the suburban, rural, and remote regions with large geographical space but dense population distributed in small areas (Luo and Wang 2003). To accurately generate the geographical locations of PWCs of LGAs, grid population in Australia in 2012–2013 is calculated by the average of grid population data in 2010 and 2015 with spatial resolution of 1 km, which is sourced from NASA Socioeconomic Data and Applications Centre (Center for International Earth Science Information Network – CIESIN – Columbia University 2016). The location of PWC is as population-weighted coordinates within an LGA, which is calculated by

$$\begin{cases} x_0 = \dfrac{\sum_{i=1}^{n} \rho_i x_i}{\sum_{i=1}^{n} \rho_i} \\ y_0 = \dfrac{\sum_{i=1}^{n} \rho_i y_i}{\sum_{i=1}^{n} \rho_i} \end{cases} \tag{1}$$

where x_0 and y_0 are coordinates of PWC of a LGA, x_i ($i = 1, 2, \ldots, n$) and y_i are coordinates of population grid within the LGA, and ρ_i is the population value at ith grid. PWCs and corresponding population of 564 LGAs (2013) in Australia (ABS 2013) are computed and shown in Figure 1.

In addition to the health-care resources in hospitals and demands of residents, the spatial and temporal variations of spatial population accessibility to hospitals are also potentially affected by the geographical locations and the traffic conditions affected by weather conditions. The spatial difference of accessibility is explored from three stages of spatial scales, LGA, state or territory, and remoteness area. The geographical remoteness

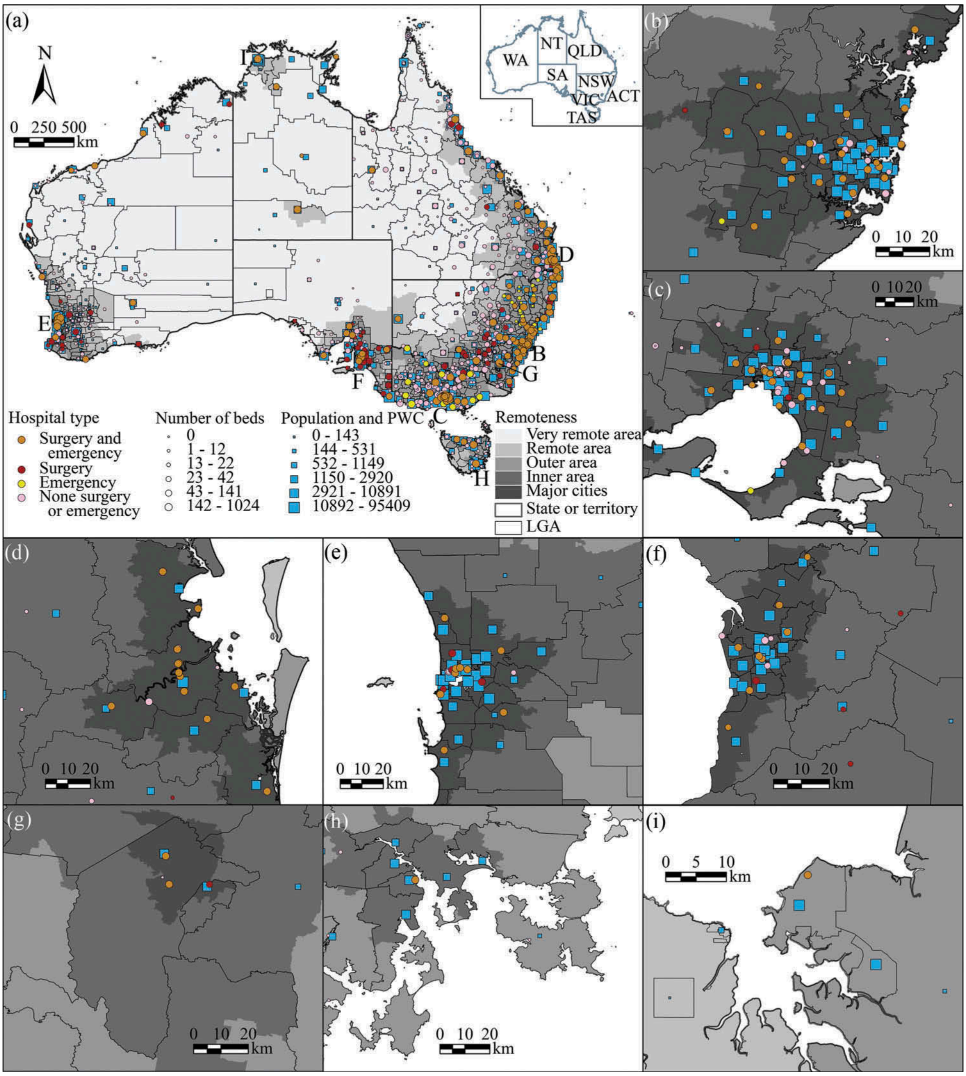

Figure 1. Distributions of hospitals, population-weighted centroids (PWCs) of local government areas (LGAs) and their populations in Australia (a) and the capital cities of states or territories: (b) Sydney, (c) Melbourne, (d) Brisbane, (e) Perth, (f) Adelaide, (g) Canberra, (h) Hobart, and (i) Darwin.

structure is a critical undertaking of government services in Australia, such as census statistics (ABS 2011). The Australian Bureau of Statistics (ABS) defines five primary levels of remoteness areas across the nation by the Australian Statistical Geographical Classification Remoteness Structure: major cities, inner area, outer area, remote area, and very remote area (ABS 2011). Remoteness structure is also an effective indicator to differentiate the varied performance of health-care services nationally in Australia (McGrail and Humphreys 2014).

Weather condition, especially the severe weather near road network, has a negative impact on accessing health-care services, and it is a barrier for residents to seek specialized hospitals (Blanford et al. 2012; Makanga et al. 2017). Geospatial data of road network, including primary and secondary roads, with 86,989 road segments is collected in Australia (MapCruzin). Since the real monitoring data of traffic speed and the speed limits of all road segments are unavailable, the default speed limit of primary and secondary roads defined by states and territories is used as a proxy variable of traffic speed of road segments. The speed limit in built-up regions is 50 km/h except for NT with 60 km/h, and the speed limit outside built-up regions is 100 km/h except for WA and NT with 110 km/h (Wolhuter 2015). In general, precipitation and its duration can affect vehicle speed and thereby have an impact on the travel time-determined spatial accessibility. In this paper, the spatiotemporal variation of precipitation is characterized using the monthly remote sensing data of precipitation rate (mm/h) with the spatial resolution of 0.25° (~25 km) during July 2012–June 2013 from the Tropical Rainfall Measuring Mission (TRMM) 3B43 (version 7) product (Huffman et al. 2007). Monthly precipitation data is resampled and computed to the data with the spatial resolution of 10 km and the unit of mm/week (Song et al. 2016) (Figure 2). Previous studies show the negative impacts of precipitation on traffic conditions that light rain may cause a 3–13% or 1.9 to 12.9 km/h reduction of traffic speed, and heavy rain leads to a 3–17% or 4.8–16.0 km/h reduction depending on precipitation and time of day (Program, FHWA Road Weather Management 2009; Rahman and Lownes 2012; Akin, Sisiopiku, and Skabardonis 2011). In this paper, by summarizing these studies, the statistical relationship between precipitation and potential impact on traffic speed is defined as

$$v_p = \begin{cases} v_d & p < \tau \\ v_d\left(1 - \alpha\frac{p}{\delta}\right) & p \geq \tau \end{cases} \tag{2}$$

where v_d is the default speed limit and v_p is the estimated speed in a road segment, p is precipitation rate (mm/week), τ and δ are critical values between dry month and light rain month, and that between light rain and heavy rain months, respectively, and α is a precipitation-caused speed reduction rate. Based on the above discussion of the associations between traffic speed and precipitation or heavy rain, approximately consistent parameters are set in this paper, where τ = 1 mm/week, δ = 42 mm/week or 0.25 mm/h, and α = 5%. Distributions of two critical values for light and heavy rain are mapped in Figure 2. For instance, given the default speed limit of a road segment v_d = 100 km/h and monthly average precipitation rate p = 20 mm/week, the estimated speed is v_p = 97.6 km/h, which means that precipitation leads to a 2.4 km/h or 2.4% reduction of traffic speed in this road segment. If the precipitation is 100 mm/week on this road, the estimated speed will be 88.1 km/h, which is decreased 11.9 km/h or 11.9% of traffic speed. These examples demonstrate that the proposed statistical relationship presents a reasonable and conservative estimation of the potential impact of precipitation on the reduction of traffic speed.

