Exploiting COVID-19 related traffic changes to evaluate flow dependency of an FCD-defined congestion measure

Megan M Bruwer and Simen J Andersen
Stellenbosch University, Stellenbosch, South Africa

Abstract
Traffic congestion poses a significant problem in urban areas globally, and yet no measure of congestion is universally applied. Various studies have evaluated congestion measures, however, none have identified and demonstrated a best-practice congestion metric that can compare congestion between road segments, networks, and city zones. Furthermore, no studies have proven the link between a congestion metric and traffic flow, despite suggestion by Lomax et al. in their seminal 1997 Quantifying Congestion report that an appropriate congestion metric should vary predictably according to flow. This paper aims to address these gaps in traffic congestion literature. Various congestion measures are evaluated according to standard criteria. Although this process has been followed before, this paper adds a unique criterion that requires congestion to be quantifiable from commercial floating car data (FCD), due to its extensive availability and relative affordability. The most appropriate congestion measure is evaluated to be the speed reduction index (SRI). The application of the SRI to describe spatiotemporal congestion patterns and flow dependency is then demonstrated in a case-study analysis in South Africa. This analysis exploited traffic impacts of the COVID-19 pandemic in 2020 (particularly, the stepwise increase from severely reduced traffic flows as lockdown levels eased), to evaluate SRI. The wide range of flows enabled an unprecedented regression analysis comparing congestion level and flow. The results of the regression analysis are highly significant ($p < 0.001$) indicating that SRI-based congestion measurement tracks flow variation. This study further identified that unidirectional congestion, quantified by the SRI, is impacted by high bi-directional flow along arterials. These findings confirm the appropriateness of the SRI quantified from commercial FCD to measure congestion.

Keywords
congestion, floating car data, speed reduction index, COVID-19 traffic impact, urban traffic

Introduction
Traffic congestion is one of the major issues facing urban areas, resulting in constrained economic growth, increased fuel use, and higher emissions (Barthelemy, 2016; Rao and Rao, 2012).

Corresponding author:
Megan M Bruwer, Stellenbosch University, Private Bag X1, Matieland, Stellenbosch, Western Cape 7602, South Africa.
Email: mbruwer@sun.ac.za
Interestingly, while the term “congestion” is widely used to describe poor mobility, there is no universally applied numerical engineering measure describing congestion despite numerous studies that evaluate congestion measures (Aftabuzzaman, 2007; He, et al., 2016; Rao and Rao, 2012). Aftabuzzaman (2007) and Rao and Rao (2012) conducted extensive literature reviews on various congestion measures, however, neither demonstrated the application of congestion measures to evaluate their efficacy, nor did either study recommend a single suitable congestion measure. Afrin and Yodo (2020) expanded on these literature reviews by testing numerous congestion measures in a case study analysis of the temporal variation of congestion. They compared the ability of each measure to identify the correct peak congestion period as a way of evaluating their applicability, but also did not suggest which congestion measure is most applicable for universal application. The seminal work of Lomax et al. (1997) evaluated numerous congestion measures according to a set of criteria that have been widely used in later literature to evaluate congestion metrics. Their detailed report suggested that time-based congestion measures (such as travel time and speed), and measures that evaluated congestion according to an acceptable traffic state condition, are the most appropriate to define congestion. Unfortunately, at the time that their report was published, speed and travel time were difficult to measure, and their proposed congestion measurement methods relied on complex surrogate procedures to estimate average speed (Lomax, et al., 1997), limiting their widespread adoption.

Speed data measurement is no longer an obstacle due to a relatively new georeferenced trajectory based Big Data source called floating car data (FCD) (Barthelemy, 2016; Behnisch, et al., 2019; Li, et al., 2018) that allows transport practitioners to analyze speeds and traffic operations. Traditional traffic data collection methods that use roadside sensors are often laborious and expensive, limiting distribution of data collection points. Conversely, FCD is collected over the entire road network by consumer-owned smart phones and navigation devices, using existing communications (Lovisari, et al., 2016) and requiring no road-side infrastructure. Commercial FCD providers such as TomTom, HERE and INRIX collect, clean, analyze, and disseminate readily usable FCD (Foreman, 2012; TomTom, 2011). Numerous studies have proven the efficacy of commercial FCD to evaluate traffic trends (Adu-Gyamfi, et al., 2015; Altintasi, et al., 2019; Hu, et al., 2016; Verendel and Yeh, 2019). The event of FCD strengthens the argument for speed and travel time-based congestion measurement.

The criteria that Lomax et al. (1997) put forward to evaluate congestion measures included a suggestion that congestion measures should be flow dependent, meaning that the measure would reflect a predictable change in congestion according to changes in traffic flow. This would allow congestion measures to predict changes to congestion based on forecasted traffic growth. As far as the authors can discern, this criterion for congestion measurement has never been tested in literature. Lomax et al. (1997) identified the supposed independence of speed-based congestion measures from flow as their only disadvantage, and this paper sets out to prove that a speed-based congestion measure is, in fact, flow dependent. This paper therefore aims, first, to confirm if a speed-based congestion measure is the most appropriate congestion metric through literature review, and second, to establish if a speed-based congestion measure can evaluate spatiotemporal congestion patterns and is significantly related to traffic flow, indicating flow dependency.

