

Estimating road vehicle speed from high-resolution satellite imagery for environmental applications: A case study of Barcelona

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ABSTRACT

Data on road traffic speeds is needed for air and environmental noise pollution modelling, for regulatory control, exposure assessment and assessing health impacts. However, vehicle speed data is often not available and national speed limits, by road classification, may be used as a proxy instead. This may contribute to uncertainties in model predictions. This study presents novel methods, applied to satellite imagery, to calculate vehicle speed road by road for entire cities, demonstrating their use in Barcelona. The approach exploits the fraction of a second gap between eight multi-spectral sensors onboard the WorldView-2 and -3 satellites and was used to estimate speeds for 128,206 vehicles on motorways, trunk, primary, secondary and tertiary roads from 10 satellite images. The average estimated vehicle speeds ranged from 69 km/h on motorways to 31 km/h on tertiary roads. Satellite-derived vehicle speeds showed good agreement with Directions API speeds on a subset of roads ($R^2 = 0.71$, NMGE = 0.23 and RMSE 13.4 km/h). A Normalised Mean Bias of 0.04 suggests that on average the satellite and Directions API estimates were similar. Using Directions API as the benchmark, satellite-derived estimated speeds yielded values of RMSE of 13.4 km/h, compared with and RMSE of 25.7 km/h using road type national speed limits, for a subset of roads. In this pilot study, therefore, satellite-derived vehicle speeds yield a 48% reduction in error over using the national speed limit by road type. This paper shows that high-resolution satellite imagery has potential to quantify vehicle speed in cities.

1. Introduction

Road traffic speed data is a fundamental data source for a range of different applications including traffic management, urban planning, and environmental noise and air pollution modelling for regulatory support and studying adverse health outcomes via epidemiological studies. Currently, however, there is a lack of information on vehicle speed variability across road networks. Often, traffic data sets are collected at point locations on a subset of roads in a city using systems such as Automatic Number Plate Recognition (ANPR), Automatic Traffic Counters (ATC's) or manual counts. These traditional vehicle-count methods have limited spatial and temporal coverage (Stuparu et al., 2020) and are expensive and time-consuming to collect (Larsen et al., 2013). In some cities, traffic models have been created to estimate vehicle flow which are more spatially detailed, but they tend to be limited to main roads

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(Department for Transport, 2020). In environmental modelling (e.g., air pollution and noise modelling) road speed limits may be used as a proxy for vehicle speed (Faulkner and Murphy, 2022). Another data set which can give some indication of the likely average speed by road type is Google's Directions API. The Directions API predicts the duration of a route between two locations using historical average time-independent traffic conditions (Google, 2022).

Satellite imagery offers a rich, global data resource that is rapidly developing, with data available at increasingly higher spatial and temporal resolution. There are new opportunities to exploit the improvements in the spatial and temporal resolution of satellite imagery to potentially predict traffic flows and speeds in a cost-effective approach that could potentially be applied globally. Currently, multi-spectral satellites such as the WorldView-3 satellites have spatial resolutions of up to 30 cm (Maxar 2024). These recent advances in spatial resolution have greatly improved the capability to identify vehicles in satellite imagery (Mace et al., 2018; Zhihuan et al., 2018; Sheehan et al., 2023) and estimate vehicle speed (Salehi et al., 2012; Marchesi et al., 2012; Bar and Raboy, 2013; Gao et al., 2014).