2.3. MKD2SFCA-based assessment of spatial accessibility

MKD2SFCA model is applied on the assessment of nationwide spatial accessibility to public hospitals by incorporating the reliable M2SCFA model and a continuous kernel density function of decay distance for weighting distance impendence parameters. The result of spatial accessibility is a BPR adjusted by the weighted interactions of both hospital side and demand side in each LGA. There are two steps to calculate the spatial population accessibility of LGA at the location of PWC to hospitals. First, BPR is computed for all pairs of hospitals and PWCs within a given threshold of travel time. The computation equation is

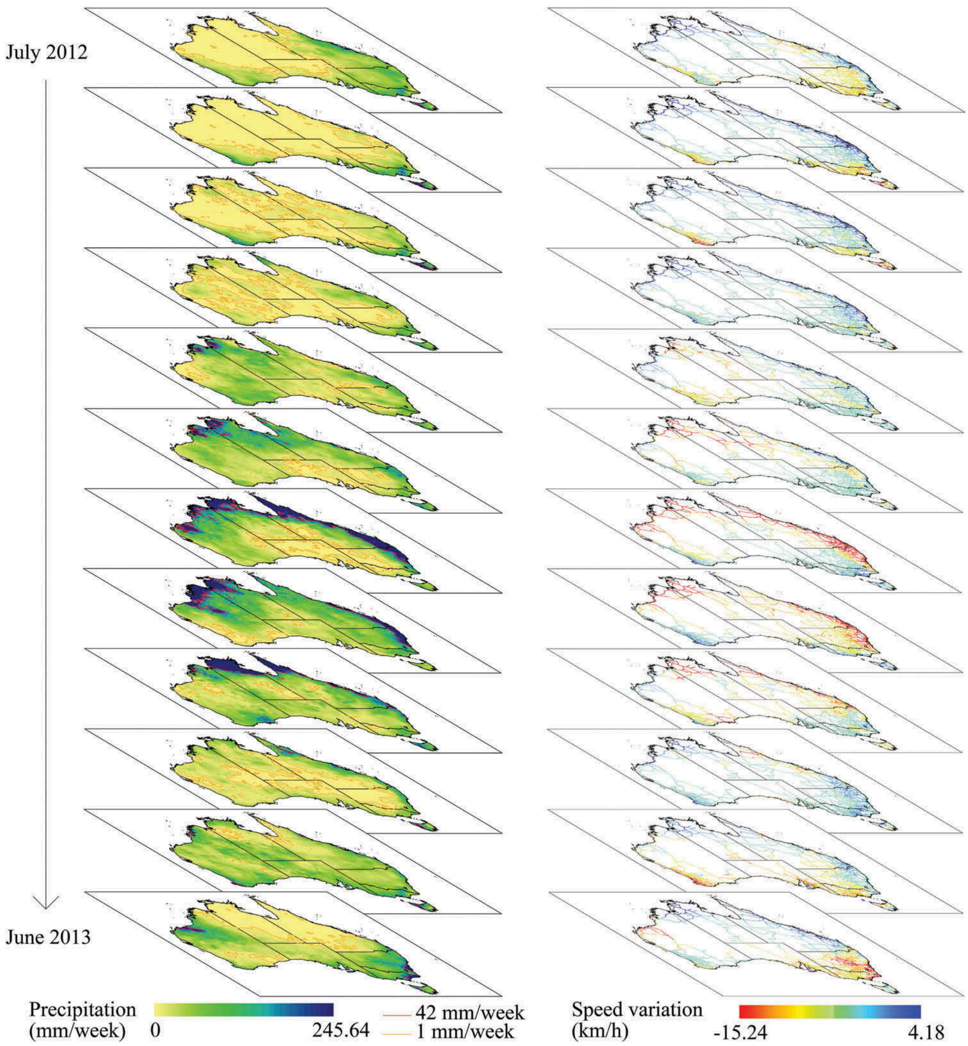

Figure 2. Monthly precipitation and its impact on the spatiotemporal variations of traffic speed from July 2012 to June 2013 in Australia.

$$R_{i,j} = \frac{B_j f\left(t_{i,j}\right)}{\sum_{i \in \left[t_{i,j} \leq t_0\right]} C_i f\left(t_{i,j}\right)} \tag{3}$$

where $R_{i,j}$ is an adjusted ratio of number of beds in jth hospital to population in ith LGA, B is the number of beds, t_0 is a given threshold of travel time for the range of health-care services, $t_{i,j}$ is the travel time between jth hospital and PWC of ith LGA, C is the population of a LGA that located within the range of $t_{i,j} \leq t_0$, and $f(t)$ is an impedance function describing the preference of residents to the relatively near hospitals with less travel time. In this paper, a Gaussian kernel is used for the density function $f(t)$ due to its slow rate of reduction and avoiding rapid dropping to zero. $f(t)$ is calculated by

$$f(t) = \begin{cases} e^{-\frac{t^2}{n}} & t \leq t_0 \\ 0 & t > t_0 \end{cases} \tag{4}$$

where n is the number of PWCs of LGAs within the range of $t \leq t_0$.

The second step is to search all hospitals within the given threshold of travel time t_0 for each PWC of LGA. The spatial population accessibility of a PWC to hospitals is a sum of weighted-adjusted BPR:

$$A_i = \sum_{j \in \left[t_{i,j} \leq t_0\right]} R_{i,j} f\left(t_{i,j}\right) \tag{5}$$

where A_i is accessibility of PWC of ith LGA. A_i with a higher value reveals a better spatial accessibility to hospitals, which means easier access and more health-care resources, and that with a lower value indicates the shortage in this LGA (Cheng et al. 2016). Thus, the spatial accessibility generated by MKD2SFCA model can be summarized as

$$A_i = \sum_{j \in \left[t_{i,j} \leq t_0\right]} \frac{B_j f\left(t_{i,j}\right) f\left(t_{i,j}\right)}{\sum_{i \in \left[t_{i,j} \leq t_0\right]} C_i f\left(t_{i,j}\right)} \tag{6}$$

In this paper, monthly spatial accessibility is computed across Australia from July 2012 to June 2013. Temporal variation of population accessibility to public hospitals is primarily caused by on-road precipitation especially heavy rain, and it is assessed by transforming the monthly variation of accessibility to the equivalent number of beds reduction. The equivalent beds reduction was calculated for each remoteness area using a linear regression:

$$A_{k,l} = \beta_k p_{k,l} + \varepsilon_k \tag{7}$$

where β_k is the equivalent beds reduction rate within kth remoteness area, $A_{k,l}$ and $p_{k,l}$ are spatial accessibility and mean on-road precipitation in lth LGA within kth remoteness area, and ε_k is a random error. Further, once β_k is determined, the corresponding percentage of reduced equivalent beds to all beds in Australia is

$$q = \sum_k \frac{\beta_k p_k' C_k}{B_k} \tag{8}$$

where q is the percentage of reduced equivalent beds to all beds, p_k', C_k, and B_k are the range of monthly average on-road precipitation, total population, and total number of beds in hospitals in kth remoteness area. The molecular is a sum of reduced equivalent number of beds in the kth remoteness area.

