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Dynamic public transit accessibility using travel time cubes: Comparing the effects of infrastructure (dis)investments over time

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ABSTRACT

We put forward a new data object called the public transit travel time cube and demonstrate how the cube can be used in the analysis of transit travel time changes over space and time. The travel time cube contains the shortest path transit travel time between sets of origins and destinations in the city, at all times of day. Once computed, a wide range of investigations become readily available to the transit planner or transportation researcher. We conduct three demonstrative analyses using travel time cubes for the Wasatch Front, Utah and the Portland region in Oregon. Our studies investigate how travel times were impacted by service cuts and expansions in the two regions respectively and the impact this had on jobs accessibility. We also use the travel time cube to study the last mile problem, and compute the travel time savings and the stability gained by solving the last mile problem with bicycling. The paper concludes with an expanded discussion on the merits of the travel time cube and outlines four avenues for continued research.

1. Introduction

Accessibility is largely understood as the ease with which people can reach destinations (Hansen, 1959). Cities in which inhabitants are more able to reach appropriately matched jobs, public services, leisure locations, and social contacts, likewise produce opportunities for more rapid economic growth (Banister & Berechman, 2000), and a higher quality of life for its inhabitants (Frank, 2000). In urban areas, public transportation plays a critical role in providing low cost, energy efficient, and socially equitable means of accessibility (Pucher, 2004), yet techniques for measuring the spatiotemporal patterns of transit-based accessibility remain understudied. A large proportion of transit accessibility measures focus on the ease with which people can reach bus stops and train stations, rather than investigating how well the transit service provides access to actual destinations (Mavoa, Witten, McCreanor, & O'sullivan, 2012). Understanding access to destinations necessitates a travel time analysis through the transit network, which can be computationally cumbersome and requires access to digitized pedestrian and transport networks. When performing travel time analyses, it is important to realize that since travel by public transit is subject to the schedule-based fluctuations in the provision of service, incorporating temporal dynamics into our accessibility measures should increase their validity (Farber, Morang, & Widener, 2014).

In this study, we explore the spatiotemporal patterns of public transit accessibility by focussing on schedule-based origin-to-destination (OD) travel times and their fluctuations over the course of the day. Our approach is based on the development and analysis of public transit travel time cubes, a data structure containing the estimated transit-based OD travel time between all locations in a region, at all times of day. In this article, we put forward our technique for creating the travel time cube, the technical procedures we develop to analyze the vast array of computed travel times, and demonstrate the use of travel time cubes in understanding changes in spatiotemporal patterns of accessibility through a series of case studies.

The rest of the paper is organized as follows. First we provide a review of the literature. In the next section, we describe the public transit travel time cube and the techniques used to create and analyze it. Following this, we present three case studies that highlight the use of travel time cubes in the comparison of spatiotemporal patterns of accessibility. Finally, we conclude the paper with a summary of our contributions and ideas for future research.

2. Literature review

Within the transportation planning context, accessibility is understood as the ease or propensity of interaction between people and locations (Hansen, 1959). In this light, the provision of transportation infrastructure and services directly influences accessibility, and a recent turn in transportation planning places accessibility at the forefront of planning objectives (Martens, 2016). Since many reviews of the accessibility literature already exist (Geurs & Van Wee, 2004; Levinson & Krizek, 2005; Páez, Scott, & Morency, 2012; Geurs, De Montis, &

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Reggiani, 2015), in this paper, we focus our review on the literature most salient to the development and use of travel time cubes.

The development of the travel time cube stems from earlier research that brought to light the temporal variability that exists in transit-based access to destinations (Lei & Church, 2010; Lei, Chen, & Goulias, 2012; Polzin, Pendyala, & Navari, 2002) and the investigation of this temporal variability within a variety of applied accessibility studies (Farber et al., 2014; Owen & Levinson, 2015; Legrain, Buliung, & El-geneidy, 2015; Farber, Ritter, & Fu, 2016; Boisjoly & El-geneidy, 2016; Fransen et al., 2015; Xu, Ding, Zhou, & Li, 2015). All of these works use the variation in transit supply to measure accessibility changes over the course of the day. However, the phenomenon of transit travel time variations is by no means the sole domain of accessibility researchers, with many contributions being made in the study of resilience (e.g. Cats & Jenelius, 2014), generalized measures of connectivity which attempt to summarize the travel times and operational characteristics of multiple paths connecting each pair of origins and destinations in a region (e.g. Kaplan, Popoks, Prato, & Ceder, 2014), and the role of travel-time reliability in mode choice (e.g. Bhat & Sardesai, 2006). The travel time cube differs to these approaches most directly by focussing on only the single shortest path connecting origins and destinations at any given time, and by capturing a single characteristic of that path, the overall travel time, rather than a summary of multiple characteristics such as reliability, number of transfers, etc., that are often used when computing connectivity. While limiting the degree of nuance embedded in our measures, the real advantages of our proposed approach are its limited data requirements, the ease of computation, and the relative ease of interpretation and communication of the measurement, the latter being paramount goals of accessibility measures (Geurs & Van Wee, 2004).

The present work builds on the existing literature by bringing into focus a generalized depiction of a data object, the public transit travel time cube, which can be seen as the precursor of analyses of transit travel time dynamics. We wish to highlight the relative ease of computing complex transit travel times using a desktop GIS, free toolboxes, and open data sources adhering to data standards. Combined, this means that the calculation of the travel time cube is fairly straightforward for non-technical academics and transport planners who wish to evaluate temporal aspects of accessibility. We further present three example analyses that demonstrate how computing transit travel time cubes may be of use in a variety of research applications. Additional applications, modifications to what is stored in the cube, or alternatives for how the cube can be created are manifold, and we intend for the formalization of the cube in this article to lead to future research developments and applied case studies in this area.

3. Methods

The public transit travel time cube is a three-dimensional array, $T=[t_{i,j,m}]$, of estimated transit travel times where i and j index locations and m indexes trip departure times. In the case where i and j are traffic analysis zones (TAZs) or census geography units, and m is computed for all minutes of the day, the dimension of the cube is $N\times N\times M$, where N is the number of zones in the region and M is the number of minutes in the day (i.e. 1440). In this particular case, the travel time cube contains the public transit travel time from all origins to all destinations at all times of day, and thus represents the latent structure of public transit connectivity in a region.