The multi-spectral (MS) sensors on the WorldView-2 and -3 (WV2/3) satellites are arranged such that there is a fraction of a second gap between each multi-spectral band capture. This results in the potential to detect object movement between the multi-spectral bands and estimate vehicle speed based on the spatial displacement of the detected objects (e.g. a single car) between the bands. There have been several papers attempting to extract the shift in location of moving objects to estimate vehicle speed with varying accuracy (Salehi et al., 2012; Marchesi et al., 2012; Bar and Raboy, 2013; Gao et al., 2014). The basis for these studies was temporal change-detection methods, which differ in technical aspects but follow the same general approach: 1) roads are extracted from the imagery, 2) the vehicle location is extracted, and 3) if a vehicle is determined as moving, the speed is estimated. Variations in the approach include, for example, Easson et al. (2010) who used image differencing to recognise moving vehicles, and Salehi et al. (2012) who used Principal Component Analysis (PCA) to detect the change of a vehicle's location in two MS images from WV2. Other methods include Marchesi et al. (2012) who used the Coastal Blue and Blue bands on WV2 (to create a high spectral contrast between roads and vehicles) and a non-linear edge detection sobel filter and region growing algorithm for image segmentation to extract moving vehicles from the imagery. Bar and Raboy (2013) used a spectral and spatial (SNS) approach to detect moving vehicles in WV2 images. Finally, Gao et al. (2014) suggested an improved SNS method which incorporated a local ERGAS index analysis (ERGAS-SNS) to identify moving vehicles in WV2. The accuracy of these studies to identify moving vehicles in an image scene varied between 68% and 91%. However, none of these methods evaluated the accuracy of the estimated vehicle speeds.

Typically, these studies used small and relatively noise-free images to develop and test methods. For example, these methods were applied to small subset areas of San Francisco, California, USA (Gao et al., 2014), New Brunswick, Canada (Salehi et al., 2012), and Multan, Pakistan (Marchesi et al., 2012), focusing on highways and urban roads which are very open and wide, and are not impacted from shadow from vegetation or buildings. Therefore, it is unknown whether these methods can be applied to imagery covering entire cities, which may contain a lot of noise such as buildings, vegetation and varying lighting conditions such as shadow.

Currently, available speed data such as road speed limits may provide default speed values by road type. An alternative is to derive the speed of a road from the modelled route duration of a directions request from the Directions API. The Directions API is part of the Google Cloud Platform and provides directions, distance and duration information between two locations (Google, 2022). The Directions API predicts the duration of a route using historical average time-independent traffic conditions and can vary over time with updated average traffic conditions (Google, 2024). There has been limited research into the accuracy of Directions API to estimate route durations and the derived road speed estimates. In one study, Wagner et al. (2020) found the Directions API live traffic information route requests had longer durations than real test drive GPS data for one street in Krefeld, Germany, (relative error of 16.5 ± 10 %). The authors suggested that the Directions API provides an average route duration of all driver and vehicle types and includes a buffer to account for traffic lights or a parked car (Wagner et al., 2020).

In this study we investigated the potential of using satellite data to estimate vehicle speed. To do this, we developed a novel method for estimating speed of vehicles on all roads in the city of Barcelona, utilising high-resolution World View 2 and 3 satellite imagery. To test the potential of the method, we compared the performance of satellite-derived vehicle speeds with Google's Directions API data as a benchmark (i.e., dependent variable). Performance of the satellite-derived estimates for vehicle speed was compared to the default of using road speed limits by road type.

2. Materials and methods

2.1. Data description

2.1.1. Satellite imagery

WorldView-2 (WV2) and WorldView-3 (WV3) multi-spectral (MS) and panchromatic (PAN) satellite imagery for Barcelona was used in this study. Both satellites have a daily-sun synchronous orbit, passing over Barcelona at approximately 11 a.m. The WV2 and WV3 satellites have spatial resolutions of up to 0.46 m and 0.31 m for the PAN band and 1.85 m and 1.24 m for the MS bands, respectively. The sensors on the World View (WV) satellites are arranged with two sets of four Multi-Spectral (MS) sensors either side of a Panchromatic (PAN) sensor. The MS1 group consists of Red, Green, Blue and Near-infrared (NIR)-1 sensors, and the MS2 group consists of Red Edge, Yellow, Coastal Blue and (NIR)-2 sensors (Marchesi et al., 2012; Gao et al., 2014). Due to the physical layout of the sensors on the satellite, there is temporal lag between each of the MS band images, equating to a lag of 0.332 s between the furthest apart MS spectral bands (Coastal Blue and Red). The temporal lag between the sensors enables vehicle movement detection, as a vehicle can be identified by the satellite at slightly different times (Salehi et al., 2012; Marchesi et al., 2012; Gao et al., 2014). The WV satellites use a bi-directional configuration of sensors, which collect data using the "push-broom" technique, and have a scan line rate

