New Approaches to Oil Vulnerability Mapping for Australian Cities:
The Case of South-East Queensland, the 200km City

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Abstract: Australian cities are extremely dependent on oil for transportation, with relatively high automobile mode shares. ‘ Forced car ownership’ is prevalent, especially in the outer suburbs of capital cities due to poor public transport services and connectivity. The potential harm caused by oil dependence and uncertain supply can be seen as a form of vulnerability. This paper develops and applies new approaches to better understand oil vulnerability and its spatial patterning. A new oil vulnerability framework that builds on previous approaches is provided, drawing on climate change vulnerability concepts of exposure, sensitivity and adaptive capacity. GIS-based oil vulnerability mapping is used to reveal the different dimensions across the urbanised coast of South-East Queensland (SEQ). This study is compared with previous approaches, notably Dodson and Sipe’s (2007) VIPER Index, and current regional transport and urban patterns. Consistent with previous studies, outer suburbs away from well-serviced public transport corridors are least prepared for sudden oil shock events, though subtle nuances are revealed using the new methods. This study revealed the multiple dimensions of oil vulnerability with a new visual classification technique. The resultant index could help planners and policy makers to holistically identify areas at high risk and provide more targeted responses. The new indicators and vulnerability mapping methods have a potential to be expanded to other urban jurisdictions within and beyond Australia.

1. Introduction

Australian cities are among some of the most car-dependent in the world. However, oil prices have been increasingly volatile since the 2000s. They reached extremely high levels in 2008 and 2011-2014, as shown in Figure 1. Despite the recent price falls, oil prices are still much higher than the levels between the 1980s and 1990s when suburban growth was expanding rapidly.

![Figure 1: Oil price fluctuations since 1987](Source: US Energy Information Administration, 2015)
Cities with high reliance on oil-based transport remain susceptible to the impacts of higher or fluctuating oil prices. However, progress on transport energy transition is slow, despite various governmental efforts to promote public transport and alternative fuel (Rotmans et al., 2001; Solomon and Krishna, 2011). This can be seen as a form of path dependency caused by vested interests in oil-related businesses and massive built-in oil consumption infrastructure and equipment (Cherp et al., 2011; Dodson, 2013; Geels, 2011). Car dependent urban forms also create 'lock-in' effect that makes transition to non-oil using modes a difficult task at individual and societal levels (Briggs et al., 2015; Unruh, 2000). Meanwhile despite fuel efficiency gains from newer vehicles, outer suburbs remain more affected by oil price increases due to longer average driving distance, lower socio-economic status and driving vehicles with less fuel efficiency (Li et al., 2013). If oil supply diminishes, and prices spike beyond 2008 peak levels, widespread disruption is likely in car-dependent societies and transportation systems. Calls for further research have been made to investigate the effects of increasing oil price on cities in order to better understand the dynamics of energy and financial stresses on urban structures and patterns (Dodson and Sipe, 2012; Renne and Fields, 2013). In response, new methods are tested to provide better ways to understand urban transport oil vulnerability in coastal SEQ, a fast growing 200km long conurbation strip comprising Brisbane, the Gold Coast, and the Sunshine Coast. The potential of adaptive measures that reduce urban transport oil vulnerability are investigated and the resultant conceptual framework is proposed to help guide future research.