In our implementation of the cube, travel times are computed using General Transit Feed Specification (GTFS) data, a pedestrian network file, and the *Add GTFS to Network Dataset* toolbox for *Esri ArcGIS Network Analyst*. A GTFS package is a set of text files consisting of all the information required to reproduce a transit agency's schedule, including the locations of stops and timing of all routes and vehicle trips. Given a set of origins and destinations and a departure time, we use the *Esri OD Cost Matrix* tool to compute the shortest path travel time on the multimodal network (pedestrian plus transit) that includes ingress, egress, waiting, transfer and in-vehicle travel times. The ingress, egress and transfer walking times are computed using a uniform speed of 4.8 km/h along the pedestrian network. The algorithm returns a matrix of origin-destination shortest path travel times which may include "walk-only" routes if walking is faster than using transit. Intra-zonal trips consist of OD pairs with the same centroid, and therefore have a "zero" travel time. Custom *Python* scripts are used to iterate matrix computations over the minutes of the day, and to assign concurrent *OD Cost Matrix* estimations to the available processors on a multiple core server running *Esri ArcGIS* in a *Windows* environment. A full suite of *Python* scripts and documentation are available from the authors upon request. Similar data objects built with tools by *Esri* and other developers have been used elsewhere in the literature to investigate issues of accessibility, social equity, and mode choice (Lei et al., 2012; Farber et al., 2014; Owen & Levinson, 2015; Farber et al., 2016).

This methods section focusses on the specific data sources and analytical steps taken to construct a travel time cube. Many alternative approaches may exist. For example, Owen and Levinson (2015) use an open source software tool to compute travel times in their study of continuous accessibility. Furthermore, while GTFS datasets are available for thousands of regions around the world, it may be desirable to create the travel time cube using alternative sources of information such as real-time vehicle location feeds, 4-step or activity based travel demand models, or other similar transit network assignment models.

Analysis of the travel time cube is achieved through summarizing and visualizing its various cross-sections. For example, holding an origin and a departure time constant, the vector $T_{i,:,m}$ contains the scheduled travel time from origin i to all destinations provided a trip start time, m. Similarly, the vector $T_{:,j,m}$ contains travel times from all origins to a specific destination at a particular time of day. Each of these vectors is suitably visualized by mapping them either at zones of origin or destination. Alternatively, we can hold an OD pair constant and extract a third vector, $T_{i,j,:}$ which can be plotted as the time series of travel times from i to j over the course of the day. Each of these queries can be thought of as a single column or row being extracted from the three dimensional data cube (Fig. 1), and the mapping and plotting of such vectors represents the atomic methods for visualizing the cube. In practice, multiple rows or columns can be summarized before visualization. For example, the mean travel time from an origin to all destinations over the course of the day is a meaningful measure of the accessibility of a place in a transit network, while the standard deviation of the vector $T_{i,j,:}$ describes the amount of variation in travel time between two locations over the course of the day.

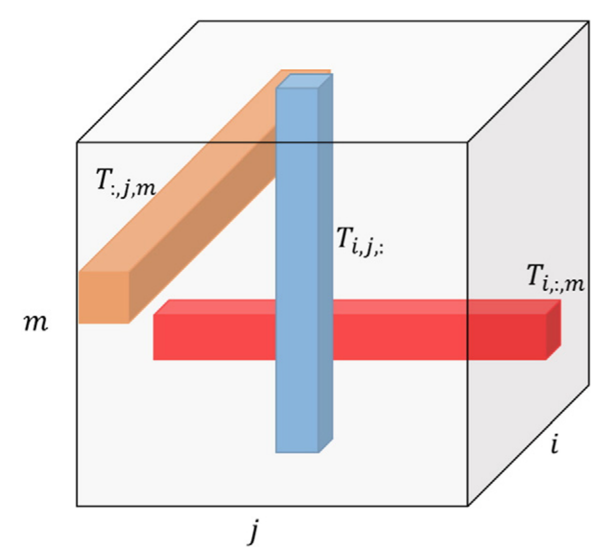
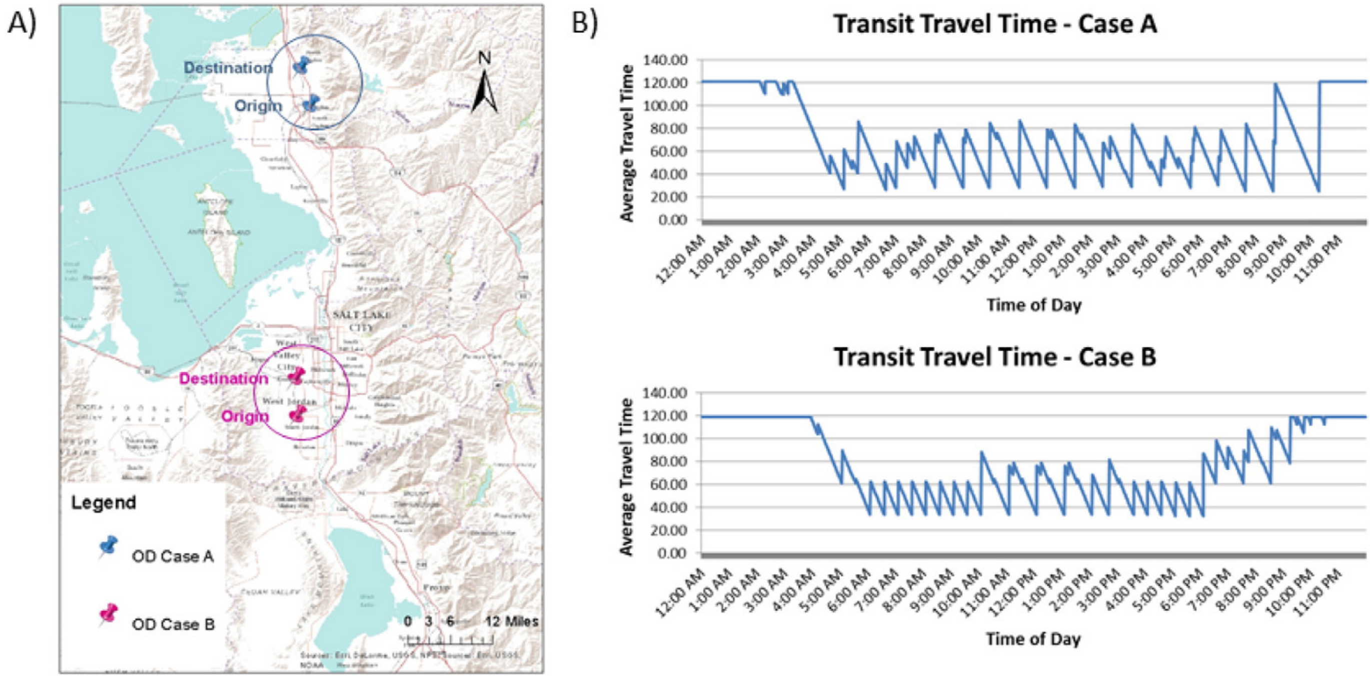


Fig. 1. Illustration of the travel time cube and its atomic vectors. The axes represent origins (i), destinations (j), and minutes of the day (m). Each location in this three dimensional matrix contains a shortest path travel time from i to j at time m.