(which at time of image acquisition indicates the number of lines the charged-coupled device image sensor scans per second) of 20,000 lines per second (Coffer et al., 2022).

In total, ten satellite images collected over the period 2017 to 2019 were used. The images had varying coverage of Barcelona; four images covered the entire city, and six images covered part of the city. In this study for consistency, PAN imagery of 50 cm and MS imagery of 2 m was used for both the satellites. The imagery was pre-processed by Maxar to Level 3, which includes orthorectification with Maxar's finer Digital Elevation Model (DEM) and atmospheric correction. The MS imagery was pansharpened to a spatial resolution of 50 cm using the PCI Geomatics software (version Geomatica, 2018) and the University of New Brunswick pan-sharpening method (Zhang, 2004). The satellite images were split into 1500×1500 pixel tiles, which had an overlap of 20 pixels (10 m) to ensure vehicles present at the edges of the tiles were not cut off.

2.1.2. Vehicle detections

The vehicles in the satellite imagery were detected using the Deep Learning (DL) Object Detection (OD) algorithm 'You Only Look Once' (YOLO) version 3 which had been optimised for use on WorldView imagery (Jocher, 2019). The OD model was trained on 1500×1500 pixel sized Red, Green, Blue (RGB) images, a manually created training data set with a single vehicle class and 9 anchor boxes (i.e., predefined boxes with varying aspect ratios used by the model as a prior during training to help determine the size and location of model detections) specific to the Barcelona vehicle training data set (comparison of other models and model parameters were compared in Sheehan et al. (2023)). The OD model had a precision (i.e., proportion of model detections that are correct) of 0.69, a recall (i.e., proportion of vehicles in the image scene identified by the model) of 0.79 and a F1 score (a performance metric that provides an overall evaluation of a model by combining the precision and recall metrics into a singular value) of 0.74 (Sheehan et al.,