Spatial variation of the monthly spatial accessibility is assessed by identifying its spatial clusters. LISA is utilized to present the geographically local autocorrelations or clusters that are statistically significant spatial outliers in accessibility (Anselin 1995; Ge et al. 2017). LISA is a relative indicator that is only meaningful within a given significance level (McKinley et al. 2013). The local clusters here are explored with the statistical significance level of 0.05. In the results of LISA analysis, a hot-spot region indicates that an LGA has high accessibility and its surrounding LGAs are of high accessibility simultaneously, and a cold-spot region is an LGA that has low accessibility and low-value neighbors (Ge et al. 2017).

3. Results

3.1. Impact of precipitation on traffic speed

Monthly variation of traffic speed at road segment level is computed using the proposed statistical equation between precipitation and traffic speed. Figure 2 illustrates the monthly traffic speed distributions affected by precipitation, where the speed variation is the monthly speed minus the annual mean speed. Figure 3 shows the distributions of the estimated annual mean speed of road segments in Australia. On-road precipitations are distinct spatially and temporally. In July 2012–June 2013, the estimated monthly average on-road precipitation ranges from the minimum of 8.42 mm/week in October 2012 to the maximum of 30.03 mm/week in February 2013. In this paper, month precipitation of 1 and 42 mm/week are defined as critical values between dry month and light rain month, and that between light rain and heavy rain months, respectively. The on-road precipitations on more than 66.37% the number of road segments are higher than 1 mm/week in every month in a year. On-road precipitations higher than 42 mm/week appear on more than 39.53% of road segments at least in 1 month, and on more than 16.38% the number of road segments over 3 months. In January, February, March, and June 2013, 29.06%, 36.15%, 12.29%, and 14.21% of the number of road segments suffered from heavy rain, respectively, but less than 1% of road segments encounter heavy rain in other months.

Figure 4 summarizes the monthly average precipitation rate, average traffic speed, and the percentage of speed reduction compared with the default speed limit in each LGA for

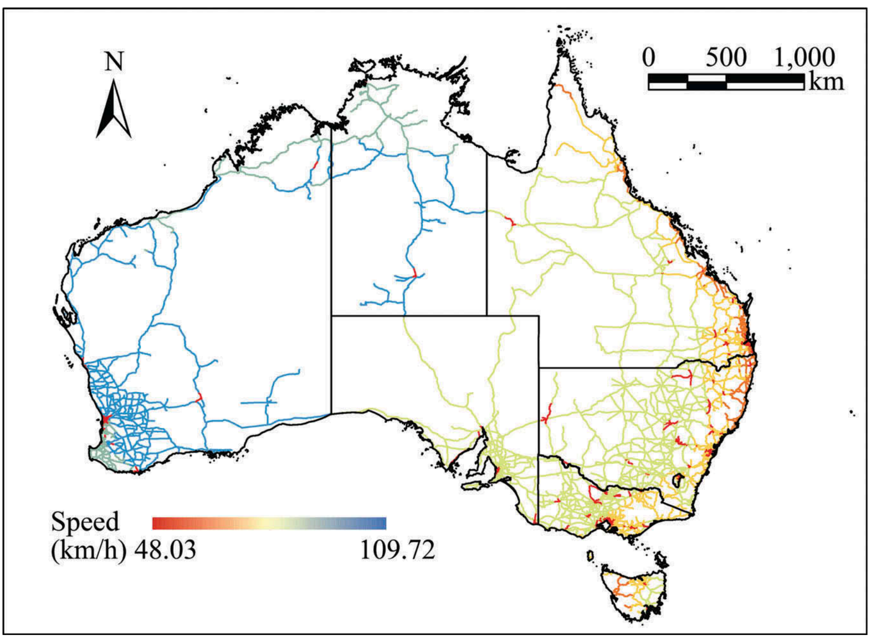

Figure 3. Spatial distribution of estimated annual mean speed in each road segment across Australia.

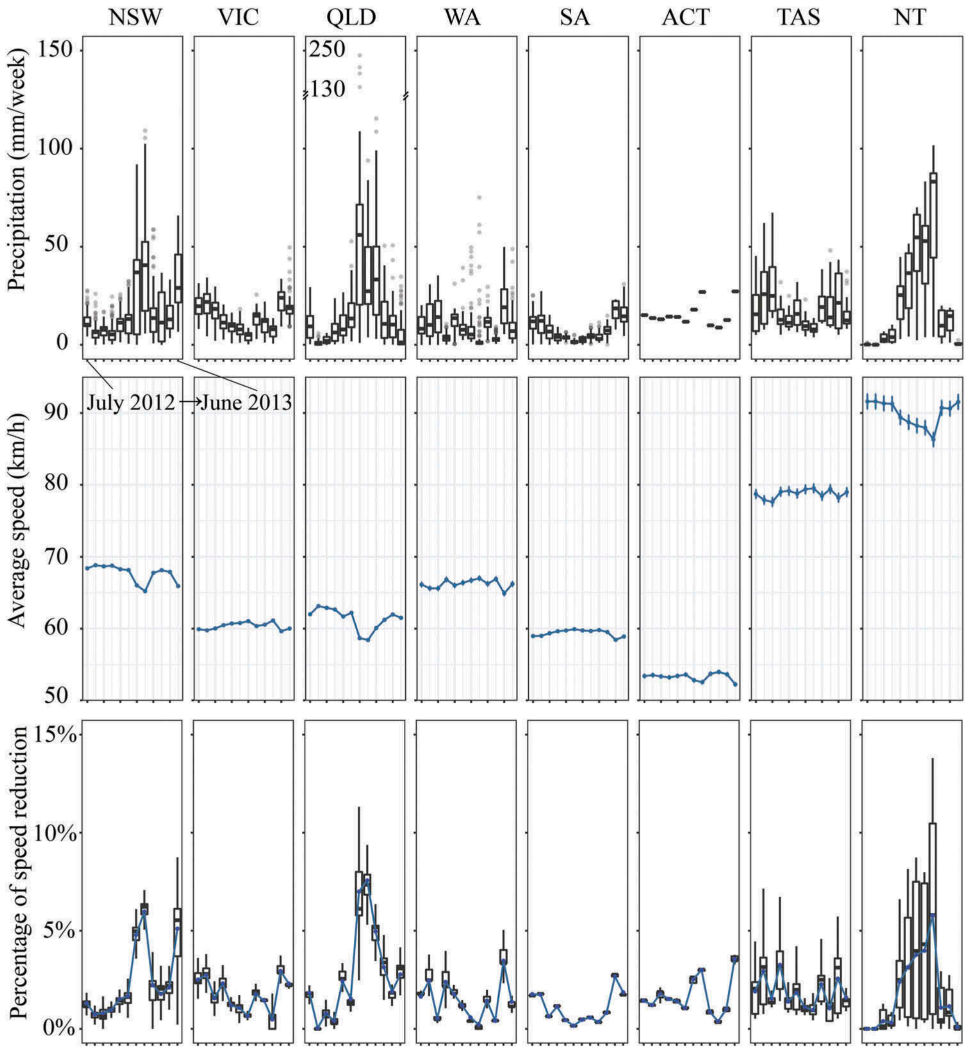

Figure 4. Statewide statistical summary of monthly precipitation and average vehicle speed in Australia.

eight states or territories, respectively, in Australia. Traffic speed is associated with the seasonal variation of on-road precipitation. The monthly average reduction rate of speed ranges from 1.00% to 3.57%. More than 1% of average speed reduction caused by precipitation appears in more than 10 months in ACT and TAS, more than 8 months in NSW, QLD, and WA, and more than 5 months in SA and NT. Continuous rainfall, especially heavy rain, leads to more than 5% of traffic speed reduction in NSW in January and June, in QLD from January to February, and in NT in March 2013.