C)

	Average Travel Time (Mins.)	SD of Travel Time	Dominant Frequency (Mins.)
OD Case A	76.9	30.5	60.0
OD Case B	77.5	30.4	60.0, 30.0

Fig. 2. Using Fourier transforms to discriminate between OD pairs with similar travel time moments but different latent frequencies of connectivity.

While the mean and standard deviation of $T_{i,j,:}$ are useful summary measures of average travel time and travel time variability respectively, they are not sensitive to the periodicity in the time series. This means that OD pairs with vastly different levels of service caused by different vehicle headways may have similar means and standard deviations. Fig. 2 displays such a case. As one can observe, the time series for case A is characterized by hourly service throughout the daytime, while for B it is characterized by 30 min service during peak periods, and hourly service during the middle of the day. Despite these differences, the two time series have similar means and standard deviations of travel time. We introduce a measure based on Fourier Transforms (FT) in order to capture the dominant frequencies latent to the connectivity between each pair of locations in the region. Our method begins by decomposing a time series using the Fast Fourier Transform algorithm (Cooley & Tukey, 1965), which produces a distribution of frequencies that combine to reproduce the actual time series. We identify the mode of the frequency distribution and select all frequencies that appear with at least 75% of the frequency of the mode. This "short-list" of dominant frequencies is used to characterize the regularity of connectivity between locations. Importantly, we cannot use simple headway calculations from the schedule because our OD pairs consist of locations that are connected by multiple routes and routes that are composed of transfers. Using our FT-based measure, the differences in connectivity between the cases seen in Fig. 2 are numerically discernable.

3.1. Case study one: comparison of transit travel times over time

In this case study, we demonstrate how travel time cubes can be used to assess changes in travel times associated with changes to the provision of transit supply including network modifications (e.g. new routes, deletion of routes, and modification of routes) and level-of-service modifications (e.g. operating hours and headways). Such analyses are required to understand relationships between transit supply and mode share (Legrain et al., 2015) or assessing whether social equity objectives are met (Foth, Manaugh, & El-geneidy, 2013). In this case, we conduct a retrospective analysis of travel time cubes for TriMet's services in Portland, Oregon, and UTA's services in the Wasatch Front, Utah. These two cases are selected because of the significant changes made in their networks, with TriMet cutting bus services by approximately 10% to accommodate for budget shortfalls following the Great Recession, and the UTA investing in both light rail (Trax) and commuter rail (FrontRunner) expansions. To conduct this case study, the travel time cubes are computed over a typical weekday's 24 h period in each time period for each city. Population weighted census block group centroids form the spatial units in our travel time cubes. The population-weighted locations better represent, at least in the case of origins, the starting points of trips. This is especially true in the larger zones at the fringe of the study areas, which often include large sections of wilderness and rural lands.

Fig. 3 presents route maps of the two systems at two different time points. These simple visualizations of the transit supply are neither useful in communicating overall changes in supply or the impact of these changes on travel times.[1] As an alternative, the descriptive summary of the GTFS data found in Table 1 quickly informs on the scale and types of changes in supply. It contains a summary of transit supply in each region, at each point in time (2011 to 2014 for UTA and 2009 to 2013 for TriMet), as encapsulated in official GTFS packages shared with us by the transit agencies. Our summary focuses on typical

[1] The authors recognize that more could be done to improve the visualization of the transit networks using a more detailed symbolization scheme.

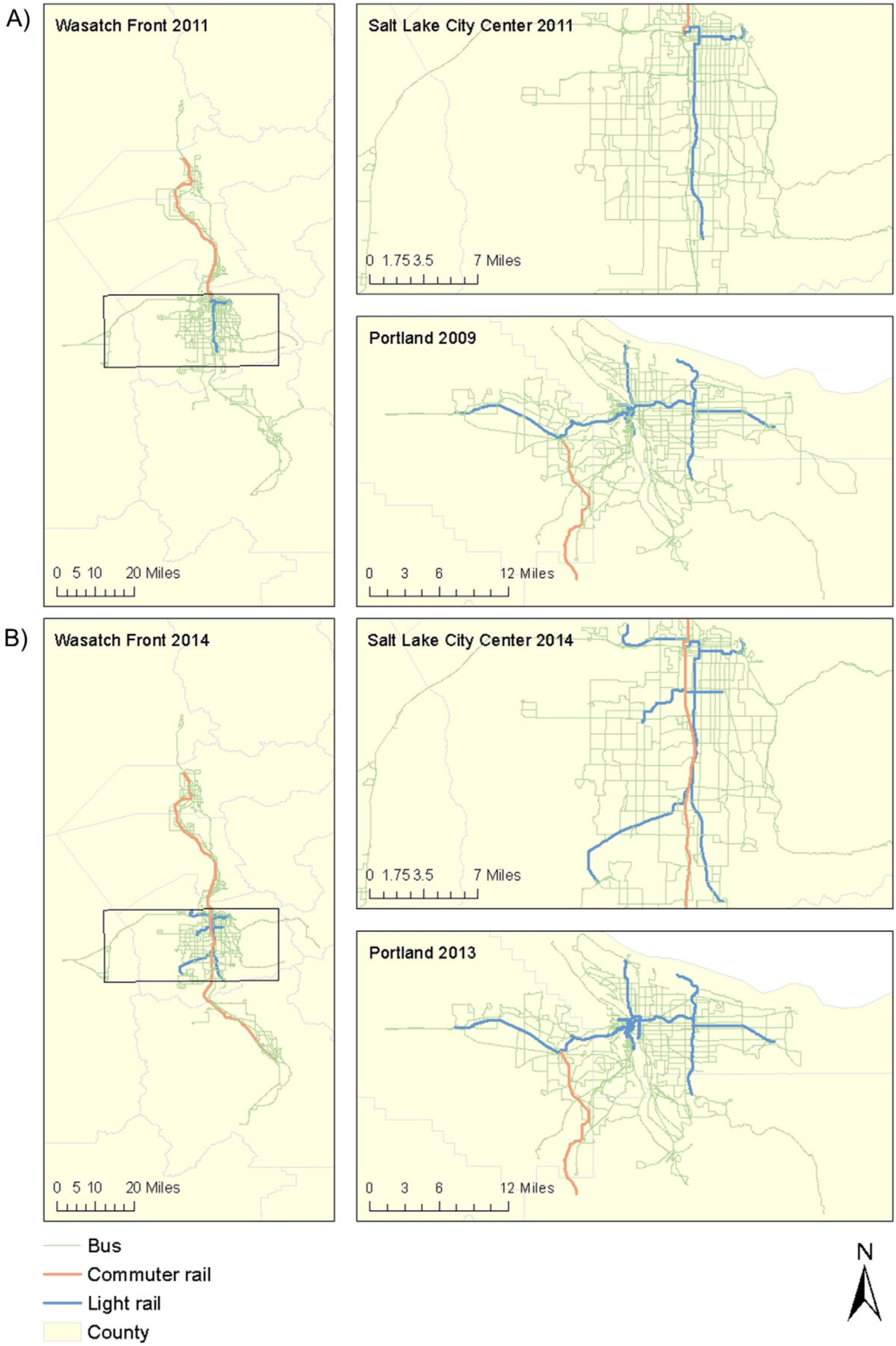


Fig. 3. Cartographic depiction of network changes between A) time period 1 and B) time period 2.

