Mapping spatial patterns of bus usage under varying local temperature conditions

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ABSTRACT

Weather influences our daily travel decisions in a number of important ways. At the individual scale, weather has been shown to influence trip-making behaviours where inclement conditions can induce re-scheduling, re-routing and cancellation of a planned journey. Furthermore at the transit system-level, poor weather can increase traffic congestion and reduce operational efficiencies. While some research has examined the weather–transit relationship, focus on the spatial dimension remain in their infancy. In this paper we adopt a visual analytic approach to spatially explore the complex weather–transit relationship at a micro geographical scale. We demonstrate that through spatially integrating a large disaggregate smart card database of bus ridership with hourly local weather measurements we can reveal how ‘heat stress’ changes the way in which passengers use the public transit system in subtropical Brisbane, Australia. Our approach has the potential for broader application across other public and private transport and climatic contexts to unveil the way in which weather influences our daily travel behaviour.

1 Introduction

Weather affects our daily transit decisions in its capacity to influence whether, when and how we travel (Böcker, Dijst, & Prillwitz, 2013). Existing scholarly evidence has highlighted behavioural changes in individuals’ trip-making decisions including re-scheduling, re-routing and modal shift during adverse weather conditions such as rainy, hot and cold days, e.g. De Palma and Rochat (1999), Sabir, Ommeren, Koets, and Rietveld (2010). Furthermore, the combined effect of these individual travel decisions across a public transport network has major implications for congestion, environmental pollution, public health and well-being, given that public transport serves a crucial role in maintaining the daily mobility and activity requirements of urban populations. With predictions of marked changes in our future daily weather patterns that include increases in the number and severity of extreme weather days (Hansen et al., 2006) understanding the dynamics of the weather–public transport usage relationship is of growing importance.

Studies on the effects of extreme weather events on travel behaviour have revealed that individuals are typically wary of travelling citing the relative importance of a trip as a crucial factor in shaping their decision to travel (Cools, Moons et al., 2010; Zanni & Ryley, 2015). The relative importance of a given trip also concords with the results of studies in Scotland (Al Hassan & Barker, 1999) and Shenzhen, China (Zhou et al., 2017) that each show that weather is much more influential during weekends (Al Hassan and Barker, 1999) and off-peak hours (Zhou et al., 2017) where travellers are more likely to be in a position to adjust their travel plans to suit the prevailing conditions. Weather has also been shown to exert an effect across various of modes of travel including active transport (Corcoran, Li, Rohde, Charles-Edwards, & Mateo-Babiano, 2014; Nankervis, 1999), bus (Arana, Cabezudo, & Peñalba, 2014; Tao, Corcoran, Hickman, & Stimson, 2016), train (Brazil et al., 2017), subway (Singhal, Kamga, & Yazici, 2014), general road traffic (Cools, Moons, Creemers et al., 2010), inter modal transfer (Gong, Currie, Liu, & Guo, 2017) as well as influence modal choice (Anta, Pérez-López, Martínez-Pardo, Novales, & Orro, 2016).

Previous scholarship investigating how weather exerts effects on people’s public transport use have largely relied on multivariate statistical methods such as regression modelling, wherein public transport ridership was regressed on variables including temperature, precipitation and wind speed typically at an aggregate or system-wide level, see, for example, the work by Guo, Wilson, and Rahbhe (2007). However, few studies have visualised changes in public transport ridership in association with variations in local weather conditions through approaches such as Flow-comap; weather; public transport; bus

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across a metropolitan region. We contend that visualising the weather–transit relationship holds the potential to reveal the spatial heterogeneity of public transport users’ behavioural response to local variations in weather, and in doing so form part of a new evidence base that can be deployed to better inform the provision of public transport services to cater for passengers’ travel needs.

In this paper, we combine smart card records with hourly weather data with the aim of visualising the effects of apparent temperature (a thermal comfort index) on bus travel in sub-tropical Brisbane, Australia’s third largest metropolitan region.

2 Data

The data employed in this study were drawn from three sources. First, smart card transaction data were obtained from TransLink, Brisbane public transit agency. The data captures transaction records for over 80% of public transport (i.e. bus, train and ferry) trips made in Brisbane over a period of six months (November 2012 to April 2013). The key information stored in a smart card transaction record includes service route, direction, boarding and alighting time stamps and stops. In this study, we solely focused on bus trips given that bus travel serves as the main public transport mode for commuting trips in Brisbane (accounting for over 60% of all public transport journeys). On average, approximately 200,000 bus trips are made on any given weekday.