2. Conceptualising Oil Vulnerability

The concept of oil vulnerability emerged as a future-looking concept to deal with the dual challenge of Peak Oil and climate change. Dodson and Sipe (2005) appeared to be the first to use this term in their ‘Vulnerability Index for Petroleum Energy Rises’ (VIPER) to describe socioeconomic impacts of increasing oil price on households in relation to transport. Their studies involved area indexing of a number of oil vulnerable indicators, shown visually on maps. They found that outer suburban areas are significantly more oil vulnerable than inner city areas, given they tend to be car dependent and poorly serviced by public transport but with lower socio-economic conditions and higher relative mortgage debt (Dodson and Sipe, 2008). Public and academic attention to oil vulnerability in Australia prompted government response at federal, state and local levels in the form of inquiries, reports and new planning instruments (Australian Senate, 2007; Queensland Government, 2009; Sunshine Coast Regional Council, 2010; Tasmanian Government, 2012). Yet the effectiveness and longevity of these responses is uncertain. Meanwhile, with readily available census data sources, Dodson and Sipe’s approach has been adopted by a number of researchers with localised versions used in Canada (Arico, 2007; Akbari and Nurul Habib, 2014), Melbourne (Fishman and Brennan, 2009), SEQ region (Runting et al., 2011) and six cities in the US (Sipe and Dodson, 2013). Paralleling advances in computation complexity in urban land-use and transportation modelling, advanced microsimulation and activity modelling techniques has been employed in more recent studies (Lovelace and Philips, 2014; Rendall et al., 2014). There remain research gaps on the relationship of oil vulnerability factors and transport infrastructure. This includes a lack of a clear conceptual framework for oil vulnerability studies, unlike more mature vulnerability fields such as climate change (Janssen et al., 2006; Choy et al., 2010; Measham et al., 2011), disaster management (Birkmann, 2007; Cardona, 2007) and development aid (Chambers, 1989; Watts and Bohle, 1993; Alwang et al., 2001).

The concepts from prevailing accepted frameworks of vulnerability provide a useful guideline in categorising oil vulnerability variables. Pioneering research on oil vulnerability conducted by Dodson and Sipe implicitly defines the term as ‘the potential exposure of households to adverse socioeconomic outcomes arising from increased fuel costs.’ In recent studies, Lovelace & Philips (2014) interpret oil vulnerability as the combination of local-level variables that would make coping with high oil prices harder and hence define oil vulnerability as ‘a combined probability and magnitude of negative effects resulting from high oil price or shortage scenarios’. In view that oil vulnerability research at the urban level has not been fully defined before, and without any preceding guidance, a commonly used framework by the Intergovernmental Panel on Climate Change (2001) is adapted as a framework for further oil vulnerability research. Oil vulnerability is therefore defined in this research as ‘the degree to which a system is susceptible to, or unable to cope with, adverse effects of oil price variability and extremes’. Three major components are adapted for oil vulnerability (Figure 2):
- Exposure (E) represents to what extent energy-related events are able to affect the system. It is usually measured by oil consumption variables, such as car ownership or distance of travel.

- Sensitivity (S) represents the degree to which a system is affected by both energy and non-energy drivers. It is often measured by social variables, such as income or socio-economic wellbeing.

- Adaptive capacity (AC) represents the ability of a system to change in a way that makes it better equipped to manage its future exposure and/or sensitivity to oil price influences. Adaptive capacity can be short term or long term and can include capacity for substituting mobility for other means of communication.

Adaptive capacity can involve complex social, economic and cultural adjustments, but there are difficulties in conceiving and measuring these. While there is potential in utilising information commutation technology (ICT) for trip substitution, the effect is contested: some suggest face-to-face meetings remain important and ICT may actually create more personal or business contact opportunities that could induce more travel demand (Aguiléra et al., 2012; Litman, 2005). Previously, public transport has been assessed by simple buffer analysis of public transport stops with room for further improvement (Runting et al., 2011). For long-term resilience, urban factors that can reduce oil use, such as widespread adaptation of alternative fuels or public transport remain largely untouched in existing oil vulnerability assessments.