3.2. Spatial accessibility to public hospitals

Cumulative population coverage of hospitals is a direct method to describe and compare the performance of health-care services in different regions. In this paper, cumulative population coverage is computed as a function of travel time to the nearest hospital from each PWC of LGA. Figure 5 presents the cumulative population coverage in Australia, in each state or territory, and in each remoteness area. Table 1 summarizes the average travel time from PWCs of LGAs to the nearest hospitals in different remoteness areas and population coverage by travel time of 30, 60, 120, and 240 min. In Australia, more than 50% of population at PWCs have access to their nearest hospitals within 5 min, over 90% of population can reach hospitals within 15 min, and more than 99% of residents live within 34-min range of hospitals. It is estimate that about 39,191 (0.17%) of residents live in the regions over 2 h from the nearest public hospitals, and all population are within 4-h coverage of hospitals. Further, the population coverage of hospitals varies in different locations. For instance, 80% of population can be covered by hospitals with 8-min range in SA, 14-min range in WA, 21-min range in TAS, and 37-min range in NT. In average, 80% of residents in major cities have access to hospitals within 10 min. Residents in inner area, outer area, and remote area may spend 15–16 min, but those who live in very remote area need 58 min. In addition, all residents in outer area are covered by 60-min range of hospitals. Residents in major cities, inner area, and remote area live within 120-min travel to hospitals, and those in very remote areas are covered by 240-min range. Within a 30-min range of public hospitals, percentages of residents who live in major cities, inner area, outer area, remote area, and very remote area are 69.08%, 20.15%, 9.13%, 0.87%, and 0.76%, respectively.

The monthly accessibility to hospitals is visualized in a map with two statistical indicators: annual mean accessibility and the coefficient of variance (CV) of monthly accessibility in each LGA. CV is a percentage ranging from 0 to 1, computed as the ratio of standard deviation to the mean, showing the extent of accessibility variability in different months in relation to the mean accessibility. Further, CV also indicates the potential impact of precipitation on the variation of spatial accessibility. Figure 6 shows the spatial distributions of annual mean population accessibility from PWCs to all public

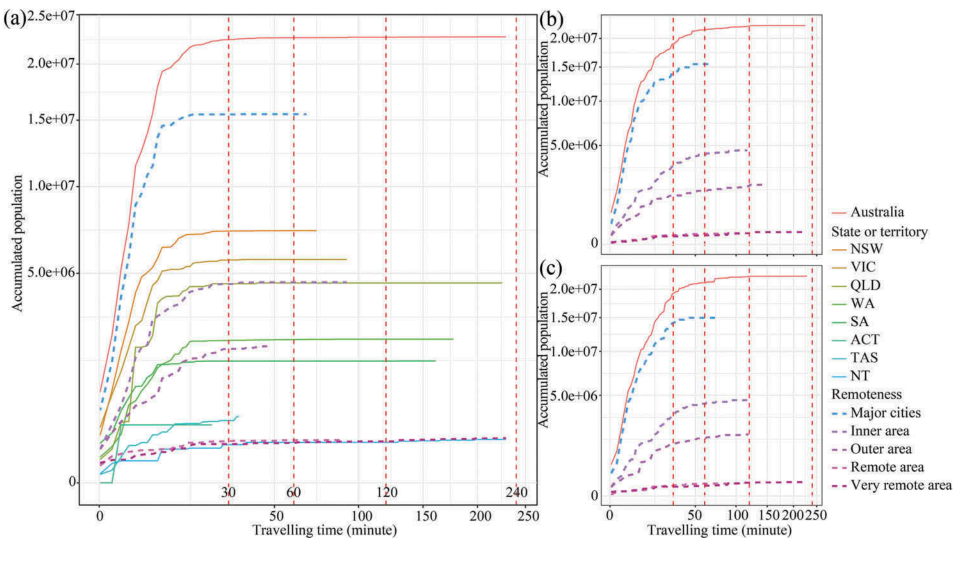

Figure 5. Cumulative distributions of population within states or territories and remoteness areas to the nearest hospitals: All hospitals (a), hospitals that provide emergency care (b), and hospitals that provide surgery service (c).

Table 1. Average travel time from PWCs of LGAs to the nearest hospitals and population coverage by travel time of 30, 60, 120, and 240 min.

	Average travel time (min)						Population coverage by travel time (%)			
		Remoteness areas								
Hospital type	Australia	Major cities	Inner area	Outer area	Remote area	Very remote area	30 min	60 min	120 min	240 min
All	13.1	12.4	23.5	27.2	19.2	41.7	81.7	92.6	98.5	99.0
Providing emergency care	19.0	10.3	19.9	21.8	16.3	31.7	83.8	95.2	98.6	99.0
Providing surgery service	23.4	12.1	20.7	20.4	19.2	41.7	84.8	93.5	98.9	99.0