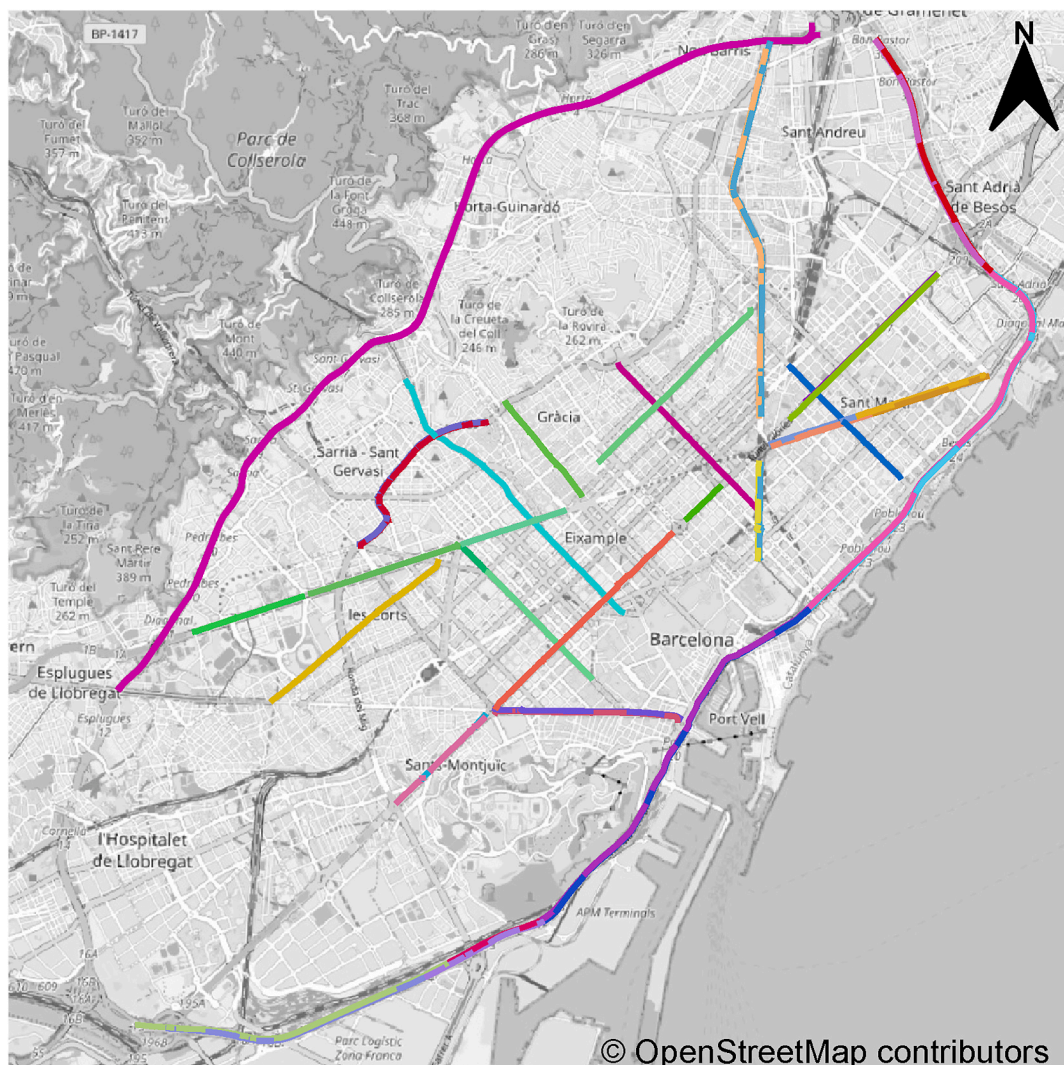


Fig. 1. Directions API routes: the different colours represent the different road request segments.

2023).

The trained OD model was used to detect vehicles in all ten image scenes over Barcelona. Once the vehicle detections were produced, duplicate detections due to overlapping regions between image tiles and within the image tiles where the model identified vehicles which were too physically close together or identified one object as vehicles of different sizes were removed. After removing duplicates, there were 1,030,288 vehicles identified in the ten satellite images across Barcelona.

2.1.3. Open Street Map roads

The vehicles were allocated to a road segment in Open Street Map (OSM), an open-source geographic data set that has been built and updated by a community of mappers ([OpenStreetMap contributors, 2020](#)), using nearest neighbour assignment. A subset of thirteen OSM road types was used for the analysis: trunk, trunk link, motorway, motorway link, primary, primary link, secondary, secondary link, tertiary, tertiary link, service, living street and residential. Trunk roads are a road type which includes important, major roads which are not motorways ([Open Street Maps, 2024](#)). The type of vehicles that can travel on a trunk road is the same as a motorway (e.g. motorcycles, passenger cars, Large Goods Vehicles (LGV's), Heavy Goods Vehicles (HGV's, e.g. lorries and trucks)). The link roads were combined into the main road category resulting in seven road categories (trunk, motorway, primary, secondary, tertiary, service, living street and residential). The OSM road types are used to display the satellite-derived vehicle speed estimates as these different road types enable different flows and speeds of traffic. The OSM road types does not affect the estimation of vehicle speed.