This research question is answered according to the following approach: A literature review compares the benefits and shortcomings of various congestion evaluation methods. In addition to the criteria identified by Lomax et al. (1997) to evaluate successful congestion measures, this research requires that congestion be quantified using only commercial FCD obtained from third-party suppliers to ensure the wide applicability of the congestion measure. The most appropriate congestion measure is then selected and examined within a testbed environment in Stellenbosch, South Africa, to demonstrate that the measure can be used to evaluate both spatial and temporal congestion variation on an arterial road network. Finally, the mechanism of congestion growth
according to flow for unidirectional and bidirectional travel on an arterial road is investigated through regression analysis, comparing flow and congestion level.

Analysis of the flow dependency of congestion was made possible by exploiting the peculiar traffic conditions that were observed in 2020 due to the COVID-19 pandemic which resulted in a wide range of traffic flows. The South African government implemented a stepwise lockdown approach to reduce the spread of the SARS-CoV-2 virus, with the most severe movement restrictions placed on the population early in the pandemic and easing over the course of 2020. Traffic flows increased as lockdown levels progressed to less severe stages, allowing previously impractical comparison of congestion intensities at numerous traffic levels.

Quantifying congestion

Congestion occurs when travel demand exceeds the capacity of a transport facility (Medley and Demetsky, 2003) resulting in low speeds (Rao and Rao, 2012). Congestion is widely accepted to describe the state of traffic which is intolerable to travelers associated with an unacceptable decrease in speed or increased travel time (Lomax, et al., 1997). Congestion appears when speed reduction is noticed by drivers, typically coinciding with a 30–40% reduction in free-flow speed (Lomax, et al., 1997). Free-flow speed exists when there are so few vehicles on the road that speed selection is not influenced by other vehicles, typically in off-peak periods. Congestion can either be recurring or non-recurring and can occur at an isolated point or over an entire road network (Medley and Demetsky, 2003). Recurring congestion occurs regularly and predictably when demand exceeds capacity, for example, during morning and afternoon weekday peaks. Non-recurring congestion is caused by a particular incident, such as an accident or temporary road closure that reduces roadway capacity, or by an event causing an irregular increase in travel demand.

Numerous studies have considered methods to numerically describe congestion according to several traffic state variables. Aftabuzzaman (2007) and Rao and Rao (2012) grouped congestion measures according to four traffic state metrics, namely: speed, travel time, delay, and level of service (LOS) linked with flow. The application of these traffic state metrics to describe congestion are presented below.

Speed

High traffic flow increases vehicle density, requiring drivers to reduce speed to accommodate shorter following distances (Garber and Hoel, 2015). Operating speed can therefore be used to evaluate congestion. Numerous road authorities use an absolute measure of speed to define congestion: the Korea Highway Corporation registers a freeway as congested if speed falls below 30 km/h and the California Department of Transport define a freeway congested when average speed is less than 35 mile/h for 15 min or more (Rao and Rao, 2012). More complex methods of using speed to observe congestion include scale and ratio measures. Scale ratings quantify congestion according to a hierarchy of speed classes. Pattara-atikom, et al. (2006) classified congestion on main roads in Bangkok, Thailand according to three levels: red (< 7 km/h), yellow (7–13 km/h) and green (> 13 km/h).

The speed reduction index (SRI) defined by Lomax, et al. (1997) is a ratio measure that describes the relative change in operating speed ($u$) from free-flow speed ($u_{FFS}$). The SRI, calculated according to equation (1), results in a continuous scale from 0 to 10, with 0 indicating free-flow conditions and increasing values designating higher levels of congestion up to 10, which indicates traffic breakdown (speed = 0 km/h). Congestion occurs when the SRI exceeds 4, corresponding to a 40% reduction in speed from free-flow, the point at which road users become aware of congestion (Afrin and Yodo, 2020; Lomax, et al., 1997)
The Speed Performance Index (SPI), another speed ratio measure, compares average operating speed to maximum possible speed according to equation (2) (Afrin and Yodo, 2020; He, et al., 2016). The SPI is reported according to a continuous scale from 0 to 100, with lower ranges indicating heavy congestion. Mild congestion ranges between an SPI of 25 and 50 and heavy congestion between 0 and 25 (Afrin and Yodo, 2020).

\[
SPI = \left( \frac{v_{avg}}{v_{max}} \right) \times 100
\]  

(2)

There are numerous advantages of using speed to measure congestion. Speed is inherently understood by road users as a measure of mobility. Operating speed can be assessed against free-flow speed to quantify a magnitude of congestion (Lomax, et al., 1997). Various operational measures, such as lost time, vehicle operating cost, fuel use, and emissions are directly related to speed and speed data can be collected for a particular road segment, a route or on an area wide basis (Rao and Rao, 2012) allowing local and area-based measurement of congestion. Finally, periods of reduced speed can be observed, allowing the temporal extent of congestion to be examined.