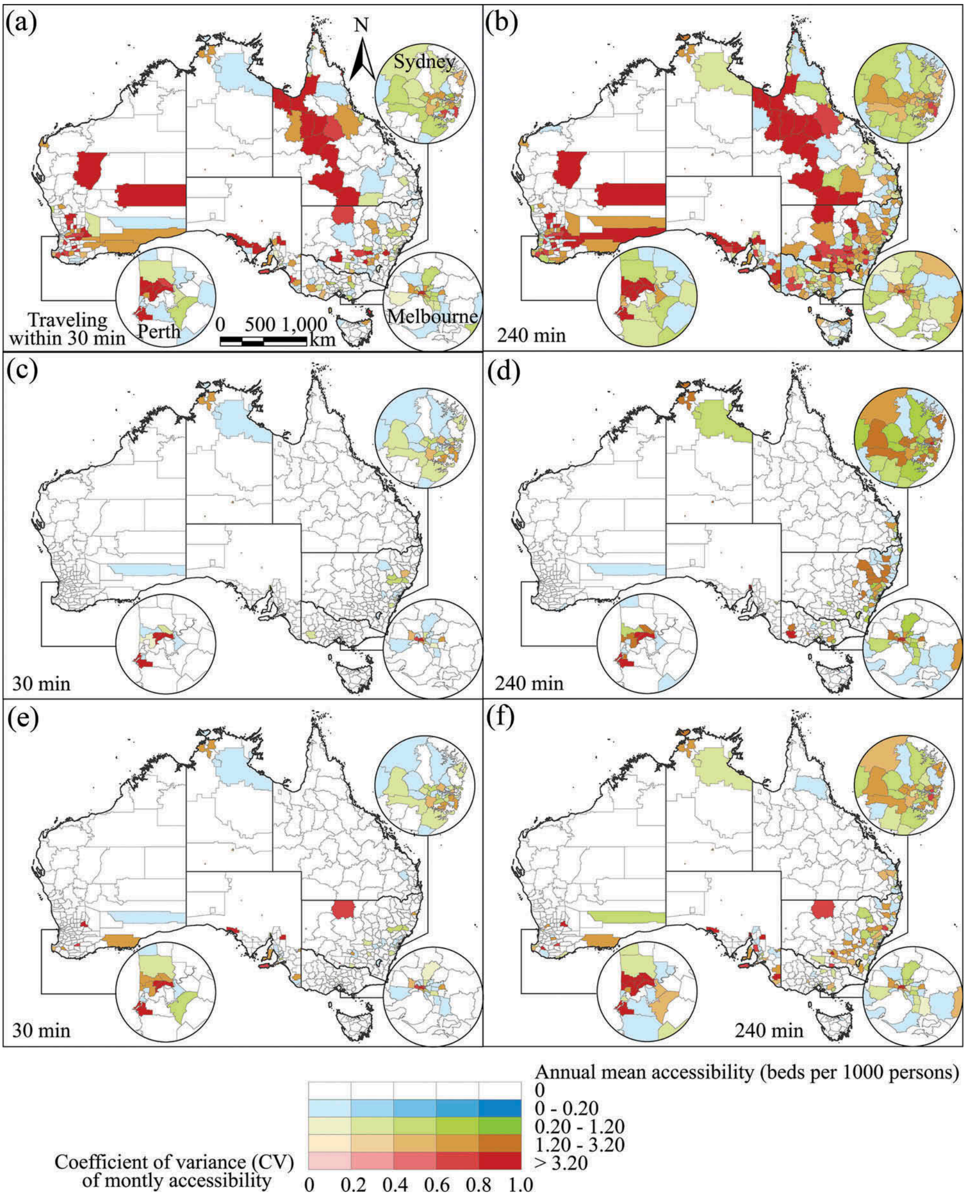

Figure 6. Distributions of spatial accessibility of traveling within 30 and 240 min to all public hospitals (a and b), accessibility to hospitals that provide emergency care (c and d), and accessibility to hospitals that provide surgery service (e and f), respectively.

hospitals, hospitals that provide emergency care, and hospitals that provide surgery service, respectively. To simplify the display of results and highlight the spatial difference and variations, only the distributions of accessibility within 30- and 240-min travel time are presented. Since 67.06% of population are gathered in eight capital cities, where 20.74%, 19.24%, and 8.56% of national population, respectively, are distributed in Sydney, Melbourne, and Perth (ABS 2017b), but other regions with large areas are sparsely populated with a few residents, distributions of spatial accessibility in Perth, Sydney, and Melbourne are enlarged in the maps. In general, for all three types of hospitals, accessibility is increased and the range of high accessibility is enlarged with the increase of threshold of travel time from 30 min to 240 min. In addition, LGAs with high accessibility to all public hospitals are distributed in both major cities and other areas, but those with high accessibility to hospitals that provide emergency and surgery services are primarily distributed in major cities and sparsely distributed in other areas. There are 142 LGAs where there are no public health services (BPR = 0) and 118 LGAs with the spatial accessibility of traveling within 240 min smaller than 0.001 beds per 1000 persons, which means residents within at least 24 LGAs without beds in hospitals can access hospitals in the neighbor LGAs. Similarly, residents within at least 15 LGAs (402 LGAs with BPR = 0 and 387 LGAs with accessibility = 0) and 27 LGAs (361 LGAs with BPR = 0 and 334 LGAs with accessibility = 0) can access public hospitals that provide emergency and surgery services in the nearby LGAs, respectively, even when there are no beds in hospitals within their local LGAs.

3.3. Spatial and temporal variation of accessibility

Figure 7 shows the equivalent beds reduction of temporal variation of spatial accessibility caused by monthly variation of precipitation to public hospitals, the corresponding percentages of reduced equivalent beds to all beds, and their relationships with the

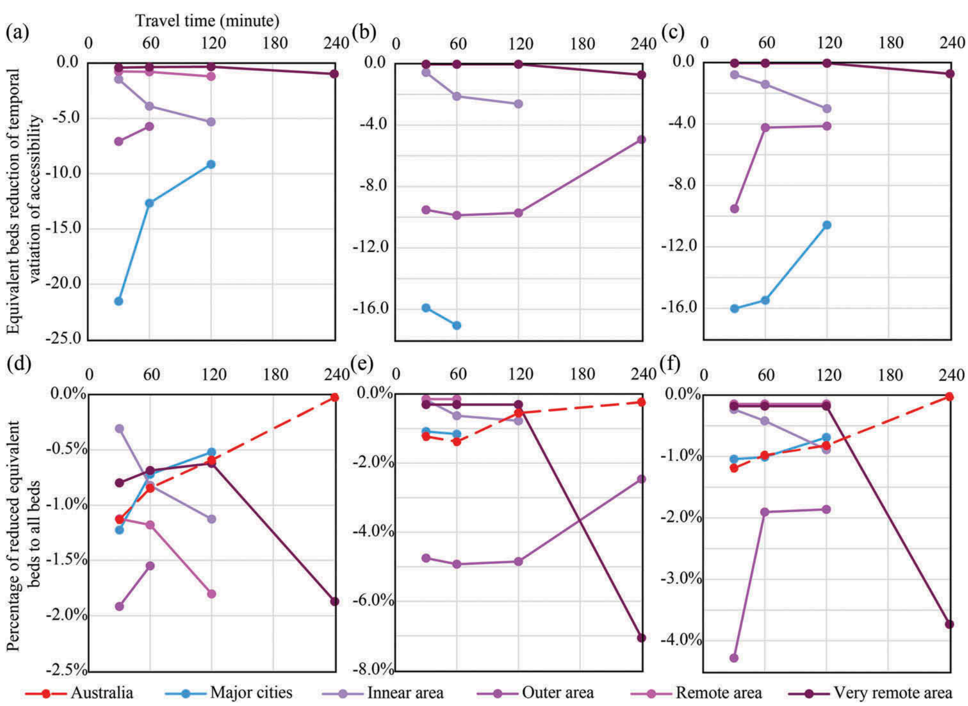

Figure 7. Equivalent beds reduction of precipitation caused temporal variation of spatial accessibility to all public hospitals (a), hospitals that provide emergency care (b), hospitals that provide surgery service (c), and corresponding percentage of reduced equivalent beds to all beds in Australia and in each remoteness area (d, e and f).

thresholds of travel time to hospitals in each remoteness area and in Australia. The maximum reductions of equivalent beds due to monthly variation of precipitation appear in major cities for all public hospitals and hospitals supporting emergency and surgery services. With the increase of 1 mm/week of monthly precipitation, the reductions of spatial accessibility to three types of hospitals are equivalent to respectively 9–22 beds, 16–17 beds, and 11–16 beds in major cities. With the expand of travel time threshold from 30 to 240 min, the percentages of reduced equivalent beds are generally decreased, and they are close to zero when travel time is 240 min. Compared with the minimum monthly average on-road precipitation, the maximum monthly precipitation leads to 1.13%, 1.38%, and 1.19% of reductions of national equivalent beds of accessibility to all public hospitals within 30-min travel time, to hospitals that provide emergency care within 60-min travel time, and to hospitals that provide surgery service within 30-min travel time.

Figure 8 illustrates the spatial variation of accessibility by the statewide statistical summaries. For the health-care services in all public hospitals, the accessibility in inner area is lower than that in major cities even when its BPR is not significantly low, but the accessibility in outer area, remote area, and very remote area is not lower (and may even be higher) than that in major cities. Especially, accessibility in outer and remote areas of QLD is much higher than other states or territories. For health care in hospitals that have emergency and surgery services, accessibility in major cities is higher than other remoteness areas, except for the outer area in QLD where mean spatial accessibility is higher than that in major cities. In addition, the results also demonstrate that BPR is higher than most of the accessibility across the nation. This means that BPR is an overestimated indicator of health-care resources that residents can share, but the true accessibility to