Second, weather data (covering the same period as the smart card data) were accessed from the Australian Bureau of Meteorology. The data contained hourly measurements of three weather parameters, temperature, wind speed and humidity for 14 individual weather stations located across Brisbane. Drawing on these data we calculated ‘apparent temperature’ using the hourly measurements of temperature, relative humidity and wind speed (after Steadman, 1994) to generate an index of perceived human comfort (Figure 1). Following Steadman (1994), the calculation of apparent temperature drew on the two equations below:

\[ AT = T_a + 0.33 \times e - 0.7 \times WS - 4 \]  

(1)

where, \( AT \) is apparent temperature; \( T_a \) is temperature (in °C); \( e \) is humidity (in hPa); and \( WS \) is wind speed (in m/s).

and:

\[ e = \frac{rh}{100} \times 6.105 \times e^{17.27 \times \frac{m}{Wr}} \]  

(2)

where, \( rh \) is relative humidity (in percent).

This index permits us to investigate how varying levels of ‘heat stress’ induce changes in the spatial patterns of bus usage. While temperature can to some extent represent how comfortable a weather condition is for outdoor activities and travel; other weather factors, particularly humidity and wind, may impose additional influence on the level of thermal comfort (or discomfort) felt by individuals (Nguyen, Schwartz, & Dockery, 2014; Steadman, 1984). For example, high humidity can amplify the feeling of heat stress during hot weather, while the onset of wind may have the opposite (cooling) effect. Given this, apparent temperature has been devised as a composite index to more realistically capture such thermal discomfort as a function of multiple weather factors. The equations for calculating apparent temperature here assume the condition of an adult walking outdoors in the shade (Steadman, 1994). Drawing on the computation method, some scholars have reported a significant association between apparent temperature and outdoor activity, such as taking an outdoor walk (e.g. Chan & Ryan, 2009). However, few studies have examined the impact of this heat stress index on travel by public transport. For our case study context, Brisbane, the minimum hourly apparent temperature for the period under investigation was 5.4°C with a maximum of 40.4°C, a mean of 23.1°C and a standard deviation of 3.9°C. We next produced a set of 4380 kriged surfaces of apparent temperature for hourly intervals to cover the same period as the smart card data.

Last, General Transit Feed Specification (GTFS) (Google Developers, 2012), an open data specification provides the common format through which detailed geographic and service information for the public transport (e.g. the stops on a bus route) is disseminated. For our case study context, Brisbane, the bus network data in GTFS specification was sourced via the State government agency (Queensland Government, 2017). This allows us to add the geographic location for each bus stop captured in the smart card data.

3 Method

A new geo-visual technique, the flow-comap (Corcoran et al., 2014; Tao, Rohde, & Corcoran, 2014), was employed to map spatial patterns of bus passenger flows (captured by the difference in flow volumes) and their relationship to variations in apparent temperature. The flow-comap is an augmentation of two well established cartographic techniques, the flow map and the comap or Conditional Map (Brunsdon, 2001). Flow maps have been widely employed for more than a century (Minard, 1980) to depict the movement of objects across geographic space. Figure 2 is a flow map of Brisbane bus passenger flows where the thickness of the line indicates larger numbers
of bus passengers, and classified using a natural breaks classification in order to minimise intra-class and maximise inter-class variation (Jenks & Caspall, 1971). As such the resulting flow-comap represents the ‘best’ arrangement of passenger flows into a set of classes. To construct the flow map entailed the following two steps.

- First, smart card data were joined with the GTFS based on matching bus route and stop id to create over 6 million detailed individual travel trajectories at a stop-to-stop level.
- Second, using the reconstructed travel trajectories, flow-matrices (i.e. the number of passengers traveling between any two bus stops) were calculated and used to create the flow map.