**Study Area – the 200km city of South-East Queensland**

Figure 3 shows the urban extent of SEQ. This expansive urban region is facing a transport energy challenge given its overall low-density development with most travel by automobile (Spearritt, 2009). Extensive programs of motorway infrastructure (e.g.: tunnels, bridges) building remain the usual response to address traffic growth (Mees and Groenhart, 2012). Despite some positive signs of public transport revival, marked by the commencement of light rail on the Gold Coast in 2014, the car is still the dominant travel mode. From the most recent travel surveys, private vehicle mode share in SEQ for all trips remained over 80% with public transport accounting merely 8% in 2009 (Queensland Transport and Main Roads Department, 2009). This presents a significant oil vulnerability risk.
Figure 3: Urban areas and transport infrastructure of South-East Queensland
3. Methodology

Dodson and Sipe’s (2007, 2008) approach used census statistics to create a rough measure of vulnerability by ranking the proportion of households deemed to be vulnerable (owning more than 2 cars, driving to work, socio-economic disadvantage and having a home under mortgage). New metrics not included in Dodson and Sipe’s approach, such as public transport coverage, frequency and active transport, are included for the first time. Table 1 outlines the expanded set of variables used in this study with their respective vulnerability component groupings.

Table 1: The variables used to derive the associated vulnerability components

<table>
<thead>
<tr>
<th>Vulnerability Component</th>
<th>Variable</th>
<th>Transformed Value</th>
<th>Data Source</th>
<th>Rationale</th>
</tr>
</thead>
<tbody>
<tr>
<td>Exposure</td>
<td>E1) Estimated average number of motor vehicle owned per dwelling</td>
<td>Converted into z-scores (standard deviation) of equal weighting</td>
<td>• 2011 Australian Census</td>
<td>Oil consumption for both work and non-work trips</td>
</tr>
<tr>
<td></td>
<td>E2) Estimated oil-based fuel use of low occupancy vehicles (LOVs) per commuting trip (see Table 2)</td>
<td></td>
<td>• 2011 Australian Census • 2014 Motor Vehicle Survey</td>
<td>Oil consumption for work trips</td>
</tr>
<tr>
<td></td>
<td>E3) Weighted average commuting distance</td>
<td></td>
<td>• 2006 Australian Census</td>
<td>Oil consumption for work trips</td>
</tr>
<tr>
<td>Sensitivity</td>
<td>S1) Median weekly household income</td>
<td>Converted into z-scores (standard deviation) of equal weighting</td>
<td>• 2011 Australian Census</td>
<td>Short-term ability to pay for increasing oil prices</td>
</tr>
<tr>
<td></td>
<td>S2) Socio-Economic Indexes for Areas (SEIFA): Index of Relative Socio-economic Advantage and Disadvantage (IRSAD)</td>
<td></td>
<td>• 2011 Australian Census</td>
<td>Long-term ability to pay for increasing oil prices</td>
</tr>
<tr>
<td>Adaptive Capacity</td>
<td>AC1) Proportion of mode share that does not consume oil (railways, trams, walk and cycle)</td>
<td>Converted into z-scores (standard deviation) of equal weighting</td>
<td>• 2011 Australian Census</td>
<td>Ability to use non-oil based transport</td>
</tr>
<tr>
<td></td>
<td>AC2) Proportion of area within 400m of public transport stop ranked by level of service in weekdays (see Table 3)</td>
<td></td>
<td>• 2015 Translink General Transit Feed Specification (GTFS) data</td>
<td>Ability to use public transport instead of driving</td>
</tr>
<tr>
<td></td>
<td>AC3) Walkability indices (Walk Score, 2015, see Table 4)</td>
<td></td>
<td>• 2015 Walk Score (Suburb level)</td>
<td>Ability to walk or cycle instead of driving</td>
</tr>
<tr>
<td></td>
<td>AC4) Employment density (jobs / sq.km)</td>
<td></td>
<td>• 2011 Australian Census</td>
<td>Ability to walk or cycle to work</td>
</tr>
<tr>
<td></td>
<td>AC5) Percentage of area within 400m buffer of electric public transport corridors (Railways and tramways)</td>
<td></td>
<td>• 2015 Translink data</td>
<td>Ability to provide non-oil based transport in the long run</td>
</tr>
</tbody>
</table>

Exposure (E)