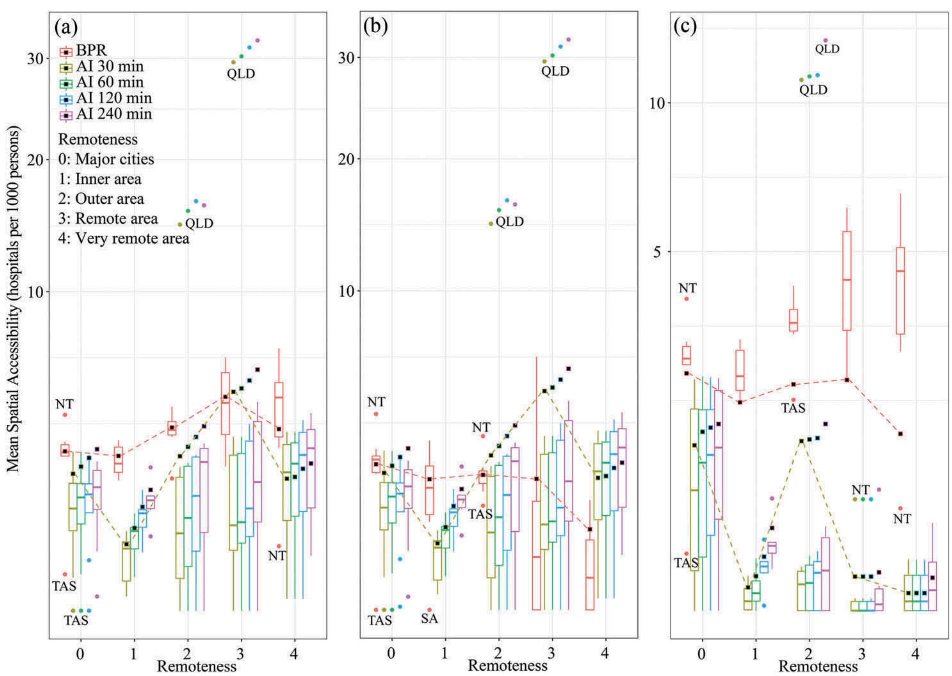

Figure 8. Statewide statistical summary of bed-population ratio (BPR) and spatial accessibility separated by remoteness for all hospitals (a), hospitals that provide emergency care (b), and hospitals that provide surgery service (c).

health-care services is affected by various variables such beds and population in the neighbor LGAs, traffic conditions of road network, etc.

Temporally varied spatially local clusters of accessibility are analyzed by the LISA statistic. Spatial clusters of accessibility are computed monthly for the accessibility of traveling within 30, 60, 120, and 240 min to all public hospitals, hospitals with emergency care, and those providing surgery service, respectively. Since the spatial clusters of accessibility is gradually varied from 30-min to 240-min travel time, to simplify the presentation of results and highlight the difference and changes of spatial clusters, spatial clusters of accessibility within 30 and 240 min and corresponding assessment to three types of hospitals are presented in Figures 9, 10, and 11, respectively. Table 2 lists their statistical summary with the cumulative number of months, percentage of monthly mean population to all national population, and minimum, maximum, and mean accessibility in hot-spot and cold-spot regions, respectively, where cumulative number of months presents the cumulative months of LGAs located in clusters.

Figure 9 A, D, G and J shows the respective sum number of months of hot-spot (H–H) and cold-spot (L–L) regions of accessibility with the travel time threshold of 30, 60, 120, and 240 min explored by LISA statistic with the base map of corresponding annual mean accessibility. Locations of spatial clusters are varied with the increase of travel time thresholds. For instance, clusters in SA are primarily gathered in Adelaide, the capital city of SA, for the accessibility with 30-min travel time, but they are gradually moved to the outer and remote areas, even very remote areas in SA, with the increase of travel time threshold. Further, hot-spot and cold-spot clusters are also monthly varied in different remoteness areas and across nation (Figure 9). The annual mean population in hot-spot and cold spot regions accounts for 4.7–10.1‰ and 29.6–53.7‰ of all national population,

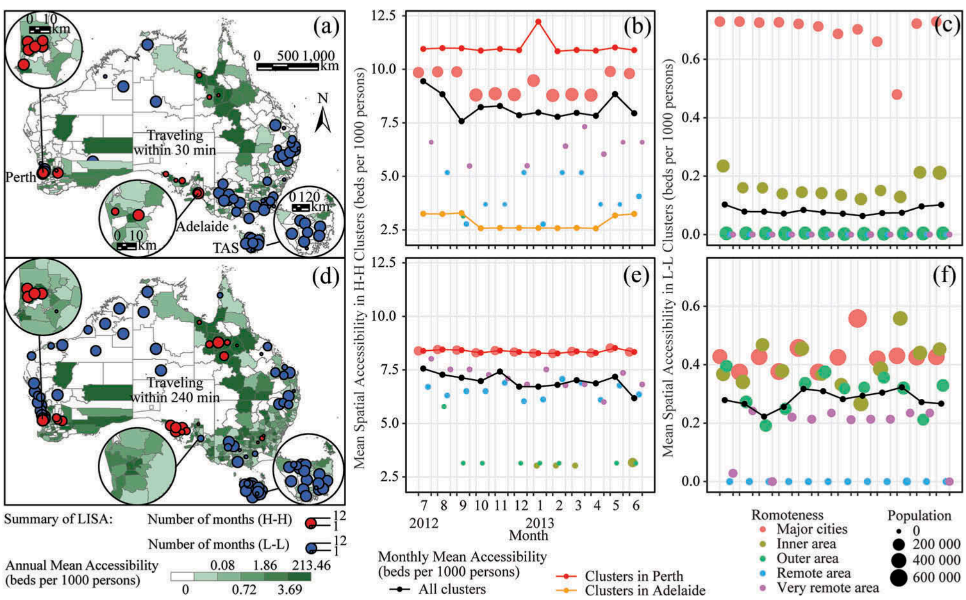

Figure 9. Maps of annual mean spatial accessibility to hospitals and the summary of spatial local autocorrelations, the corresponding time series of mean spatial accessibility in high–high (H–H) clusters, and those in low–low (L–L) clusters for the traveling to hospitals within 30 min (a, b and c) and 240 min (d, eand f).

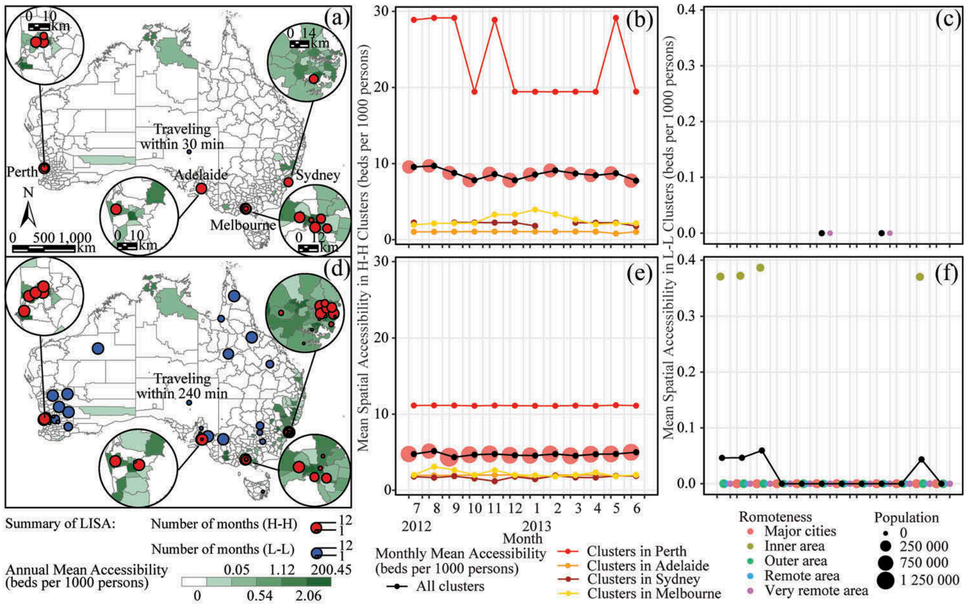

Figure 10. Maps of annual mean spatial accessibility to hospitals that provide emergency care and the summary of spatial local autocorrelations, the corresponding time series of mean spatial accessibility in high–high (H–H) clusters, and those in low–low (L–L) clusters for the traveling to hospitals serving for emergency within 30 min (a–c) and 240 min (d–f).