The second cartographic technique, the comap is founded on the principal of ‘small multiples’ (Tufte, 1990) to visualise changes in the relationship between two variables using a matrix of plots. Here we combine the two techniques (i.e. the flow map and the comap) to examine the relationship between a pair of variables (in our case the number of bus passengers at a given location in the public transit network) that are conditioned using a third variable, z (in our case a measure of time). Using this method it is possible that we can then examine variations in the number of bus passengers at a location in the public transit network (x and y) and their variation given different values of time (z). See Figure 3 for a flow-comap of Brisbane bus passenger flows. As you will see from Figure 3 there are four maps panels that collectively describe the spatial patterns of bus passenger flows over a 16.5 hour period, namely from 06:00 to 22:30. The flow-comap draws on the ‘small multiple’ principal through the use of the four map panels each of which have overlapping temporal periods that collectively permit us to visualise how bus passenger flows vary as a function of a gradual change in an external variable, in our case by hour of day. Overlapping intervals are an important feature of the comap that are designed to ensure that a similar amount of data is represented in each map panel and that the overlap between classes is of a consistent size. The overlapping intervals feature helps to ensure that the resulting patterns that are depicted across each of the map panels are not an artefact of how time is classified into discrete intervals. The overlap between neighbouring intervals exerts a smoothing effect and can be adjusted (to have a larger or smaller overlap) to fit the data being mapped. In the case of our bus passenger flow data, a 30 minute overlap between neighbouring intervals was found to be the most appropriate given that it revealed a set of interesting patterns. Map panels A and C depict the morning and afternoon peak hour periods, respectively and B and D capture bus passenger flows during off-peak travel periods.

We next augment the flow-comap represented in Figure 3 to examine the way in which apparent temperature brings about shifts in bus ridership and how this varies across Brisbane’s bus network. To achieve this and compute the resulting flow-comap entails the following five steps.

- First, each smart card record was spatially joined with the apparent temperature representing the weather conditions at the time the passenger boarded the bus.
- Second, by joining smart card data with the GTFS-based network data on matching bus route and
Stop id individual travel trajectories were constructed.

- Third, using the reconstructed travel trajectories, the flow-matrices were calculated.
- Fourth, apparent temperature was classified into four categories by computing its quartile ranges.
- Fifth, drawing on the flow-matrices and quartile ranges of apparent temperature, three standardised differences of flow volumes were computed – Quartile 2 minus Quartile 1; Quartile 3 minus Quartile 1 and Quartile 4 minus Quartile 1. The first subtraction (Quartile 2 minus Quartile 1) examines bus trips where there are relatively ‘small’ variations in apparent temperature, the second subtraction (Quartile 3 minus Quartile 1), ‘larger’ differences in apparent temperature and the final subtraction (Quartile 4 minus Quartile 1) represent the trips that were taken in the ‘largest’ differences in apparent temperature. The standardised differences resulting from the three subtractions provide the input data necessary to produce each flow-comap (Map). The Map depicts each of the three subtractions as columns in the flow-comap labelled as; ‘Small’; ‘Medium’ and ‘Large’ for both inbound and outbound trips.

4 Results and discussion

The Main Map, depicts spatial variations in bus ridership flows over a single day period (in total accounting for 16.5 hours that align to the bus timetable for a given day) for three different levels of apparent temperature for both inbound (left-hand panel of flow-comaps) and
outbound journeys (right-hand panel of flow-comaps). It can be seen that over the day pronounced differences in flow volumes occur along a number of routes, with some highly distinct patterns obtained for different time periods and travel directions. For example, for inbound trips during the morning period, increases in apparent temperature (e.g. from Quartile 1 to Quartile 3 or 4) appears to be associated with a marked decrease in flow volumes along some routes that connect the far south of Brisbane, while increasing flow volumes along some routes connecting locales around the inner-ring area of Brisbane. Yet during the rest of the day (particularly during the afternoon period), some south routes also experienced increases in flow volumes with elevations in apparent temperature. The differences in spatial patterns of flow volumes in association with variations in heat stress, we contend, is in part attributed to the difference in built environment related with the individual routes. For example, the inner-ring routes that were shown to experience increase in passenger flows may also serve for the more densely built-up areas, which arguably provide more shelter against weather. By comparison, the southbound routes, particularly those located in the outer ring areas, are more likely to be associated a reduction in sheltered stops, hence may act as to discourage bus use during weather conditions in which heat stress is higher.