**Travel time and delay**

Travel time increases with traffic flow. Delay is the difference between actual travel time and the travel time that would be achieved along the same route during free-flow conditions (Garber and Hoel, 2015). Congestion is observed when travel time exceeds that which is acceptable under light traffic conditions (Lomax, et al., 1997). Using an absolute travel time measure of congestion, a USA study determined that perceived unacceptable congestion resulted in 10% of commuters taking longer than 60 min to reach their workplace (Rao and Rao, 2012). Travel time can also be used to calculate ratios to quantify congestion, similarly to speed. The Congestion Index (CI) compares actual travel time to free-flow travel time, according to equation (3) (Afrin and Yoda, 2020; Aftabuzzaman, 2007; Hamad and Kikuchi, 2002). A CI approaching 0 indicates free-flow traffic. A CI greater than two indicates very congested flow (Hamad and Kikuchi, 2002), corresponding to a travel time three times higher than for free-flow. Theoretically, CI has no upper limit.

\[
CI = \frac{(travel\ time) - (free\ flow\ travel\ time)}{(free\ flow\ travel\ time)} = \frac{delay}{free\ flow\ travel\ time}
\]  

(3)

Various other travel time ratios are also used to define congestion. The Travel Rate (TR) (Equation (4)) is the rate at which a road segment is traversed in minutes per kilometer (Lomax, et al., 1997). TR is used to define Delay Rate (DR), which compares actual TR to “acceptable TR” (Equation (5)). Standard acceptable TRs are dependent on road classification and area type (Aftabuzzaman, 2007), limiting the applicability of DR on road classes and areas where standard values have not been defined.

\[
TR = \frac{\text{travel time (min)}}{\text{segment length (km)}} = \frac{60}{\text{speed (km/h)}}
\]  

(4)

\[
DR = Actual\ TR - Acceptable\ TR
\]  

(5)
LOS and traffic flow

The Highway Capacity Manual 2010 (HCM2010) classifies traffic state according to LOS, a stepwise scale from A to F (Transportation Research Board, 2010). LOS A denotes free-flow conditions, worsening to LOS E, when roadway capacity is reached. LOS F identifies oversaturated traffic. LOS is defined according to various traffic state parameters depending on road and traffic control type. Road segment LOS is determined according to average speed for urban streets and traffic density for multi-lane highways and freeways. LOS at intersections is calculated from control delay per vehicle. The methods to calculate LOS are therefore different for each road and intersection type and readers are referred to the HCM2010 for calculation methodologies.

HCM2010 LOS is closely linked with the v/c ratio of flow (or volume – v) to capacity (c) (Afrin and Yodo, 2020). Congestion occurs when the v/c ratio exceeds 1.00, defined as LOS F (Transportation Research Board, 2010). Other sources indicate the congestion threshold to correspond to a v/c ratio of 0.77 (Aftabuzzaman, 2007). Although the v/c ratio is widely used to describe congestion levels, a recent case study determined that the v/c ratio consistently failed to identify the most congested period detected by all other congestion measures (Afrin and Yodo, 2020).

Appraisal of congestion measures

Lomax, et al. (1997) proposed a set of attributes that contribute to a successful congestion measure. These attributes have become the standard evaluation criteria for congestion metrics and have been widely used and adapted in literature (Afrin and Yodo, 2020; Aftabuzzaman, 2007; Rao and Rao, 2012). For this paper, four attributes, derived from the standard set, have been selected to appraise and compare congestion measures: 1) the congestion measure should enable spatial comparison of congestion on various road classes and geographical areas; 2) it should reflect road network quality of service; 3) the measure should be understandable to transport practitioners and general road users; and 4) the congestion measure should be computable from commercial FCD.

The fourth criterion is adapted from the requirement that data to calculate a congestion measure should be easily and inexpensively collected (Lomax, et al., 1997). Commercial FCD readily meets these requirements as FCD can be obtained from third-party traffic data providers in a readily usable format; consequently, no data collection instrumentation or raw data manipulation are required to analyze congestion. Commercial FCD have been widely used for numerous traffic studies. Adu-Gyamfi, et al. (2015) determined that historical FCD obtained from a commercial data provider were able to reliably identify recurrent daily congestion trends. Two commercial FCD suppliers, INRIX and TomTom, generate city-wide congestion ratings, ranking congestion according to delay to monitor annual change in regional congestion (Barthelemy, 2016; Cohn and Kools, 2014; Reed and Kidd, 2019). Verendel and Yeh (2019) used HERE FCD from 45 cities to analyze variation of traffic trends over different urban areas. Altintasi, et al. (2019) determined that commercial FCD could be used for long-term monitoring of urban traffic to observe average speed and evaluate recurrent and non-recurrent congestion. Hu, et al. (2016) found that commercial FCD are useful for traffic trend analysis and performance measurement along arterial networks. Like Adu-Gyamfi et al. (2015), Hu et al. (2016) determined that FCD are better suited to describe aggregated, long-term traffic trends than real-time traffic observations.

Appraisal of the congestion measures introduced in the previous section are presented by grouping the measures into three categories, namely: 1) absolute and scale measures, 2) ratio and index measures, and 3) flow-based measures.


**Absolute and scale measures**

Absolute measures of congestion (total delay and actual speed) and scale ratings such as the segmented speed hierarchy proposed by Pattara-atikom, et al. (2006) are described by the numeric value of average speed or travel time, which are readily reported by FCD. Absolute measures and scale ratings do not allow comparison between different facilities and geographic areas (Aftabuzzaman, 2007) because acceptable speed, travel time and delay vary significantly depending on the size of the city, road class and time of day (Barthelemy, 2016). For the same reason, absolute values are not able to report the traffic state quality of service, while scale ratings overcome this limitation by relating service quality to boundary values of absolute speeds. Both absolute and scale measures provide a description of local congestion conditions easily understood by road users because speed and travel time are commonly encountered measures of mobility.