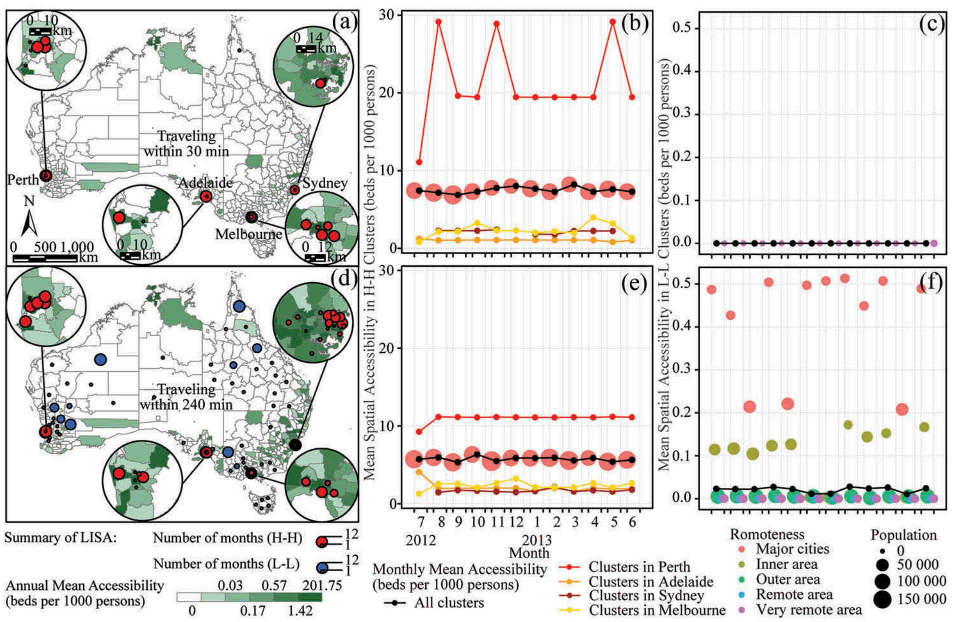

Figure 11. Maps of annual mean spatial accessibility to hospitals that provide surgery service and the summary of spatial local autocorrelations, the corresponding time series of mean spatial accessibility in high–high (H–H) clusters, and those in low–low (L–L) clusters for the traveling to hospitals serving for surgery within 30 min (a–c) and 240 min (d–f).

respectively, where the ratios vary by travel time. Hot-spot regions are not just located in major cities, but also include some of the remote and very remote areas. The percentage of cumulative number of months in major cities of hot-spot regions is 74% for accessing to hospitals within 30 min and 27% for accessing to hospitals in 240 min, where the percentage of cumulative number of months presents the cumulative months of LGAs located in clusters divided by all months of LGAs. Most of the population in cold-spot regions live in major cities, inner and outer areas, instead of remote and very remote areas. Only 1–5% of population live in 6–22% of LGAs in very remote areas of cold-spot regions which varies in different thresholds of travel time. Meanwhile, monthly mean accessibility of hot-spot regions clustered in Perth is higher than the national average accessibility. In addition, Table 2 also shows that with the increase of travel time of accessing to all public hospitals hot-spot clusters will cover fewer population in major cities and cold-spot regions will cover more population in very remote areas.

Figures 10 and 11 show that the hot-spot regions of accessing to hospitals that provide emergency and surgery services are primarily clustered in major cities of Perth, Adelaide, Sydney, and Melbourne, but few of them are located in rural and remote areas in Australia. Monthly mean accessibility and population in the hot-spot clusters also vary temporally due to the impacts of precipitation on the road network. Annual mean population in major cities of hot-spot and very remote areas in cold spot regions of accessing to hospitals that provide emergency care account for 24.5–40.9‰ and 0.04–11.5‰ of national population, respectively, and the respective ratios of accessing to hospitals supporting surgery service are 20.3–23.0‰ and 0.26–27.1‰. Also, with the increased travel time to access these hospitals, cold-spot regions will cover fewer very remote areas.

4. Discussion

Nationwide travel time-based MKD2SFCA model is employed in computing spatial population accessibility to public hospitals in Australia, which reveals that the accessibility is significantly varied temporally and across space. MKD2SFCA model provides a reliable measure of spatial accessibility and makes sense in the real-world health systems, especially for the large spatial scale health system in a nation and the accurate evaluation of its overall performance when considering local variations. Multi-source data with high spatial resolution is utilized to characterize the potential factors associated with the spatial and temporal variations of accessibility to hospitals, where grid population estimation data is used to compute PWCs of LGAs and TRMM remote sensing product is applied on calculating on-road precipitation and its impact on traffic speed. Thus, nationwide spatiotemporal accessibility is calculated as the monthly accessibility with travel time of 30, 60, 120, and 240 min in 564 LGAs to all public hospitals and hospitals that provide emergency and surgery services, respectively. Spatial autocorrelation is performed to explore local hot-spot and cold-spot clusters of accessibility.

Both spatial and temporal variations of accessibility are evaluated from multiple perspectives to investigate the performance of the national public health system in Australia. From the angle of spatial variation, accessibility to hospitals and its local clusters is analyzed within different states or territories and remoteness areas. Results show that accessibility in outer, remote, and very remote areas is not lower (and may even be higher) than that in major cities, and the hot-spot clusters of LGAs with high accessibility distribute in both major cities, remote, and very remote areas. This result indicates that Australian authorities of public health have spent efforts on improving the

Table 2. Statistical summary of spatially local cluster analysis for population accessibility with the travel time of 30, 60, 120, and 240 min to all public hospitals and hospitals that provide emergency and surgery services.

		Cumulative number of months		Percentage of mean population (‰)		Accessibility (beds per 1000 persons)						
							Hot-spot			Cold-spot		
Hospital type	Travel time (minute)	Hot-spot	Cold-spot	Hot-spot	Cold-spot	National mean	Min	Mean	Max	Min	Mean	Max
All	30	121 (74%)[a]	428 (6%)[b]	10.06 (98%)[c]	29.61 (1%)[d]	1.84	7.58	8.22	9.45	0.06	0.08	0.10
	60	117 (79%)	581 (10%)	9.35 (99%)	34.39 (3%)	2.04	7.30	8.08	9.46	0.06	0.09	0.12
	120	163 (44%)	559 (15%)	6.13 (91%)	43.82 (3%)	2.29	6.84	7.38	8.39	0.12	0.15	0.18
	240	176 (27%)	592 (22%)	4.68 (78%)	53.70 (5%)	2.56	6.18	6.99	7.56	0.22	0.28	0.32
Providing emergency care	30	100 (100%)	2 (100%)	24.48 (100%)	0.04 (100%)	0.60	7.76	8.64	9.70	/	/	/
	60	181 (100%)	25 (64%)	40.67 (100%)	1.90 (15%)	0.66	4.41	5.05	5.78	0.00	0.00	0.00
	120	187 (100%)	66 (55%)	39.26 (100%)	4.34 (19%)	0.70	4.41	4.92	6.13	0.00	0.00	0.00
	240	196 (100%)	181 (37%)	40.94 (100%)	11.47 (8%)	0.82	4.34	4.72	5.15	0.00	0.02	0.06
Providing surgery service	30	125 (100%)	13 (100%)	20.30 (100%)	0.26 (100%)	0.74	6.88	7.49	8.21	0.00	0.00	0.00
	60	138 (100%)	69 (71%)	20.88 (100%)	0.97 (76%)	0.83	6.44	6.86	7.30	0.00	0.00	0.00
	120	163 (100%)	335 (32%)	22.38 (100%)	14.03 (11%)	0.94	5.35	5.82	6.60	0.00	0.01	0.01
	240	164 (100%)	640 (30%)	23.02 (100%)	27.14 (7%)	1.06	5.32	5.74	6.33	0.01	0.02	0.03