This component measures the risk exposure of households to increasing oil price. Variables selected for this component made reference from those used in the VIPER index. However the selection of ‘more than 2 cars’ is changed to computing the ‘average car ownership per dwelling’ of motor vehicle responses in the census. The census questionnaire only provides response categories reporting up to ‘four or more’ motor vehicles owned. It is assumed the respondent households owning more than 5 cars are not common, given the very low numbers involved. The 2006 values of journey to work distance are used in...
this study as it is readily available to this author and travel distance in SEQ overall remained largely the same between 2006 and 2011. For variable E2 regarding the average fuel use of low-occupancy vehicles, this is computed by the average fuel use value from the Motor Vehicle Survey of Australian Bureau of Statistics (2013) as shown in Table 2. This reflects the fuel use differences of cars, trucks and motorcycles as surveyed in the census. It is difficult to estimate the exact fuel use of taxi because part of the journey is unoccupied by the passenger. Previous literature has suggested taxis have higher VKT and fuel use (ranging from 33% to 190%) than car trips depending on the length of the unoccupied journey after serving passengers (Hillman and Whalley, 1983; Stead, 1999). There is, however, no reliable data for Australia on the fuel use intensity of taxi trips. For this study, it is assumed the fuel intensity of a taxi trip would be the same as a car trip. Only the ‘main mode of work’ is included in this analysis, with the limitation that multi-modal travel is not accurately captured. To reflect a more accurate fuel use of areas, a weighted average commuting distance is estimated from the network distance (road distance) between origin–destination (O-D) zones and the reported commuting figures.

### Table 2: Fuel use loadings used for variable E2

<table>
<thead>
<tr>
<th>LOV types for journey to work in ABS Census</th>
<th>Average per capita fuel consumption (L/100km)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Car (as driver) and Taxi</td>
<td>11.1</td>
</tr>
<tr>
<td>Car (as passenger)</td>
<td>Included in driver count</td>
</tr>
<tr>
<td>Motorcycle</td>
<td>5.9</td>
</tr>
<tr>
<td>Truck</td>
<td>22.6</td>
</tr>
</tbody>
</table>

(Source: ABS, 2013)

**Sensitivity (S)**

This component measures the ability to withstand future oil price increases. In the VIPER study, SEIFA is employed as it is a robust measure to denote relative advantage or disadvantage in socio-economic status (Australian Bureau of Statistics, 2006). The SEIFA values represent a longer-term ability to withstand risks as the level of income, education level and ownership of economic assets are also accounted for in this index. To reflect a more short-term ability to respond, median household income is included as a direct measure despite SEIFA having included income level within its weighting.

**Adaptive Capacity (AC)**

This component has been the least surveyed area in previous oil vulnerability assessments. Runting et al’s (2011) study included a simple buffer of public transport stops with 400m (or 5 min walking distance buffer). However, this is a crude measure of public transport service and accessibility. With increasing proliferation of public transport data in the form of General Transit Feed Specification (GTFS) and GIS analytical capacities, it is possible to estimate public transport service level by its frequency (Antrim and Barbeau, 2013; Keller, 2012). A pedestrian walk-shed distance of 400m is calculated with road network data. The level of service is measured by a stop frequency scoring scheme similar to the one used in the Land Use & Public Transport Accessibility (LUPTAI) Index (Pitot et al., 2006). While it is acknowledged that frequency does not represent actual accessibility, it remains an important indicator of public transport usability (Walker, 2012). In addition, the potential to use active transport is considered by an objectively measured walkability index - Walk Score™. Walk Score™ utilises suburb level accessibility data and has been validated in American research for revealing walking patterns and better health outcomes (Duncan et al., 2011). In Australia, such validation is lacking for the time being and this is noted as a potential limitation.