Table 1
Numerical summary of changes in service delivery.

	Wasatch front			TriMet		
	Bus	Light rail	Commuter rail	Bus	Light rail	Commuter rail
Number of stops						
Time 1	6415	31	8	7106	127	5
Time 2	6118	56	16	6732	159	5
Change	−297	25	8	−374	32	0
Percentage change	−5%	81%	100%	−5%	25%	0%
Number of routes						
Time 1	123	3	1	82	6	1
Time 2	114	4	1	79	6	1
Change	−9	1	0	−3	0	0
Percentage change	−7%	33%	0%	−4%	0%	0%
Route kms						
Time 1	4959	68	71	2582	184	25
Time 2	3683	105	144	2572	194	25
Change	−1276	37	73	−10	10	0
Percentage change	−26%	54%	103%	0%	5%	0%
Route kms travelled						
Time 1	96,072	5683	3594	108,921	19,823	750
Time 2	85,497	13,893	7311	97,547	19,975	750
Change	−10,575	8210	3717	−11,374	152	0
Percentage change	−11%	144%	103%	−10%	1%	0%

weekday services, which do contain differences to the Saturday and Sunday levels of service. For UTA, observe that the period is marked by a 144% increase in route-kilometers travelled via light rail (+8210 km) and 103% increase in commuter rail (+3717 km). This was met by an 11% decline (−10,575 km) in bus kilometers travelled. This type of modal trade-off between operational expenditures during times of rail expansion is well documented in the literature (Grengs, 2002), and is subject to criticism for unjustly servicing the needs of rail users (typically higher income and white) at the expense of bus users elsewhere in the city (typically lower income and racialized).

In the TriMet region, bus route-kilometers travelled was reduced by 10% (−11,374 km). At the same time, the increase in other modes is quite small, with no change in commuter rail delivery and only a 152 km increase in light rail. So unlike Salt Lake City, the big cuts to bus services were not compensated by increased capacity on other modes. It should be mentioned that all light rail services offered by the UTA run in dedicated lanes separated from traffic, while those in Portland are streetcars that run in mixed-traffic. So, while we refer to both these systems as light rail, they are actually two different types of services.

While numerical and (to a lesser extent) graphical summaries of transit networks are helpful in understanding the change in service from infrastructure- and operations-oriented points of view, they do very little to convey how these changes have affected travel times or accessibility in the region, arguably the most relevant ways to measure the distribution of benefits provided by the system. We therefore suggest the use of travel time cubes to summarize the impact of the changes on travel times in the region. Fig. 4A displays the most aggregated type of summary measure of travel time cubes, the overall travel time average between all destinations in the region. We display this numerically and aggregated over all times of day:

$$\text{Overall Average Travel Time} = N^{-2}M^{-1}\sum_{i,j,m} T_{i,j,m}$$

and disaggregated over the course of the day as time series plots:

$$\text{Time Dependent Average Travel Time} = N^{-2}\sum_{i,j} T_{i,j,m}, \forall m,$$

for the Wasatch Front (Fig. 4B) and Portland (Fig. 4C). These analyses yield some rather unique results. First, we can observe that the changes in service provision resulted in a 10-min decline in average travel times in the Wasatch Front, and a 3.5-min increase in Portland. Considering that these are averages over all OD pairs and at all times of day, the changes are actually quite large overall. The time series plots reveal that travel times in Utah were the most improved due to extended evening services and increased services during the morning rush. For Portland, the changes in travel times were more evenly distributed by time of day.

To delve deeper into the spatial patterns of travel time changes, we next explore zone-specific aggregations of the travel time cube and present these as maps. In this example, we hold an origin constant to produce the average travel time from that origin to all other destinations in the region, over all times of day:

$$\text{Average Travel Time from an Origin} = (NM)^{-1}\sum_{j,m} T_{i,j,m}, \forall i,$$

and we keep that same zone constant as a destination to compute an average travel time from all origins to a specific zone:

$$\text{Average Travel Time to a Destination} = (NM)^{-1}\sum_{i,m} T_{i,j,m}, \quad \forall j.$$

These quantities can be mapped independently, but to determine how they have changed over the course of the years we map their percentage differences. So, for each location, we compute the percentage change in average travel time to and from that location and present this data in a bivariate choropleth map (Fig. 4D). For the Wasatch Front, we see rather clear spatial patterns of travel time changes. Travel times to/from the southern areas were largely improved by the addition of commuter rail there. However, large swathes of the inner suburbs of Salt Lake City, along the eastern benches of the Wasatch Front and into the West Valley area, experienced increases in travel times, with these neighbourhoods becoming harder to reach. Notably, the only places that became less accessible as an origin and a destination were affluent and touristic communities located within canyons heading east into the Wasatch Front. Transit services to these locations are very limited, and the removal or addition of a single bus trip would have large ramifications on mean daily travel times to and from these locations.

The map of travel time changes in Portland (Fig. 4D) tells a different story. Here, while changes overall are smaller, we do see that many places throughout the region experienced across-the-board travel time increases, or travel time increases from either the origin or destination perspective. The patterns are far less spatially clustered in comparison to the Wasatch Front, indicative of an overall reduction in service across the study area.

In addition to the changes in absolute travel times, we next turn our attention to the exploration of travel time fluctuations over the course of the day, and how changes in transit supply have impacted travel time variability from one time period to the next. To do this, we extract the most typical travel time cycle length for each OD pair using the Fourier Transform method described above. We then compute the mean cycle length for each origin in the region, and map the changes in average cycle length from one time period to the next. Fig. 5A illustrates these changes cartographically. For the Wasatch Front, a clear pattern of improved (i.e. shortened) cycle length is observed along the north/south commuter rail corridors and toward the southwestern expanses of the Trax system. However, several corridors within the city have experienced decreases in service frequency, as seen in the inset map of the city center, in addition to some already inaccessible areas at the southern, western and eastern extremities of the region. These patterns loosely correspond to those found in Fig. 4D, indicating that the changes in travel times are related to changes in service frequencies as well as the addition of new rail services in the region.