**Ratio and index measures**

TR (and by extension DR) is a ratio of travel time to segment length which is the inverse of speed. Similar to absolute measures, TR and DR vary according to road class design standards, are not applicable for wider spatial comparison and cannot describe the quality of road network service. Speed inverse is an abstract concept and not readily understood by all road users. TR can be calculated directly from FCD, while DR requires the additional definition of “acceptable TR.”

A ratio of either speed or travel time to free-flow conditions (such as the SRI, SPI, and CI) allows the comparison of congestion between different transport facilities and in different areas because ratios relate operating and free-flow speeds as a unit-less congestion index. These indices have been applied to a single road segment, a route comprising multiple segments, a network of routes and even an entire urban area (Afrin and Yodo, 2020; Cohn and Kools, 2014; He, et al., 2016; Rao and Rao, 2012; Reed and Kidd, 2019). The SRI, SPI, and CI also reflect the quality of traffic flow because boundary values have been defined that denote uncongested, congested and very congested traffic conditions. Congestion occurs when speed drops below 60% of free-flow speed (Lomax, et al., 1997) corresponding to a SRI of 4, CI of 0.67, and SPI of 60. Very congested conditions (SRI > 6.7, CI > 2 and SPI < 33) occur when speeds are less than one third of free-flow speed (Hamad and Kikuchi, 2002). All three ratio measures can be calculated using FCD as primary input.

The continuous SRI scale from 0 to 10 makes the SRI particularly understandable, describing quality of the service in evenly distinguished levels, and allowing both duration and intensity of congestion to be described (Lomax, et al., 1997). Similarly, SPI uses a continuous scale of equidistant levels from 100 to 0; however, high SPIs indicate low congestion, which can be confusing. The increments between CI values are not consistent with exponential increase in CI at high congestion levels. CI is therefore not sensitive to travel time changes during uncongested and mildly congested flow and can result in congestion being underestimated. In very congested situations, CI increases rapidly, tending to infinity as speed decreases to zero. Refer to Supplementary Figure S1, in the Supplementary Material, for a comparison of the SRI, SPI and CI as a function of speed.

**Traffic flow related measures**

LOS and v/c measures are only applicable to discrete road segments because the capacity of each segment depends on roadway geometry and traffic control. LOS and v/c therefore cannot be used to describe the congestion of a corridor or geographic area, but the standard segmentation of traffic operational conditions does allow comparison between zones and traffic facilitates and describes...
quality of service. LOS is easily understood by non-technical road users due to the stepwise scale; however, most LOS categories fall into uncongested flow, making it difficult to describe congestion variation (Lomax, et al., 1997).

LOS parameters and v/c are calculated from flow (Transportation Research Board, 2010), excluding LOS and v/c from the definition of a successful congestion measure used in this paper. Flow measures are particularly problematic when estimating congestion because traffic counts indicate flow throughput over a particular period, not actual traffic demand. Throughput can create the impression of adequate operation, while in fact long queues may be forming if throughput, constrained to capacity, cannot serve actual demand. Additionally, the capacity of urban road segments is influenced strongly by traffic progression at intersections which can lead to over-estimated segment capacity close to intersections.

**Appraisal summary**

Table 1 summarizes the congestion measures discussed in the literature review according to their ability to meet the four criteria used in this paper to describe successful congestion measures. Only the SRI meets all four criteria. Ratio measures allow the comparison of congestion on different roads and zones. The network service quality is portrayed by the SRI according to a linear scale and is therefore easy to understand. Lastly the SRI is based on speed and is therefore quantifiable using only FCD.

**Methodology**

The literature review established that a speed-based congestion measure, the SRI, is the most appropriate congestion metric. A case study analysis was then conducted to establish if the SRI can evaluate spatiotemporal congestion patterns and if the SRI is significantly related to flow. The SRI was used to evaluate spatiotemporal variation of congestion along a route and a geographic area during the first year of the COVID-19 pandemic. The study area, analysis periods, data collection, and methodological framework are described below.

**Table 1. Suitability of congestion measures according to four criteria of success.**

| Congestion measure  | Spatial comparison | Reflect quality of service | Understandable to public | Accessible data (FCD) |
|---------------------|--------------------|---------------------------|--------------------------|-----------------------|
| Absolute and scale measures | Total Delay | × | × | ✓ | ✓ |
| | Actual speed | × | × | ✓ | ✓ |
| | Speed hierarchy | × | ✓ | ✓ | ✓ |
| Ratios and indices | TR | × | × | ✓ | ✓ |
| | DR | × | × | ✓ | × |
| | SRI | ✓ | ✓ | ✓ | ✓ |
| | SPI | ✓ | ✓ | × | ✓ |
| | CI | ✓ | ✓ | × | ✓ |
| Volume measures | LOS | ✓ | ✓ | ✓ | × |
| | v/c | ✓ | ✓ | ✓ | × |
Study area

Stellenbosch is a small city in South Africa, located 40 km east of Cape Town. Stellenbosch is an intense trip attractor due to a bustling business core, resulting in heavy traffic on arterial routes heading into Stellenbosch in the morning and out again in the afternoon. Five arterial roads link Stellenbosch to surrounding areas forming a basic radial configuration (Figure 1). The arterial network merges to form a single north-south arterial road west of the town center. Collector roads extend predominantly in an east-west direction.