### Table 3: Public transport level of service scores for variable AC2

<table>
<thead>
<tr>
<th>Frequency (minutes)</th>
<th>Trips per hour calculated from GTFS data</th>
<th>Public Transport Level of Service Score</th>
</tr>
</thead>
<tbody>
<tr>
<td>10</td>
<td>6</td>
<td>5</td>
</tr>
<tr>
<td>15</td>
<td>4</td>
<td>4</td>
</tr>
<tr>
<td>30</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>60</td>
<td>1</td>
<td>2</td>
</tr>
<tr>
<td>more than 60</td>
<td>less than 1</td>
<td>1</td>
</tr>
</tbody>
</table>
Table 4: Description of Walk Score™ (2015) values for variable AC3

<table>
<thead>
<tr>
<th>Description</th>
<th>Walk Score (1 - 100)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Walker's Paradise</td>
<td>90-100</td>
</tr>
<tr>
<td>Very Walkable</td>
<td>70-89</td>
</tr>
<tr>
<td>Somewhat Walkable</td>
<td>50-69</td>
</tr>
<tr>
<td>Car-Dependent</td>
<td>25-49</td>
</tr>
<tr>
<td>Car-Dependent</td>
<td>0-24</td>
</tr>
</tbody>
</table>

(Adapted from Pitot et al. (2006))

The differences in vulnerability components for selected local government areas in SEQ are shown in Table 5. The exposure, sensitivity and adaptive capacity variables are mean adjusted by converting into z-scores (standard deviation values) for which 0 is the mean value.

Table 5: Descriptive statistics, mean values by Local Government Areas (LGAs)

<table>
<thead>
<tr>
<th>Indicator Variables</th>
<th>Brisbane</th>
<th>Gold Coast</th>
<th>Ipswich</th>
<th>Logan</th>
<th>Redland</th>
<th>Moreton Bay</th>
<th>Sunshine Coast</th>
<th>Noosa</th>
<th>All LGAs</th>
</tr>
</thead>
<tbody>
<tr>
<td>E1 (cars per dwellings)</td>
<td>1.60</td>
<td>1.72</td>
<td>1.71</td>
<td>1.81</td>
<td>1.84</td>
<td>1.78</td>
<td>1.67</td>
<td>1.56</td>
<td>1.69</td>
</tr>
<tr>
<td>E3 (average JTW distance, km)</td>
<td>10.93</td>
<td>15.70</td>
<td>17.10</td>
<td>18.11</td>
<td>16.97</td>
<td>19.66</td>
<td>18.67</td>
<td>14.73</td>
<td>14.95</td>
</tr>
<tr>
<td>S1 (income, $/week)</td>
<td>1644.55</td>
<td>1270.66</td>
<td>1282.20</td>
<td>1337.89</td>
<td>1462.05</td>
<td>1368.47</td>
<td>1124.95</td>
<td>1032.01</td>
<td>1433.41</td>
</tr>
<tr>
<td>S2 (SEIFA)</td>
<td>1055.14</td>
<td>1013.26</td>
<td>952.60</td>
<td>962.56</td>
<td>1025.83</td>
<td>994.38</td>
<td>1002.37</td>
<td>1002.63</td>
<td>1018.26</td>
</tr>
<tr>
<td>AC1 (oil-free mode share, %)</td>
<td>12.87</td>
<td>5.75</td>
<td>8.45</td>
<td>4.43</td>
<td>5.89</td>
<td>9.02</td>
<td>5.37</td>
<td>6.54</td>
<td>9.00</td>
</tr>
<tr>
<td>AC2 (public transport level of service, 1-5 scores)</td>
<td>2.40</td>
<td>1.78</td>
<td>1.54</td>
<td>1.57</td>
<td>1.56</td>
<td>1.48</td>
<td>1.09</td>
<td>1.46</td>
<td>1.88</td>
</tr>
<tr>
<td>A3 (walkability, 1-100 scores)</td>
<td>59.87</td>
<td>47.69</td>
<td>35.16</td>
<td>41.42</td>
<td>36.11</td>
<td>38.41</td>
<td>39.94</td>
<td>41.86</td>
<td>48.61</td>
</tr>
<tr>
<td>A4 (employment density, jobs/km²)</td>
<td>1340.41</td>
<td>551.79</td>
<td>214.81</td>
<td>312.95</td>
<td>252.89</td>
<td>209.03</td>
<td>332.44</td>
<td>152.46</td>
<td>734.83</td>
</tr>
<tr>
<td>A5 (area within electric public transport corridor, %)</td>
<td>16.91</td>
<td>9.94</td>
<td>12.88</td>
<td>7.83</td>
<td>7.75</td>
<td>8.29</td>
<td>3.21</td>
<td>0</td>
<td>11.68</td>
</tr>
</tbody>
</table>
GIS methods were used to conduct spatial analysis and to visualise data and to identify patterns of oil vulnerability. Standard deviation z-scores and composite aggregation of vulnerability components are used in this study, which is a common normalisation procedure in other vulnerability assessments, such as climate change (Cutter et al., 2003). The advantage of this is the spatial variance of each component can be better preserved. It can also be directly computed into a component oil vulnerability (OV) score using the equation:

$$OV = E + S - AC$$

4. Results and Discussion

The previous VIPER method looked at the Brisbane metropolitan area only for Queensland and other capital cities in Australia. This study attempts to examine oil vulnerability at a regional scale. Advancing from VIPER or VAMPIRE oil vulnerability assessment methods that use a simple percentile group ranking (i.e.: 1-5 scores assigned by percentile breaks of 10, 25, 50, 75 and 90), the methodology used in this oil vulnerability assessment preserves the variation of oil vulnerability components. Figure 4 presents a VIPER index constructed using the same data of this study at Statistical Area 1 (SA1) level, as compared to the new method. The values of the individual oil vulnerability components are shown in Figure 5. The exposure map reflects oil use patterns. The sensitivity map shows income and socio-economic status levels, which approximates the ability to withstand higher oil prices. This adaptive capacity map reflects the relative ability of each area in adapting to higher oil prices. Finally, the data was classified into nine oil vulnerability classes, based on their respective potential impact and adaptive capacity values (see Table 6). Figure 6 provides the outputs of this classification, mapped across SEQ. It reveals the detailed extent of potential oil vulnerability and adaptive capacity that has not been shown in prior studies. The red areas denote high potential impact with low adaptive capacity. These areas are mostly located in outer suburban areas. Table 7 shows the percentage of population within each oil vulnerability class by local government area (LGA).

As displayed in Figure 4, the composite measure reveals a more nuanced spatial variation of oil vulnerability than the VIPER method, which a less concentric pattern radiating out of Brisbane can be seen. This is made possible by the new variables and visualisation method employed in this research. The inclusion of public transport accessibility and walkability variables can help identify highly vulnerable areas not detected in the VIPER approach. These areas tend to be at the urban fridges and peri-urban areas, in particular within the Moreton Bay and Logan LGAs. The new approach reflects the poly-centric urban pattern of South East Queensland as outer urban centres such as Ipswich are also assessed to be less vulnerable via this new approach. Another advantage of our approach is a more systematic analysis of what constitutes overall oil vulnerability. Confirming previous studies (Dodson and Sipe, 2007; Runting et al., 2011), the central areas of Brisbane with better public transport services and higher income levels are assessed to be least vulnerable (green areas). The outer suburbs of Brisbane and the growth areas in the LGAs of Ipswich, Logan, Redland and Moreton Bay all have higher E+S value and low AC. The more distinct urban centres of Gold Coast and Sunshine Coast are also found to have higher ES and low AC despite their ability to contain employment and commuting trips. However, the Gold Coast still has areas with low E+S and high AC. This could be due to its recent introduction of light rail services which helped to boost the AC score significantly as oil-free electric public transport is considered in this assessment. Whereas for the Sunshine Coast, the low E+S and High AC areas are sparse. For a SEQ region-wide perspective, high E+S with low or mid AC population outnumbers low E+S with high or mid AC population.