2.1.4. Directions API vehicle speed benchmarking data set

There is no publicly available traffic speed data set covering the city of Barcelona. Therefore, to understand the performance of the satellite-derived vehicle speeds, the Directions API was used. The Directions API data was automatically downloaded from the Google Maps Platform with an HTTP request using the Directions API via an R script ([R Core Team, 2021](#)).

In total, fourteen different roads were sampled, covering different areas of Barcelona city and road types ([Fig. 1](#)). The route requests for each road were split into smaller segments (40 segments) to ensure the Directions API returned data for the required road. Requests for all road segments were sent to the Directions API every hour over seven months (August 2021 until February 2022 inclusive). The median speed of the route requests was calculated and varied from 13.5 km/h for Carrer del Comte d'Urgell to 88.9 km/h for a segment of the Ronda Litoral, and most routes' average speed was less than 30 km/h. Over the sampling period the route speeds varied slightly (5 km/h), however there was little diurnal variation in the route speeds. The final Directions API data set was the median speed of requests from 11 a.m. to represent the satellite image capture time that varied between 10:50 a.m. and 11:05 a.m.

2.1.5. Road speed limits

As vehicle speed data is usually unavailable, road speed limits could be used as a proxy for vehicle speed. In this study, road speed limits (i.e., default approach) by road type were assigned to the OSM roads data set and compared to the Directions API vehicle speed; the aim being to compare the performance of satellite-derived estimates against the default approach. The national speed limits of 80 km/h were assigned to motorways and trunk roads, and 50 km/h was assigned to primary, secondary roads and tertiary roads ([Ajuntament de Barcelona, no date](#)). In Barcelona, single traffic-lane streets have speed limits of 30 km/h, however these road types were not included in the 40 Directions API route requests. The road speed limits were manually checked using street view on [Google Maps \(2020\)](#).

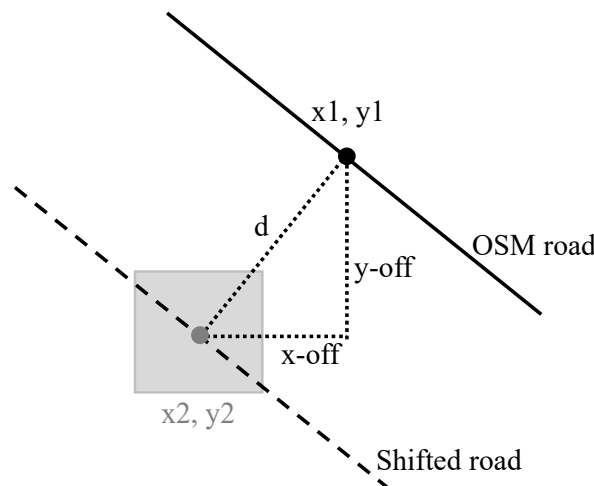


Fig. 2. Concept for shifting the nearest OSM road to the vehicle BBOX centroid where x_1, y_1 is the coordinate of the nearest point on the nearest road to the vehicle BBOX centroid, x_2, y_2 is the vehicle BBOX centroid coordinates.

2.2. Vehicle speed method

The novel method presented here to extract image pixels relating to vehicle movement and estimate vehicle speed can be summarised in three main steps: 1) road lane extraction; 2) pixel value extraction; 3) moving vehicle speed calculation. A method to remove parked vehicles and erroneous detections is detailed, followed by the comparison of the satellite-derived vehicle speeds using the Directions API average road speeds and road speed limits.

2.2.1. Road lane extraction

The search area for pixels relating to vehicle speed was reduced to road lanes, through identifying and shifting the nearest OSM road to a vehicle bounding box (BBOX) centroid (Fig. 2). The 2m resolution MS raster image was clipped first to a 5 m buffer from the vehicle BBOX centroid and second to a 1 m buffer around the shifted road.