This case study considers the congestion analysis of both a route and a zone. A 9.5 km section of the R44 (indicated in Figure 1) was analyzed. The test-route is a dual carriageway, major arterial with two lanes per direction and signalized intersections. The first 3 km of the route is rural, with a speed limit of 100 km/h. The second 3 km is peri-urban, with a speed limit of 80 km/h and long intersection spacings. The last 3.5 km is urban, with short intersection spacings and a 60 km/h speed limit. The zonal congestion analysis covers the road network within the area highlighted in Figure 1, extending to the urban edge of Stellenbosch, an area of approximately 65 km². Arterial and urban collector roads were included in the zonal analysis.

Analysis periods

Traffic congestion was investigated in 2020 during the COVID-19 pandemic. In South Africa, lockdown was enforced according to five levels of severity called alert levels (ALs). The strictest
level, AL5, was initiated at the start of the pandemic in March 2020, requiring all but essential
workers to stay at home. Travel was allowed only for essential grocery shopping and medical
reasons. As ALs progressed, more people could return to work, retail facilities opened, and social
trips resumed. Controlling movement according to individual ALs resulted in a stepwise increase in
traffic as the lockdown progressed to less severe restrictions.

Analysis was conducted over six 2-week periods in 2020: pre-lockdown (PL) and five AL
periods (AL5 to AL1), as set out in Table 2. Weekday traffic (Monday to Friday) was studied.
Analysis periods were selected to avoid public holidays and school holiday periods, except during
ALs five and four when all in-person school and non-essential work activities were suspended.

Data collection and analysis
Traffic data aggregated over a long period (such as 2 weeks) indicates typical recurring traffic
patterns with limited influence from non-recurring incidents. Historical FCD were obtained from
TomTom for the test-route and test-zone using the Route Analysis and Area Analysis tools of the
TomTom Move user interface (www.move.tomtom.com). TomTom FCD report harmonic mean
speed and percentile speeds. Traffic flows were obtained from the Western Cape Department of
Transport at a permanent traffic observation station (inductive loops) located on the outskirts of
Stellenbosch along the R44 just south of Annandale Road. The traffic at this count station is
assumed to provide a proxy for traffic patterns along the entire test-route.

The SRI was calculated from FCD reported harmonic mean speed and free-flow speed. The 85th
percentile speed in the off-peak period (between 00:00 and 05:00) was used to approximate free-
flow speed according to the method suggested by the Texas Transport Institute (Aftabuzzaman,
2007). FCD were aggregated for each hour of the day over each 2-week analysis period, except
during the off-peak period when data were aggregated over 5 hours (00:00 to 05:00). Off-peak FCD
were aggregated over a longer period to improve accuracy because of the low number of vehicles
and FCD reporting probes during this time. Data were analyzed using Microsoft Excel and ArcGIS.

Methodological framework
Figure 2 summarizes the methodological framework. The SRI analysis was conducted according to
three approaches, namely: route-based SRI analysis, zonal-based SRI analysis and regression
analysis. The route-based SRI analysis considered spatial and temporal SRI comparison separately.
For spatial evaluation, the SRI was calculated per discrete segment along the test-route in the
northbound direction. Temporal patterns of congestion fluctuation were analyzed from the SRI
calculated for the entire test-route in the northbound direction for each hour over the six analysis
periods. Zonal-based SRI analysis considered the spatial and temporal variation in the SRI
simultaneously.

Table 2. Analysis periods.

| Level | AL interval | Analysis period        |
|-------|-------------|------------------------|
| PL    |             | 10–21 February 2020    |
| AL5   | 27/03–30/04/2020 | 14–24 April 2020       |
| AL4   | 01/05–31/05/2020 | 11–22 May 2020         |
| AL3   | 01/06–17/08/2020 | 06–17 July 2020        |
| AL2   | 18/08–20/09/2020 | 07–18 September 2020   |
| AL1   | 21/09–28/12/2020 | 09–20 November 2020    |
The third SRI evaluation approach, regression analysis, was conducted to compare the SRI to flow to determine flow dependency of the SRI. The SRI was evaluated for the entire test-route in both the north- and south-bound directions and compared to flows in the north- and south-bound directions, respectively (unidirectional traffic), as well as to total bidirectional flow. Traffic flows were converted to a ratio of actual flow to maximum hourly flow observed during the PL period to generate a comparative flow ratio for all analysis periods. The statistical significance of the relationship was assessed using t-test hypothesis testing and the data variability assessed by the Coefficient of Determination ($R^2$). As far as the authors could ascertain, no analysis of the relationship between SRI-reported congestion and flow has been detailed in literature.

**SRI analysis results**

*Spatial route-based SRI analysis*

Figure 3 indicates results of the spatial route-based SRI analysis, which considered congestion variation along the test-route in the northbound direction during the morning peak hour over three analysis periods (PL, AL5, and AL1). The vertical dashed lines indicate intersection positions. For concise discussion, intersections are referred to by the numbers ascribed to each vertical line.