This assessment highlights the importance of sustainable transport. The ‘Avoid-Shift-Improve’ approach has been recognised as an effective way to reduce oil use and congestion simultaneously (Dalkmann and Brannigan, 2007; Schipper and Marie-Lilliu, 1999). Yet, better planning of urban development is imperative in reducing oil vulnerability. Outer suburban areas are seen to be highly oil vulnerable, characterised with high car use, lower socio-economic status but with low adaptive capacity. There is a strong case to make public transport more competitive and attractive given active transport has only a short range. Gilbert and Perl’s (2009) argument for electricity grid-connected vehicles to address oil vulnerability is also supported by this new assessment. Echoing Dodson and Sipe (2007; 2011) and Mees (2009), a network approach for improved public transport is urgently needed to reduce oil vulnerability in...
SEQ, which requires substantial infrastructure investment. Whilst the SEQ 2031 Transport Plan indicated expansion in railway infrastructure (Queensland Government, 2011) only the Moreton Bay Railway Link is confirmed to be completed. This research calls for greater attention on oil vulnerability and prompt investigation of providing energy-efficient transport infrastructure to help alleviate transport cost pressures of the most affected areas, in particular the red areas shown in our Figure 4’s Composite Index and Figure 6.
Figure 5: The oil vulnerability components of South-East Queensland’s more urbanised local government areas
Table 6: Oil vulnerability classification

<table>
<thead>
<tr>
<th>Adaptive Capacity (AC)</th>
<th>33% percentile below mean values</th>
<th>33% ± mean</th>
<th>33% percentile above mean values</th>
</tr>
</thead>
<tbody>
<tr>
<td>High</td>
<td>Low E + S High AC</td>
<td>Mid E + S High AC</td>
<td>High E + S High AC</td>
</tr>
<tr>
<td>Mid</td>
<td>Low E + S Mid AC</td>
<td>Mid E + S Mid AC</td>
<td>High E + S Mid AC</td>
</tr>
<tr>
<td>Low</td>
<td>Low E + S Low AC</td>
<td>Mid E + S Low AC</td>
<td>High E + S Low AC</td>
</tr>
</tbody>
</table>

Table 7: Comparison of the percentage of population of each oil vulnerability class across Local Government Areas

<table>
<thead>
<tr>
<th>Oil Vulnerability Classes</th>
<th>Brisbane</th>
<th>Gold Coast</th>
<th>Ipswich</th>
<th>Logan</th>
<th>Redland</th>
<th>Moreton Bay</th>
<th>Sunshine Coast</th>
<th>Noosa</th>
<th>ALL LGAs avg.</th>
</tr>
</thead>
<tbody>
<tr>
<td>High E+S Low AC</td>
<td>9.8%</td>
<td>29.0%</td>
<td>21.3%</td>
<td>27.0%</td>
<td>34.4%</td>
<td>32.3%</td>
<td>33.7%</td>
<td>11.0%</td>
<td>21.7%</td>
</tr>
<tr>
<td>High E+S Mid AC</td>
<td>10.9%</td>
<td>7.4%</td>
<td>7.2%</td>
<td>9.6%</td>
<td>18.5%</td>
<td>9.2%</td>
<td>2.9%</td>
<td>0.6%</td>
<td>9.4%</td>
</tr>
<tr>
<td>High E+S High AC</td>
<td>5.8%</td>
<td>2.4%</td>
<td>2.9%</td>
<td>1.5%</td>
<td>3.5%</td>
<td>1.3%</td>
<td>0.0%</td>
<td>0.0%</td>
<td>3.3%</td>
</tr>
<tr>
<td>Mid E+S Low AC</td>
<td>4.3%</td>
<td>9.4%</td>
<td>19.0%</td>
<td>11.3%</td>
<td>4.2%</td>
<td>11.8%</td>
<td>21.5%</td>
<td>26.2%</td>
<td>9.4%</td>
</tr>
<tr>
<td>Mid E+S Mid AC</td>
<td>15.2%</td>
<td>13.4%</td>
<td>7.0%</td>
<td>15.6%</td>
<td>15.4%</td>
<td>12.5%</td>
<td>14.1%</td>
<td>15.3%</td>
<td>14.0%</td>
</tr>
<tr>
<td>Mid E+S High AC</td>
<td>15.6%</td>
<td>8.1%</td>
<td>3.0%</td>
<td>4.3%</td>
<td>6.0%</td>
<td>7.3%</td>
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<td>0.0%</td>
<td>9.6%</td>
</tr>
<tr>
<td>Low E+S Low AC</td>
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<td>3.3%</td>
<td>9.7%</td>
<td>4.7%</td>
<td>7.9%</td>
<td>3.4%</td>
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<td>13.9%</td>
<td>3.5%</td>
</tr>
<tr>
<td>Low E+S Mid AC</td>
<td>6.2%</td>
<td>8.8%</td>
<td>16.9%</td>
<td>12.6%</td>
<td>6.6%</td>
<td>10.4%</td>
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</tr>
<tr>
<td>Low E+S High AC</td>
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<td>13.0%</td>
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<td>12.0%</td>
<td>6.3%</td>
<td>7.6%</td>
<td>19.9%</td>
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</tbody>
</table>