A)

Study Area	Average Travel Time (Mins.)	
	Time 1	Time 2
Wasatch Front	204.99	194.94
Portland	114.47	116.19

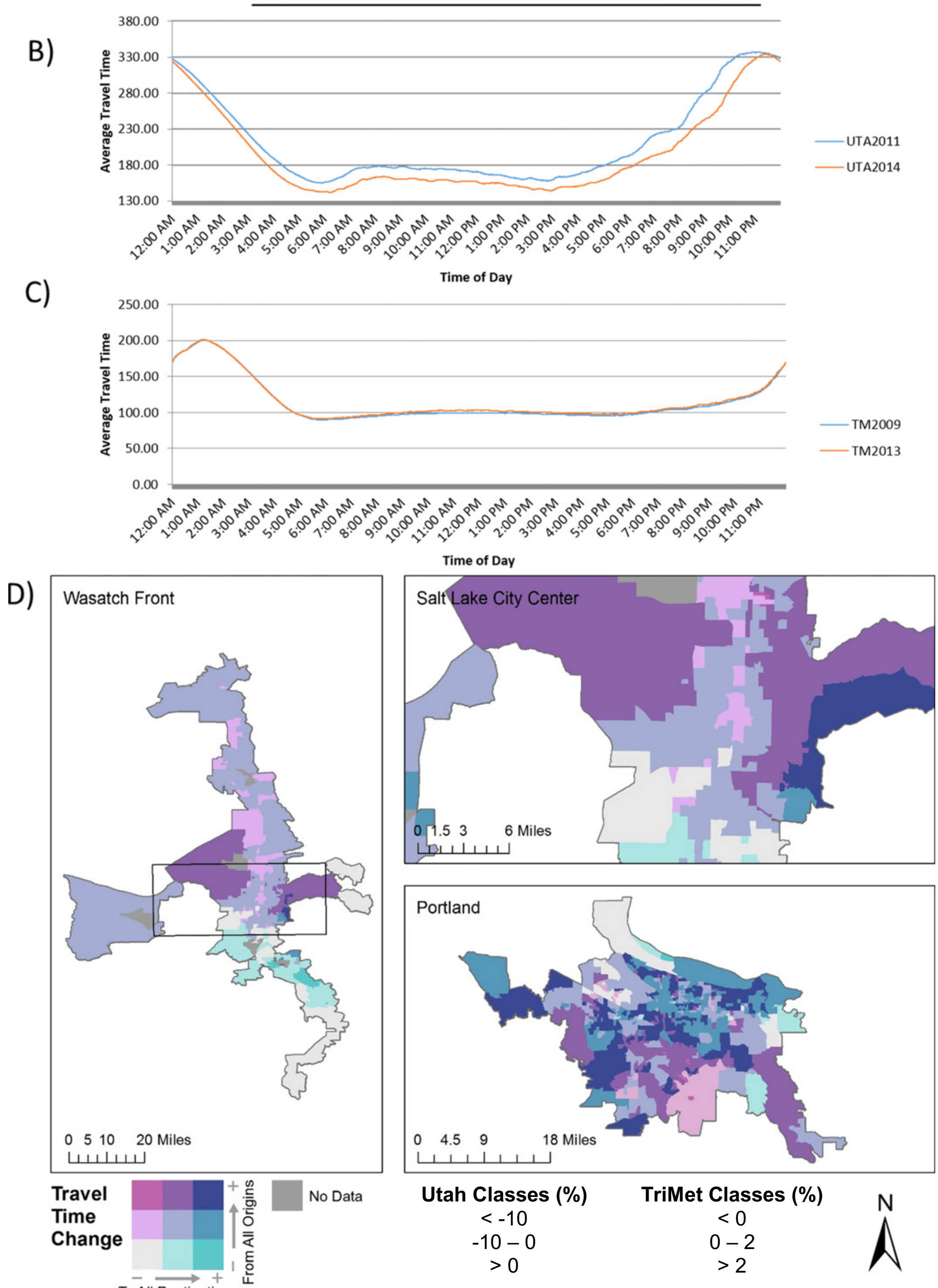


Fig. 4. Depictions of travel time changes, A) numerically, B) by time of day for the Wasatch Front, C) by time of day for Portland, and D) by change in average travel times to and from all zones in the city.

For Portland, the spatial pattern of increased travel time cycles are linear, with several axes corresponding to particular routes that experienced service cuts. On top of this, we do however observe large swathes of the city to the west and south of the center that has experienced decreases in cycle lengths indicating a slight preference for suburban commuting over inner-city service provision.