During the PL period, the entire route was congested, with the rural (km 0–3) and majority of the urban segments (km 6–9.5) falling within the “highly congested” range. During AL5, the rural and peri-urban section of the test-route were uncongested, while localized congestion still occurred in the urban area. As expected, congestion is higher in AL1 than in AL5 but still below PL levels. The most significant differences in the SRI between ALs occurred along the rural segment, and the least significant along the urban section of the route.

Figure 3 highlights how SRI calculated from FCD can be continuously indicated along a route, enabling description of queue formation, congestion hotspots and bottleneck location. The SRI consistently increases upstream of intersections and the length of the congested zone is an indication of queue length over which speeds are significantly reduced compared to off-peak speeds. For example, the queue that formed during PL at Intersection 2 extended upstream by 3 km. In AL5 and AL1, this queue was localized to Intersection 2. A bottleneck can be identified as a location that has high congestion upstream and lower congestion downstream. Intersection 11 can clearly be identified as a significant bottleneck downstream of which congestion falls sharply during all analysis periods.

*Temporal route-based SRI analysis*

Temporal route-based SRI comparison assesses congestion variation over different timeframes. Figure 4 describes the SRI calculated from the average speed along the entire route in the

![Figure 2. Methodological framework.](image-url)
northbound direction for each hour of the day in all analysis periods. Pre-Lockdown, the entire route could be classified as “congested” between 06:00 and 19:00. The morning and afternoon peak hours during which the entire route was classified as “highly congested” (SRI > 6.7), are clearly visible.

The test-route was uncongested during all hours in AL5. A stepwise increase in congestion over subsequent ALs is clear from Figure 4. During AL4 to AL1 the route became congested between 07:00 and 18:00. Temporal comparison of the SRI during AL5, AL4, and AL3 suggests that typical peak hour congestion was absent in early ALs. Congestion peaks in the morning and afternoon
became more pronounced in the least strict ALs as typical work-day traffic patterns re-emerged; however, they never reached PL levels. Uncharacteristically high midday SRI values were observed during AL1, likely caused by roadworks along the test-route. Work was suspended during the peak periods to reduce traffic impact.

**Spatiotemporal zonal-based SRI analysis**

Zonal based congestion was analyzed on arterial and collector roads within the urban edge of Stellenbosch. Figure 5 presents the SRI during the morning peak hour (07:00 to 08:00) during three analysis periods: PL, AL5, and AL1. The SRI is presented according to a color scale from green indicating free-flow conditions, to red indicating high congestion. The direction of flow with the highest congestion is shown for all routes.

Pre-Lockdown, most of the radial arterial network was congested. Specifically, arterials south, west, and north-west of Stellenbosch exhibited high SRIs for many kilometers leading into the urban center. Collector roads, particularly in the north-south direction within the town center, also exhibited high congestion. There was a drastic reduction in congestion at the start of the pandemic (AL5). Congestion was limited to a few discrete road segments in the direct vicinity of significant intersections. Arterials leading into Stellenbosch were free flowing. As lockdown regulations eased, congestion increased.

Zonal-based congestion analysis at various periods demonstrates the usefulness of the FCD-based SRI to evaluate spatial and temporal congestion patterns simultaneously. Spatially, the geographical extent of congestion is highlighted and congestion hotspots are clearly visible. The COVID-19 pandemic created unique temporal traffic variation, which is clearly identified by the SRI over the analysis periods.

**Relationship between SRI and flow**

The flow dependency of the SRI was assessed by linear regression, depicted in Figure 6. Four regression analyses were conducted. The SRIs calculated in the northbound direction were compared to the unidirectional traffic in the same direction, and to bidirectional traffic (graphs a and c, respectively). Similarly, relationships were determined for the southbound direction and depicted in graphs b and d. According to t-test results, the relationship between the SRI and flow ratio are highly significant in all four instances ($p < 0.001$), indicating that the SRI exhibits flow dependency. As expected, high SRI values occur at high flows.

Investigation of flow—SRI data for individual analysis periods highlights the impact of the COVID-19 pandemic on congestion and flow. The maximum hourly flow during AL5 is less than 20% of the maximum PL flow. Traffic flows increase in each subsequent AL. By AL1, the maximum hourly flow reached nearly 90% of the maximum PL flow. The SRI also clearly increases in consecutive ALs.

The regression analyses were conducted across all analysis periods simultaneously ($n = 120$). The regression functions are presented in Figure 6 with the corresponding $R^2$ values. The high $R^2$ values are an indication that future congestion levels could be predicted from forecasted traffic flows, which was indicated by Lomax, et al. (1997) to be a highly desirable attribute of congestion measures, and one which has not been met in subsequent literature before this study.