(Underline denotes the figure is significantly higher than overall area average)
Figure 6: Urban transport oil vulnerability classification map of potential oil price impact (exposure plus sensitivity) and adaptive capacity
5. Conclusion

This paper advances previous oil vulnerability research by establishing clear conceptualisations of exposure, sensitivity and adaptive capacity in the context of the role and impacts of oil supply and price fluctuations in transport and land use systems. The new methods use data that are readily available from the census, supplemented with other publicly available datasets. This method, therefore, can be expanded to other Australian cities with ease. Given the conceptual framework, it should also be possible to ‘plug-and-play’ urban data for cities beyond Australia for such analysis as well. Caution, however, needs to be exercised when drawing direct comparisons with other urban jurisdictions.

There is growing evidence of oil vulnerability and transport disadvantage in particular at the outer fringes of Australian metropolitan areas. Despite increased governmental awareness of oil vulnerability in Australia as reflected in recent plans and policy, the effectiveness of these measures on addressing this issue by integrated transport and land use planning remains untested. Further research on the verification of actual transport energy use and cost statistics with oil price could provide empirical evidence of oil vulnerability. Statistical tools such as regression modelling can be used to correlate other census statistics with observed travel behaviour. Recent comments of a ‘peak car travel’ phenomenon and its relation to demographic changes emerged in transport fields, which is marked by delayed licence acquisition of young people (Delbosc and Currie, in press) and the ageing of baby-boom (and car-boom) generation (Newman and Kenworthy, 2011; Zeitler and Buys, 2014). Future studies on oil vulnerability could also include age demographics and statistics of driving licence data to allow cross-comparison of driving behaviour and oil price trends. For a more fine-grained approach, household travel surveys may be used in conjunction with other census statistics to develop models to further interrogate the socio-economic determinants of oil vulnerability. Apart from data-based approaches, qualitative understanding of the perception of urban actors and decision makers can help to shed light on what policy and societal barriers are in place against the measures to better oil-proof our cities.

As a final remark, this research hopes to reignite awareness on oil vulnerability even though oil price pressure has eased due to recent global surplus in oil production. There is still ample room to improve understanding of oil vulnerability and energy transition of cities. The nexus of energy, transport and land use planning remain under researched and warrants further research. Scholarly attention in this nexus is still scant due to data limitations. Future research in this area would help to improve theoretical, conceptual and practical understanding of oil vulnerability. This can help to inform policy of transport in an energy-constrained future while responding to the global climate change challenge at the same time.

References


Queensland Transport and Main Roads Department, 2009. Travel in south-east Queensland.