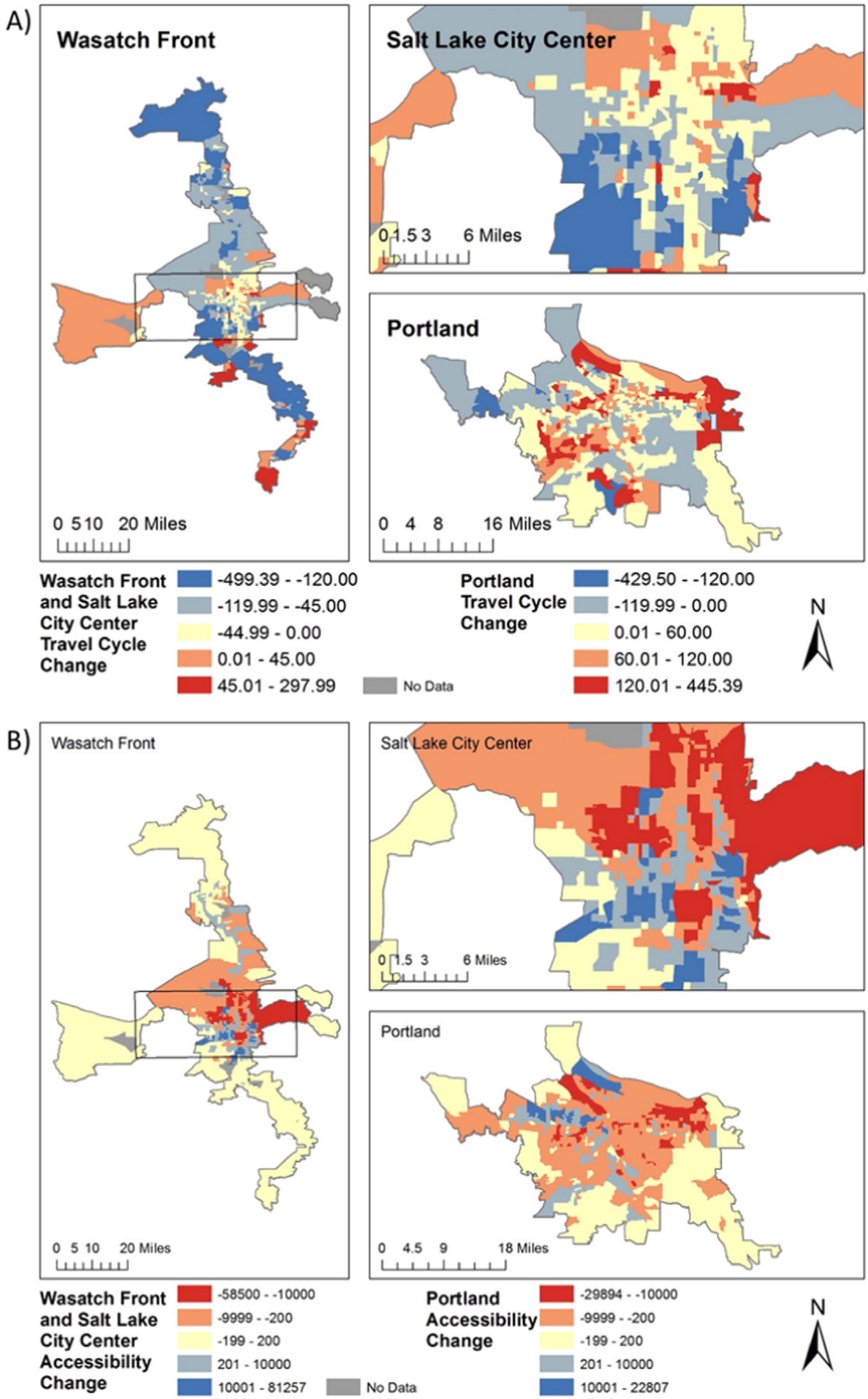


Fig. 5. Change in A) average travel time cycle (minutes) and B) jobs accessibility (number of jobs).

3.2. Case study two: assessing access to jobs using travel time cubes

In this case study, we use the travel time cube to assess how changes in travel times in each region impacted access to jobs. Cumulative opportunities measures of access to jobs are widely used in the literature to assess the distribution of transit benefits in a region (Foth et al., 2013; Páez & Farber, 2012; Sanchez, Shen, & Peng, 2004) and to predict travel behavior (Owen & Levinson, 2015). Employment counts at the block-group level were acquired from the Longitudinal Employer-Household Dynamics (LEHD) Origin-Destination Employment Statistics (LODES) data. A single jobs count file for 2011 was used for both time periods in order to control for accessibility differences caused by transit supply dynamics alone. At the time of analysis, this was the most recent vintage of the dataset available to the public. The LODES dataset has been used extensively over the past few years in accessibility research (Horner & Schleith, 2012; Owen & Levinson, 2015), and the paper by Spear (2011) provides a thoughtful overview of the pros and cons of its use in many aspects of transport planning in the United States, with the major issues including the absence of military jobs and potential miscoding of job locations for multiple-location employers.

Our accessibility score is computed as a cumulative opportunities measure within a 60-min transit travel time buffer. This single threshold is selected for the sake of demonstration, while a more thorough analysis of accessibility using travel time cubes should always compare multiple thresholds depending on the normative values in the study region or specific population focus (Páez et al., 2012; Farber et al., 2014). For each block group centroid, we calculate the total number of jobs within a 60-min journey at each minute of the rush-hour period (7 am–9 am), and then compute an average accessibility score for each zone by averaging over the 120 min. This score is more sensitive to variabilities in accessibility that are introduced by fluctuations in travel times, something that is not captured in single-point-of-time estimates of accessibility, but which may be very large, depending on the level of transit service. To be precise, the accessibility measure for zone i is computed as:

$$A_i = M^{-1}\sum_{j,m} f(T_{i,j,m})E_j$$

where E_j is the count of employment in zone j, $f(T_{i,j,m}) = \begin{cases} 1 \text{ if } T_{i,j,m} \leq 60 \\ 0 \text{ Otherwise} \end{cases}$, and all other terms are defined as above. Fig. 5B illustrates the changes in jobs accessibility between the two time periods. Accessibility was clearly impacted by the changes in transit service provision, with the population weighted mean number of jobs accessible dropping from 35,694 to 33,243 in the Wasatch Front, and 23,410 to 21,666 in Portland. These figures are quite disturbing, considering the supposed increase in transit service provision by the UTA. The spatial patterns indicate that the expansion of commuter rail did little to improve the jobs accessibility in Utah County (toward the south) using the threshold of 60 min. At the same time, the removal of bus services in the center of the city had a clear negative impact on jobs accessibility throughout much of the city. The locations that experienced increases in jobs access are within very close proximity of the various light rail Trax expansions in the region. Combined, this indicates that the short-term effect of transit expansion on jobs accessibility puts light rail ahead of commuter rail.

3.3. Case study three: the effects of bicycle use on the last mile problem

The "last mile problem" in public transportation planning concerns the distance between the transit network and actual trip endpoints that are often too long to effectively accommodate by walking. Bicycle use is suggested as a potential solution to this issue due to its low cost and faster speed of travel (Shaheen, Guzman, & Zhang, 2010; Liu, Jia, & Cheng, 2012). Yet, there is little previous work that attempts to evaluate the impact of joint bicycle and transit use on reducing travel times and increasing travel time reliability. Travel time cubes are well positioned in the use of evaluating the latter, as they contain the full-day time-series of travel times from origins to destinations. In this case study, we compare travel time patterns using two travel time cubes. The first, as previously defined, assumes a 4.8 km/h walk speed for ingress, egress, and transferring. The second assumes a 15 km/h bicycling speed for ingress, egress and transferring. In addition, due to increased boarding and alighting delays associated with travelling on transit with a bicycle, we double these delays from 15 to 30 s. Descriptive statistics of the travel time cubes are compared between scenarios in an attempt to quantify the times-savings and increased stability associated with combining bicycle use with public transit.

Upon initial investigation of the results, we discovered that the major benefits associated with travel using the bicycle accrued to those with trip endpoints (i.e. origins or destinations) at great distances from transit stops. Finding this a somewhat banal example, we focussed our analysis on the particular case of reaching destinations in downtown Salt Lake City by assuming a starting point at Salt Lake Central Station, where commuter rail, light rail, and major bus routes have termini. In this way, we can evaluate how bicycle use helps arriving passengers in the central city reach their final destinations, which may require lengthy walks, and/or long waiting and in-vehicle travel times in the case of transfers.