The $R^2$ values indicated on each graph in Figure 6 suggest that variability between the SRI and flow is higher when unidirectional traffic is considered. This would indicate that bidirectional flow describes unidirectional SRI better than unidirectional flow. In explanation of this finding, consider specifically the relationship between the SRI and unidirectional flow in the northbound direction (graph a of Figure 6). SRI was higher than would be predicted at flow ratios of around 0.4 in PL and
Figure 5. Spatiotemporal zonal-based SRI variation in Stellenbosch.
Figure 6. SRI compared to uni- and bi-directional traffic flow in the north- and south-bound directions.
AL1. Closer inspection indicated that these data points occurred during the afternoon peak period, when there is high flow in the southbound direction. In graph c of Figure 6, considering total flow, the data points of both PL and AL1 are more evenly distributed along the regression function. The small grouping of data points in AL1 result from the higher than anticipated congestion at midday because of roadworks identified in Figure 4.

The SRI values at flow ratios greater than 0.5 are underestimated according to the regression function in AL2, AL1 and PL. The points that fall well below the regression line reflect traffic conditions in the morning peak. A regression function comparing unidirectional SRI to unidirectional flow therefore overestimates congestion in the peak period when opposing flow is higher, and underestimates congestion in the peak period when flow in the direction of investigation is higher. This is corroborated by analysis of the southbound unidirectional regression relationship (graph b of Figure 6). The discrepancy in SRI estimation is not observed in the bidirectional flow comparison where all data points are considerably nearer to the regression line, indicated by the improved R² values.

The over- and under-estimation of the SRI in peak periods can be attributed to the fact that congestion in one direction is influenced by high traffic flow in the opposite direction, particularly along arterial roads. Signalized traffic control along arterial roads accommodates higher directional flows by increasing green time allocation to the highly trafficked direction in the signal phasing plan. The unanticipatedly high northbound SRI values which occur with relatively low unidirectional northbound flows in the afternoon indicate that northbound afternoon congestion is increased by high southbound traffic. This is an important finding that describes how congestion occurs during peak periods with high flows in one direction. No literature has highlighted this phenomenon, which certainly adds to the theory of congestion propagation.

The highly significant linear relationships and high R² values (R² > 0.88) identified between SRI and bi-directional flow confirms the appropriateness and comprehensibility of the SRI as a measure of congestion: the SRI increases consistently according to incremental traffic growth. This should allow future congestion levels to be estimated from forecast flow, which should be considered in future research.

The findings of the regression analyses have indicated that a speed-based congestion measure calculated from FCD in one direction can assess the impact of high flow in the direction under investigation, as well as in the opposite direction. In other words, unidirectionally determined SRI assessed from FCD can account for the impact of bidirectional traffic. This significant finding demonstrates that unidirectional traffic state is a function of flow in both directions for arterial roads and that this phenomenon can be detected by FCD through a speed-based congestion measure such as the SRI.

Conclusions and recommendations

The objective of this study was to consider appropriate congestion measurement from FCD. Firstly, the study aimed to identify a single congestion measure that best met a standard set of evaluation criteria through literature review. Secondly, the appropriate congestion measure was analyzed in a case study to demonstrate if it can detail spatial and temporal congestion patterns and then establish if the congestion measure is flow dependent to the extent that the measure could be used for future predictions of congestion. Previous literature has indicated that flow dependency of a congestion measure would be beneficial, while no studies have set out to prove if this can be achieved.

The SRI was identified to be the most applicable congestion measure, which was then analyzed in a case-study based in Stellenbosch, South Africa, that considered both a test-route and zone. The case-study clearly demonstrated the usefulness of the FCD-based SRI to evaluate spatial and temporal congestion patterns. Spatially, the SRI was able to identify locations of queue formation, congestion hotspots and bottlenecks because FCD are reported continuously along roads. Temporal
comparison of congestion was uniquely considered in this case-study at various periods of the COVID-19 pandemic response. Changes in geographic extent and level of congestion were clearly discernible from the SRI during different periods in 2020 as traffic increased incrementally with easing lockdown restrictions.

The significantly different traffic flows observed during 2020 allowed SRI values to be compared to a range of flows, enabling unique regression analyses. Uni-directional and bi-directional flows were compared to uni-directional SRI in both the north- and south-bound directions along the test-route. All four regression analyses resulted in a highly significant ($p < 0.0001$) linear relationship between the SRI and flow, proving that the SRI is flow dependent. It was found that unidirectional SRI is better described by bidirectional flow, according to the $R^2$ values. This result is significant because it indicates that congestion level along arterial roads is a function of flow in both directions: high flow in one direction increases congestion in the other direction. It also demonstrates that an FCD-reported, speed-based congestion measure can detect the impact of high flow on congestion in the opposite direction of analysis. As far as the authors can discern, no other studies have statistically compared SRI-based congestion and flow and no studies have proven that unidirectionally assessed congestion is a function of bidirectional flow along arterials.

It is the recommendation of this paper that congestion should be evaluated both spatially and temporally using the SRI calculated from commercial FCD. Further research is suggested to evaluate if future congestion levels could be predicted from forecasted traffic flows according to the significant relationship between SRI and flow identified in this paper.

Acknowledgments
The authors wish to acknowledge TomTom International BV. and The Western Cape Department of Transport, Republic of South Africa, for the kind provision of data used in this research paper in terms of data sharing agreements with Stellenbosch University. The authors would also like to thank the anonymous reviewers for their inputs which have greatly assisted to improve the quality of this paper.

Declaration of conflicting interests
The author(s) declared that there are no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding
The author(s) disclosed receipt of the following financial support for the research, authorship, and/or publication of this article: This research is financially supported by the University Staff Doctoral Programme of the Department of Higher Education and Training of the Republic of South Africa.