[a] Percentage of cumulative number of months in major cities of hot-spot regions to that in all hot-spot regions.
[b] Percentage of cumulative number of months in very remote area of cold-spot regions to that in all cold-spot regions.
[c] Percentage of population in major cities of hot-spot regions to that in all hot-spot regions.
[d] Percentage of population in very remote area of cold-spot regions to that in all cold-spot regions.

performance of health system in rural and remote regions to achieve more even distributions of health-care services. However, accessibility to hospitals that provide emergency and surgery services is much higher in major cities than that in other remoteness areas, except for the accessibility in outer area of QLD, which is higher than that in major cities. Meanwhile, hot-spot regions with high accessibility to hospitals supporting emergency and surgery services are primarily clustered in major cities and cold-spot clusters are primarily located in remote and very remote regions, especially for the accessibility of traveling within 30 and 60 min. In contrast with the relative shortage of emergency and surgery services in remote and very remote areas, the rate for emergency hospital admissions involving surgery is highest for residents living in very remote areas with 22 per 1000 persons and reduced from very remote areas to major cities (12 per 1000 persons) in the 2013–2014 financial year in Australia (ABS 2017a; AIHW 2016a). In addition, people living in remote and very remote areas have more requirements on emergency and surgery services since they have higher rates of chronic disease, mortality, traffic accidents, and overweight or obese than those who live in major cities (ABS 2015a; AIHW 2014; ABS 2015b; AIHW 2010). Therefore, health-care resources of specialized services such as emergency and surgery should be gradually improved in remote and very remote areas in the future development of health-care system.

Temporal variation of spatial accessibility is associated with the monthly varied local traffic speed, which is seasonally affected by precipitation, especially heavy rain (Makanga et al. 2017). Temporal variation is assessed from three stages. First, traffic speed is affected by precipitation. In average, monthly precipitation causes 1.00–3.57% of speed reduction, which varies in different months and across space. In addition, monthly variation of accessibility caused by precipitation is transformed as an equivalent beds reduction. For a given amount of health-care resources, which are represented by the number of beds in hospitals here, the losses of accessibility affected by precipitation and heavy rain to all public hospitals, hospitals providing emergency and surgery service equal to 1.13%, 1.38%, and 1.19% of the national health-care resources. Third, accessibility and its related population within spatial hot-spot and cold-spot clusters are investigated temporally. Nationally, the reductions in the minimum monthly mean accessibility of 30-, 60-, 120-, and 240-min travel to all public hospitals are 1.21%, 1.00%, 0.77%, and 1.04% of the maximum one. However, in hot-spot regions, the minimum monthly mean accessibility to all public hospitals is reduced by 18–23%, varying by the threshold of travel time, compared with the maximum one, and the reduction ratio reaches 31–50% in the cold-spot clusters. Thus, temporal variation of accessibility caused by precipitation and heavy rain is slightly fluctuated seen from the nationwide average values of accessibility, but it varies significantly in the spatially local clusters. In addition, the improvement of temporal variations of accessibility to public hospitals can have a positive influence on reducing seasonal diseases. For instance, the average incidence of influenza during July–September is 7.81‰, which is 9.6 times the incidence of influenza in other months (0.81‰), and the incidence also varies in different states (Australian Government – Department of Health 2018). Thus, during high incidence periods of seasonal diseases, improving accessibility is helpful for reducing incidence.

Findings from this research indicate spatial and temporal variations of accessibility with multiple potential variables including population centroids, on-road precipitation, and estimated traffic speed on each road segment. There are still limitations in this study. First, in addition to the geographical relations between hospitals and population and the health-care resources of hospitals, the utilization of health-care services is also linked with potential social factors such as income, education, insurance status, and individual preference (Love and Lindquist 1995). Individual difference is also related to the health-care services utilization that old people, children, and pregnant women require more hospital accessibility than other age groups. Next, private hospitals are also important in the whole health-care system, even their number and available beds are fewer than those in public hospitals. Third, this study presents a monthly varied traffic speed estimation approach based on the precipitation and speed association function, which is useful for temporally traffic speed estimation on road networks at a large spatial scale. However, the real monitoring data of monthly varied traffic speed is unavailable in most of the current public traffic data released by transportation authorities. Finally, this study has explored and discussed the associations between the temporal variations of traffic speed across space and precipitation or heavy rain using a relationship function, but does not involve other potential weather conditions data, such as fog and wind, since few evidence provided by research is available for determining their relationships by proper functions. Therefore, the individual potential factors and conditions of private hospitals might be considered, and temporally varied traffic speed data on the road network can be monitored and utilized in the future work to have a more comprehensive understanding of the performance of national health systems.

5. Conclusion

This paper estimates a reliable nationwide distribution of population accessibility to public hospitals, quantifies the spatial and temporal variations of accessibility, and investigates the performance of public health systems in Australia. The quantitative outcomes of spatial and temporal variations of accessibility can benefit a wise decision-making process for health-care authorities to allocate medical resources and optimize of health-care systems. From the perspective of spatial distributions of health-care resources, spatial accessibility to all public hospitals in remote and very remote areas is not lower (and may even be higher) than that in major cities, but the accessibility to hospitals that provide emergency and surgery services is much higher in major cities than other areas. This means the allocation of health-care resources should be optimized to enhance emergency and surgery services in outer, remote, and very remote areas. From the angle of temporal variation of accessibility to public hospitals, reduction of traffic speed is 1.00–3.57% due to precipitation and heavy rain, but it leads to 18–23% and 31–50% of reduction of accessibility in hot-spot and cold-spot regions, respectively, and the impact is severe in NSW, QLD, and NT during wet seasons. Spatiotemporal analysis for the variations of accessibility can provide quantitative and accurate evidence for geographically local and dynamic strategies of allocation decision-making of medical resources and optimizing health-care systems both locally and nationally.

Highlights

(1) MKD2SFCA model provides a reliable measure of spatial accessibility and makes sense in real-world nationwide health systems.
(2) MKD2SFCA-based performance investigation reveals that the accessibility is spatially and temporally varied in Australian public health system.
(3) Accessibility to all hospitals in remote areas is not lower (and even higher) than that in major cities, but the accessibility to hospitals that provide emergency and surgery services is higher in major cities.
(4) Precipitation has a significant negative impact on accessibility in hot-spot and cold-spot regions.

Abbreviations

2SCFA: two-step floating catchment area; 3SFCA: three-step floating catchment area; ABS: Australian Bureau of Statistics; ACT: Australian Capital Territory; AIHW: Australian Institute of Health and Welfare; ASGS: Australian Statistical Geographical Classification; BPR: bed-population ratio; CV: coefficient of variance; DPR: doctor-population ratio; E2SFCA: enhanced two-step floating catchment area; FCA: floating catchment area; GDP: gross domestic product; KD2SFCA: kernel density two-step floating catchment area; LGA: local government area; LISA: local indicators of spatial association; M2SFCA: modified two-step floating catchment area; MKD2SFCA: modified kernel density two-step floating catchment area; NSW: New South Wales; NT: Northern Territory; PWC: population weighted centroid; QLD: Queensland; SA: Southern Australia; SEDAC: Socioeconomic Data and Applications Centre; TAS: Tasmania; TRMM: Tropical Rainfall Measuring Mission; UHC: universal health care; VIC: Victoria; WA: Western Australia.

Authors' contributions

YZS conceived the study and performed statistical analysis. XYW supervised the study. All authors jointly drafted and critically revised the paper. All authors read and approved the final manuscript.

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