Before delving into the downtown focus, we discuss the aggregate results pertaining to the two study areas found in Fig. 6. First, we observe that cycling results in a 37% reduction in mean travel times throughout the 24-h period in Salt Lake City, and a 41% reduction in Portland. Moreover, stability in travel times is increased via the introduction of the bicycle, with a 46% reduction in standard deviation found in Portland, and a 39% reduction in Salt Lake City. The improvements in travel times tend to be consistent over the course of the day (as seen in Fig. 6**A**), with slightly larger effects starting in the evening and lasting until the middle of the night. This is presumably due to the decreased transit service at night, and therefore a large increase in travel speed using bicycle compared to trips composed of more walking and waiting. From a spatial perspective, the travel time savings are clearly most attributed to more peripheral origins, where long walking ingress times are most significantly reduced by faster bicycle speeds (Fig. 6**C**). Interestingly, the impact of bicycling on travel time stability (Fig. 6**D**) is found to have a donut shape, with higher impacts in the city center, followed by lower impacts in the inner suburbs, and then again higher in the outer periphery. The fact that stability is enhanced for trips in the center of the city indicates that the bicycle may truly be of benefit to the last mile problem there.

Next we discuss the results pertaining to passengers arriving downtown at the intermodal hub, Salt Lake City Central Station. The set of destinations for these analyses are limited to those found in Fig. 7, representing an area bounded by major municipal, land use and transportation barriers. This region comprises 9% of the region's population and 18% of its jobs. As seen in the figure, when replacing walking with cycling, travel from the intermodal hub to the rest of the study area is greatly improved. This is indicated by a 32% reduction in travel times within the morning rush hour (i.e. 7 am–9 am) and 47% reduction in standard deviation of travel time. The spatial patterns of travel time and variation improvements are quite similar, with increasing benefits accruing to farther away destinations. From the perspective of travel time reductions (Fig. 7A), we see that the concentric pattern of improvements is modified by the transit network, where areas of sparser network coverage receive additional benefit from bicycle use. The same is true for travel time stability (Fig. 7B). In both cases, travel to the west is more improved than the east, reflective of the relative share of transit routes travelling east versus west from the intermodal hub.

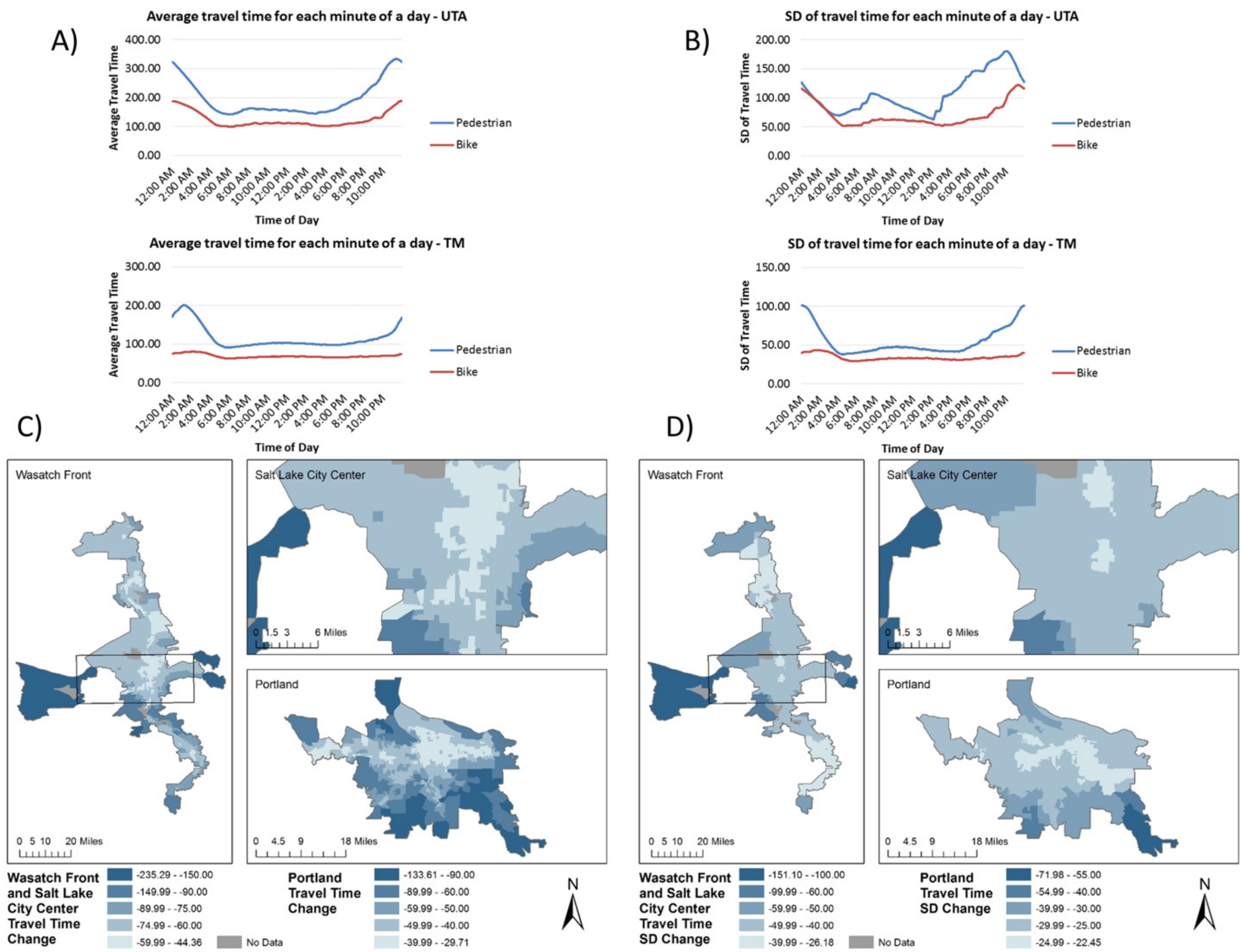


Fig. 6. A comparison of transit travel times joint with walking versus cycling. Average travel times are depicted in (A) and (C), while standard deviations of travel times are depicted in (B) and (D).

4. Discussion and conclusions

In this paper we put forward a new data object called the public transit travel time cube and demonstrated its use in three case studies that evaluate how different types of changes to the public transit network impact a variety of travel time characteristics in a region. The novelty of this approach does not come from the travel time computations themselves, but rather the exhaustive precomputation of all possible travel times in the region, at all times of day. With advances in the abilities of commercial geographic information systems to compute transit-based travel times, coupled with the prevalence of cloud computing and off-the-shelf multiple core desktop computers, computing, storing and analyzing travel time cubes is only now a truly feasible endeavor. Through a series of case studies, this paper shows how travel time cubes can unlock new ways to describe spatiotemporal patterns of travel times, use these travel times in the development of more sophisticated measures of accessibility, and help quantify the impact of accommodating joint bicycle and transit trips.