ORCID iD
Megan M Bruwer  
https://orcid.org/0000-0002-0337-9314

Supplemental Material
Supplemental material for this article is available online.

References
Adu-Gyamfi YO, Sharma A, Knickerbocker S, et al. (2015) Reliability of probe speed data for detecting congestion trends. In: IEEE 18th International Conference on Intelligent Transport Systems, Las Palmas, Spain, 15–18 September 2015. New York: Institute of Electrical and Electronics Engineers.
Afrin T and Yodo N (2020) A survey of road traffic congestion measures towards a sustainable and resilient transportation system. *Sustainability* 12(11): 4660.

Aftabuzzaman MD (2007) Measuring traffic congestion - A critical review. In: Proceedings of the 30th Australasian Transport Research Forum, Melbourne, Australia, 25–27 September 2007

Altintasi O, Tuydes-Yaman H and Tuncay K (2019) Quality of floating car data (FCD) as a surrogate measure for urban arterial speed. *Canadian Journal of Civil Engineering* 46: 1187–1198.

Barthelemy M (2016) A global take on congestion in urban areas. *Environment and Planning B: Planning and Design* 43(5): 800–804.

Behnisch M, Hecht R, Herold H, et al. (2019) Special issue editorial: urban big data analytics and morphology. *Environment and Planning B: Urban Analytics and City Science* 46(7): 1203–1205.

Cohn N and Kools E (2014) Developing an objective measure of urban congestion across the globe: the TomTom traffic index. In: ITS World Congress, Detroit, USA, 7–11 September 2014.

Foreman K (2012) Magic? How INRIX traffic crowd-sourcing really works. [Online]. Available: inrix.com/blog/magic-how-inrix-traffic-crowd-sourcing-really-works [2021, July 13].

Garber N and Hoel L (2015) *Traffic and Highway Engineering*. 5th ed. Stamford: Cengage Learning.

Hamad K and Kikuchi S (2002) Developing a measure of traffic congestion – fuzzy inference approach. *Transportation Research Record: Journal of the Transportation Research Board* 1802(1): 77–85.

He F, Yan X, Liu Y, et al. (2016) A Traffic congestion assessment method for urban road networks based on speed performance index. *Procedia Engineering* 137: 425–433.

Hu J, Fontaine MD and Ma J (2016) Quality of private sector travel-time data on arterials. *Journal of Transportation Engineering* 142(4): 04016010.

Li M, Ye X, Zhang S, et al. (2018) A framework of comparative urban trajectory analysis. *Environment and Planning B: Urban Analytics and City Science* 45(3): 489–507.

Lomax T, Turner S, Shunk G, et al. (1997) *National Cooperative Highway Research Program Report 398: Quantifying Congestion*. Washington, D.C: Transportation Research Board, Vol. 1.

Lovisari E, Canudas De Wit C and Kibangou A (2016) Density/flow reconstruction via heterogeneous sources and optimal sensor placement in road networks. *Transportation Research Part C: Emerging Technologies* 69: 451–476.

Medley S and Demetsky M (2003) *Development of Congestion Performance Measures Using its Information*. Charlottesville, Virginia: Virginia Transportation Research Council.

Pattara-atikom W, Pongpaibool P and Thajchayapong S (2006) Estimating road traffic congestion using vehicle velocity. In: 6th International Conference on ITS Telecommunications, Chengdu, China, 21–23 June 2006. New York: Institute of Electrical and Electronics Engineers (IEEE), pp. 1001–1004.

Rao AM and Rao KR (2012) Measuring urban traffic congestion – a review. *International Journal for Traffic and Transport Engineering* 2(4): 286–305.

Reed T and Kidd J (2019) *INRIX Global Traffic Scorecard*. Washington: KirklandINRIX Research.

TomTom (2011) *White Paper: Historical Traffic Information*. Amsterdam: TomTom.

Transportation Research Board (2010) *Highway Capacity Manual 2010*. Washington D.C: National Research Council.

Verendel V and Yeh S (2019) Measuring traffic in cities through a large-scale online platform. *Journal of Big Data Analytics in Transportation* 1: 161–173.

**Author biographies**

**Megan Bruwer** is a lecturer of transportation engineering and PhD candidate at the Department of Civil Engineering of Stellenbosch University. After qualifying cum laude as a transportation engineer in 2010, Megan worked as a transport engineering consultant, involved in the implementation and operational design of public transport systems and road based traffic accommodation for new developments. She joined Stellenbosch University as a lecturer in 2015. Her
research interests include the application of Intelligent Transport Systems to improve traffic data collection for transport planning and traffic management, particularly in a developing country context.

Johann Andersen is an Industry Associate Professor in Intelligent Transportation Systems at Stellenbosch University. He teaches ITS principles in both the graduate and undergraduate Civil engineering programs and guides research activities in ITS. In his capacity as CEO of Techso, a specialist consultant company, he has extensive experience in ITS planning, design and implementation in the application areas of Freeway management systems as well as Advanced Public Transportation Systems. Prof Andersen leads the Stellenbosch Smart Mobility Lab, a center for development of innovative and cost-effective solutions in ITS, not only in South Africa but also developing countries.