Concerning outbound trips, as apparent temperature increases, the change along some (particularly southbound) routes appears to be more consistent than their inbound counterparts, in that decreases in

Figure 3. A flow-comap.² (A) Passenger flows for 06:00–10:30 (B): Passenger flows for 10:00–14:30 (C): Passenger flows for 14:00–18:30 (D): Passenger flows for 18:00–22:30.
flow volumes are more discernible across most periods of the day (especially during the morning, noon and evening). An exception, however, is the afternoon period, wherein more routes saw an increase in flow volumes. A closer examination indicates that most of these routes serve for a series of major suburban shopping centres. Given this, one possible explanation is that during afternoon peak hours, as apparent temperature rises, more passengers may choose to make a stop at these shopping centres where air-conditioning coupled with other amenities (e.g. restaurants, recreational places) are readily accessible. To corroborate this assertion would require the acquisition of additional survey data to capture supplementary characteristics of these trips.

Further to the above findings, Brisbane’s south shows the greatest variations in trip volumes with changes in apparent temperature, pointing towards differences in people’s activity patterns across the study context and a higher susceptibility of these trips to heat stress especially during the morning and noon periods. A possible mechanism at work here is that in South Brisbane, there are more bus passengers who have access to other forms of transport (such as a private car) than those located in the North. In weather conditions perceived to be less comfortable (i.e. higher apparent temperatures), some bus riders from South Brisbane may more readily switch to other forms of transport to complete their trip-making. Previous research provides some tentative support for this assertion in that those taking the bus in Brisbane’s most frequently used southbound bus routes reported higher levels of car ownership than those using the bus in the north of the city (Tao, 2015). However, to more fully examine the existence of such weather induced modal-substitution further survey-based work is now required to unpack the way in which weather interfaces with other factors (e.g. resident location, access to private vehicles) to collectively influence whether, where, when and how bus riders make travel decisions.

The aim of this study was to visualise the effects of apparent temperature on bus travel in Brisbane. It demonstrates that by spatially integrating smart card data and local weather information we can geographically examine the way in which bus ridership is influenced by variations in apparent temperature. The visualisation collectively enabled us to identify where and when and which routes within the public transit network show the largest variations in ridership relative to differences in apparent temperature.

Quantifying the effects of local weather conditions on human mobility patterns revealed variations in magnitude. More specifically changes in apparent temperature were shown to be related to variations in mobility both spatially across the public transit network and temporally across the study period. Understanding how these variations in bus ridership are related to changes in weather conditions is important to operational and strategic transport planning. More specifically, our spatial analytic approach and the flow-comap, have the potential to contribute to a new evidence base whereby the routes and their constituent bus stops that are identified to see the greatest ridership variations might be targeted for upgrade. Upgrades might include changes to bus shelters to help to ameliorate the negative effects of weather. Furthermore, our findings have the potential to be used to advise adjustment to the bus schedule to better account for variations in demand.

There are a number of limitations associated with the current study that require noting. First is that we only had access to 6 months of smart card data and thus were not able to examine the effect of weather across all four seasons. Second, we did not have access to individual smart card holder characteristics. This additional information would help deepen our current analysis to understand how different types of users, such as adults, vary from children, students and the elderly in the way in which they use the bus network and then how weather impacts their travel behaviours.

Several avenues of future research emerge from this study. First, with access to a larger database of smart card data (of two or more years) we would be able to examine how different calendar events, such as weekdays, weekends, school and public holidays are impacted by weather. Second would be to integrate other modes with the public transit network, that in the case of Brisbane include the train, ferry and public bicycle, to examine the way in which weather induces both modal-substitution and disputes inter-modal transfer. Third would be to compile our visual analytic, the flow-comap into a GIS-based tool to extend its utility to the broader spatial science community and transport analysts.

5 Conclusions

Our study offers new insights into the complex weather-transit behaviour relationship through a visual exploration of local geographical dynamics. Using the flow-comap, we have revealed spatial patterns that have important operational and strategic implications for transit by identifying particular locations and times that experience the largest shifts in bus ridership in parallel with changes in weather conditions (apparent temperature). With further development of this approach there is the potential for its inclusion to form part of a transit dashboard that forms a new evidence base with the capacity to inform the (re)design of more weather resilient public transport systems.

Software

The spatial join of travel smart card and apparent temperature was performed using ESRI ArcGIS version
10.4.1. The smart card data coupled with the GTFS were pre-processed using a bespoke python script to reconstruct travel trajectories. Next, quartile ranges of apparent temperature were calculated using Microsoft Excel. Finally, the flow-matrices and standardised differences of flow volumes were computed using MySQL workbench and the final flow-comap generated using ArcGIS.

Notes
1. Flows are classified using the natural breaks classification method.
2. Flows are classified using the natural breaks classification method.

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