Going forward, we foresee many directions for continued research on travel time cubes. First, from a technological perspective, we are in need of a custom-designed visualization tool for rapid and interactive exploration of the travel time cube. Second, algorithmically, faster computation of travel time cubes would allow for more detailed comparisons of transit planning scenarios. We currently compute an OD cost matrix for every minute of the day, without any interaction between computations. It is likely that knowing the cost matrix for minute m will be useful in the computation of the cost matrix at minute $m+1$, yet our algorithms do not exploit these structural dependencies. Interestingly, this dependence turns out to be very useful in the compression of data cubes for storage, as each OD time series can be losslessly stored as a series of coordinate plots with linear splines, but we are not exploiting this serial dependence in the cube's computation. Third, the travel time cube only stores a single characteristic of public transit travel, overall travel time along a single shortest path, yet other characteristics of each trip in the cube, such as the number of connections required, the availability of multiple routes, or a disaggregation of travel times by walking, waiting, and in-vehicle times, have been shown to be very useful in analyses for systems planning (Ceder, 2015), accessibility (Kaplan et al., 2014), route choice modelling (Kaplan & Prato, 2012), and social equity (Welch & Mishra, 2013; Kaplan et al., 2014; Monzón, Ortega, & López, 2013). This would require a shift from the current GIS-based algorithms for computing travel times, to more specialized algorithms that can retrieve and store multiple characteristics of multiple paths in addition to travel time, essentially requiring an additional cube for each characteristic, or a single summary cube, bringing the concept very much in line with Kaplan et al.'s (2014) measures of connectivity. It is clear that more nuanced measures of travel times and levels of service are necessary future developments of the travel cube concept if it is to become more useful in the modelling of route choices, a technique that is inherently extremely sensitive to the characteristics of

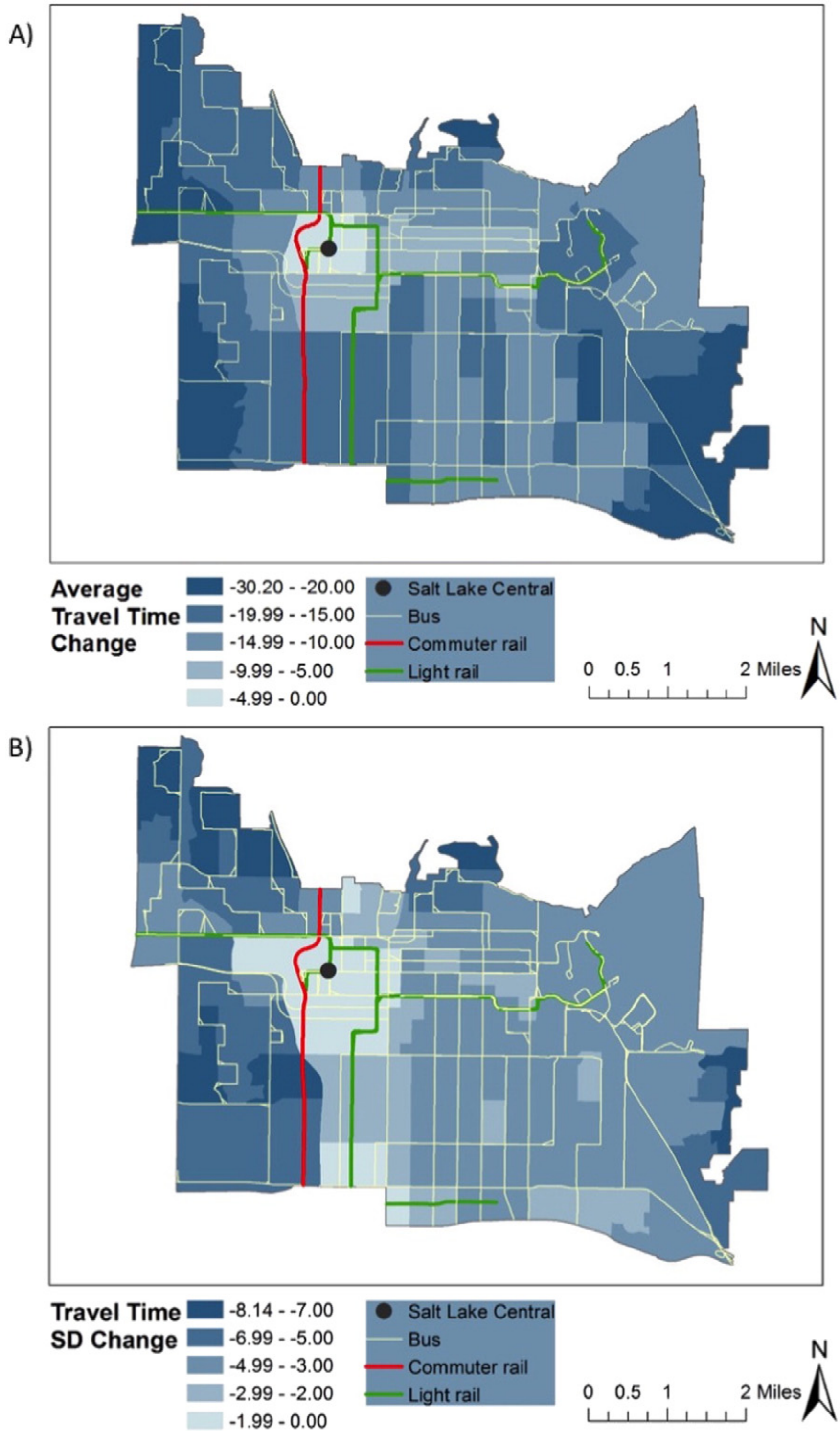


Fig. 7. Transit travel time improvements in the center of Salt Lake City associated with bicycle use.

connectivity that are currently left out of the travel time cube specification (Nielsen, 2000; Eluru, Chakour, & El-geneidy, 2012; Anderson, Nielsen, & Prato, 2014).

The aim of this paper was to introduce the reader to the vast potential of the development and analysis of public transit travel time cubes, but these demonstrations were not exhaustive. Elsewhere, travel time cubes have already been shown to be effective in broadening the investigation of food deserts into the temporal domain (Farber et al., 2014), understanding spatiotemporal mismatch between transit demand and supply from a social equity perspective (Farber et al., 2016), and proving that temporal variation in transit-based jobs accessibility impacts ones' mode choice decision (Owen & Levinson, 2015). The latter case is especially useful in pointing to future research in which travel time variability is more broadly used to identify markets of untapped potential transit riders, an objective shared by many transit agencies worldwide. Moving forward, we see great potential in the continued generalization of the cube, especially in regards to what is stored within the cube (e.g. disaggregate travel times, timing of multiple routes, etc.), the data that is used to calculate the cube (e.g. real-time vehicle and smartphone location feeds), and the large variety of applications in transit planning and accessibility modelling that may benefit from extensions into the temporal domain.

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