2.2.2. Pixel value extraction

The pixel values were extracted for each of the Coastal Blue, Blue, Green, Yellow and Red MS bands at 1 m intervals along the shifted road. The five different bands were investigated to see which combination worked best in estimating vehicle speed for different colour vehicles and vehicles near vegetation, buildings and in shadow. The extracted pixel values for each of the MS bands were normalised using the median pixel value of the spectral band in the clipped image, and the absolute of each value was calculated to remove any negative values. It was important to normalise the pixel values as, firstly, vehicles are different colours and therefore have different pixel intensities, and, secondly, dark vehicles (e.g., black) have lower pixel intensity compared to the road surface. To identify the pixels relating to vehicle movement, the x and y coordinates of the maximum normalised absolute pixel values for each MS band were extracted.

2.2.3. Moving vehicle speed calculation

The vehicle speed was estimated using the distance and the time difference between capture of the spectral bands. The distance travelled was calculated for four different band combinations: Red and Coastal Blue, Green and Coastal Blue, Blue and Coastal Blue, and Blue and Yellow. The sensors on the satellites are arranged with two sets of four Multi-Spectral (MS) sensors either side of a Panchromatic (PAN) sensor. The temporal gaps between each multi-spectral sensor and the PAN band are shown in Table 1 and equates to 0.29 s between the Red and Coastal Blue bands. To calculate the final vehicle speed, the median speed of the four different band combination speeds was calculated.

Fig. 3a shows the example of a white vehicle that has visible peaks in both the Coastal Blue (band 1) and Red (band 5) bands relating to the movement of the vehicle. Fig. 3b shows the example of a black vehicle, where the pixel values highlight that black objects have lower pixel intensities and therefore the need to take the absolute of the normalised pixel value to enable the identification of the pixels relating to the black vehicle movement. Fig. 3c shows three parked vehicles, where the grey central vehicle is the focus of this extraction. The white vehicle parked to the left of the grey vehicle has higher peaks in both the Red (5) and Coastal Blue (1) bands. As this vehicle is also parked, the peaks in the spectral bands are at the same location. This example highlights the difficulties of using different spectral bands to estimate vehicle speed as the red car to the right of the image is represented by a peak in the Red band and a trough in the Blue band. Therefore, if a blue vehicle was present in the clipped image with a peak spectral value in Blue band and trough in the Red band, an erroneous vehicle speed may be given to the vehicle.

The peaks in five different spectral bands were extracted and vehicle speed estimated for the four different band combinations (Red and Coastal Blue, Green and Coastal Blue, Blue and Coastal Blue, and Blue and Yellow). The vehicle was assigned the median vehicle speed of the four band combination vehicle speeds as the different spectral bands are influenced by different objects and noise in the image. For example, the Green band was influenced by vegetation, the Red band influenced by buildings, with all spectral bands influenced by vehicles of the corresponding colour and shadow. Fig. 4 shows an example of the extracted spectral peaks for the five bands on a motorway, a subset of the imagery that is relatively free from noise and interfering features such as buildings, vegetation, and shadow. There is an agreement between the Blue, Green and Red bands, and the Yellow and Coastal Blue bands, however the same

Table 1

Relative timing deltas between World-View 2 and 3 satellite Multispectral and Panchromatic bands for the nominal linerate forward-scan image using the centre-line for each band (Personal correspondence with Digital Globe (now MAXAR) 2020).

Multispectral Band	Time lag (s) from Panchromatic Band
Near Infrared 1	0.152
Red	0.145
Green	0.138
Blue	0.130
PANCHROMATIC BAND	
Red Edge	−0.130
Yellow	−0.138
Coastal Blue	−0.145
Near Infrared 2	−0.152

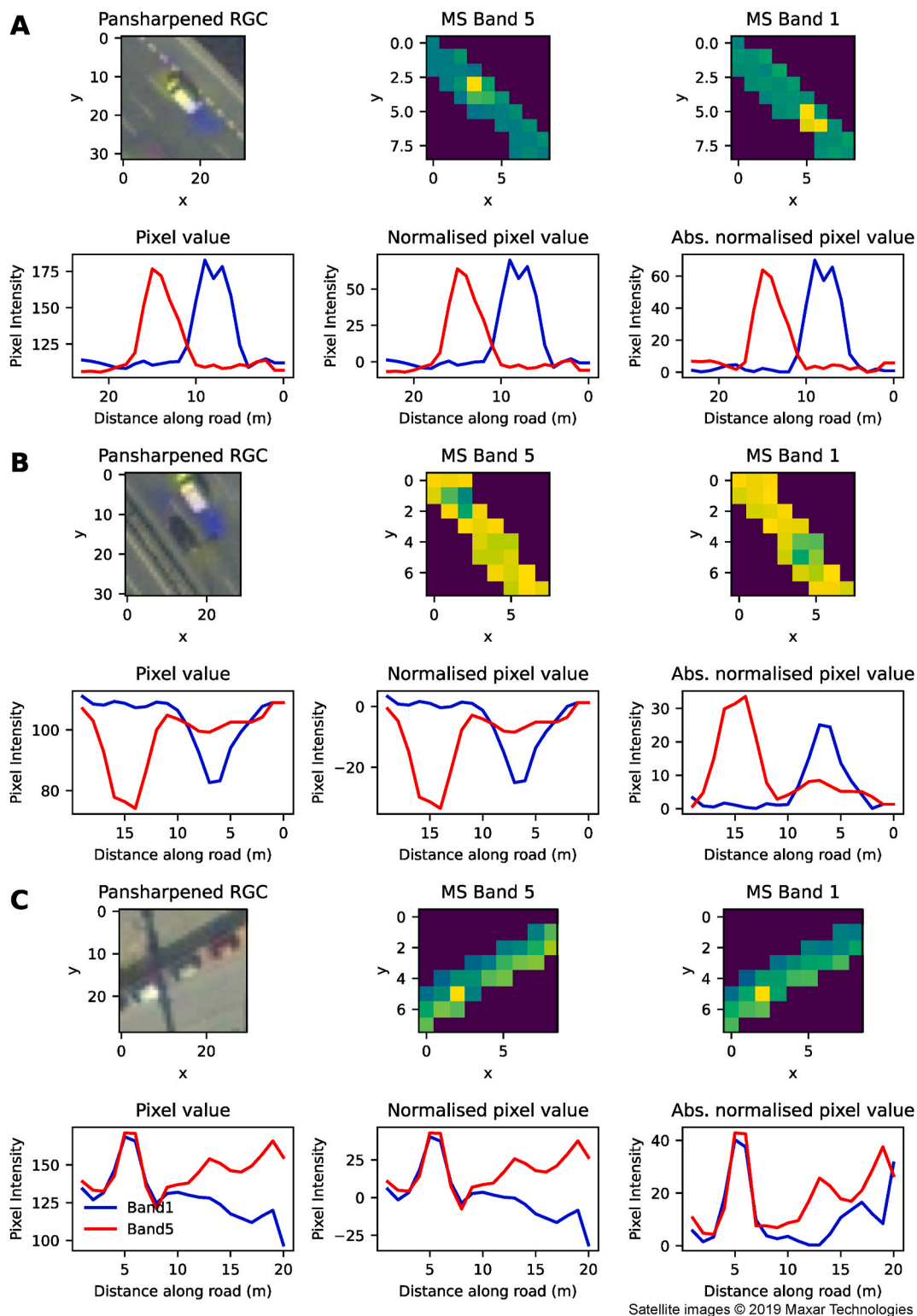


Fig. 3. The spectral pixel values for Coastal Blue (Band 1) and Red (Band 5) bands extracted at 1 m points along the shifted road network string for A) a white vehicle travelling along a motorway, B) a black vehicle travelling along a motorway C) a grey car parked in the middle of three cars. Satellite images © 2019 Maxar Technologies.

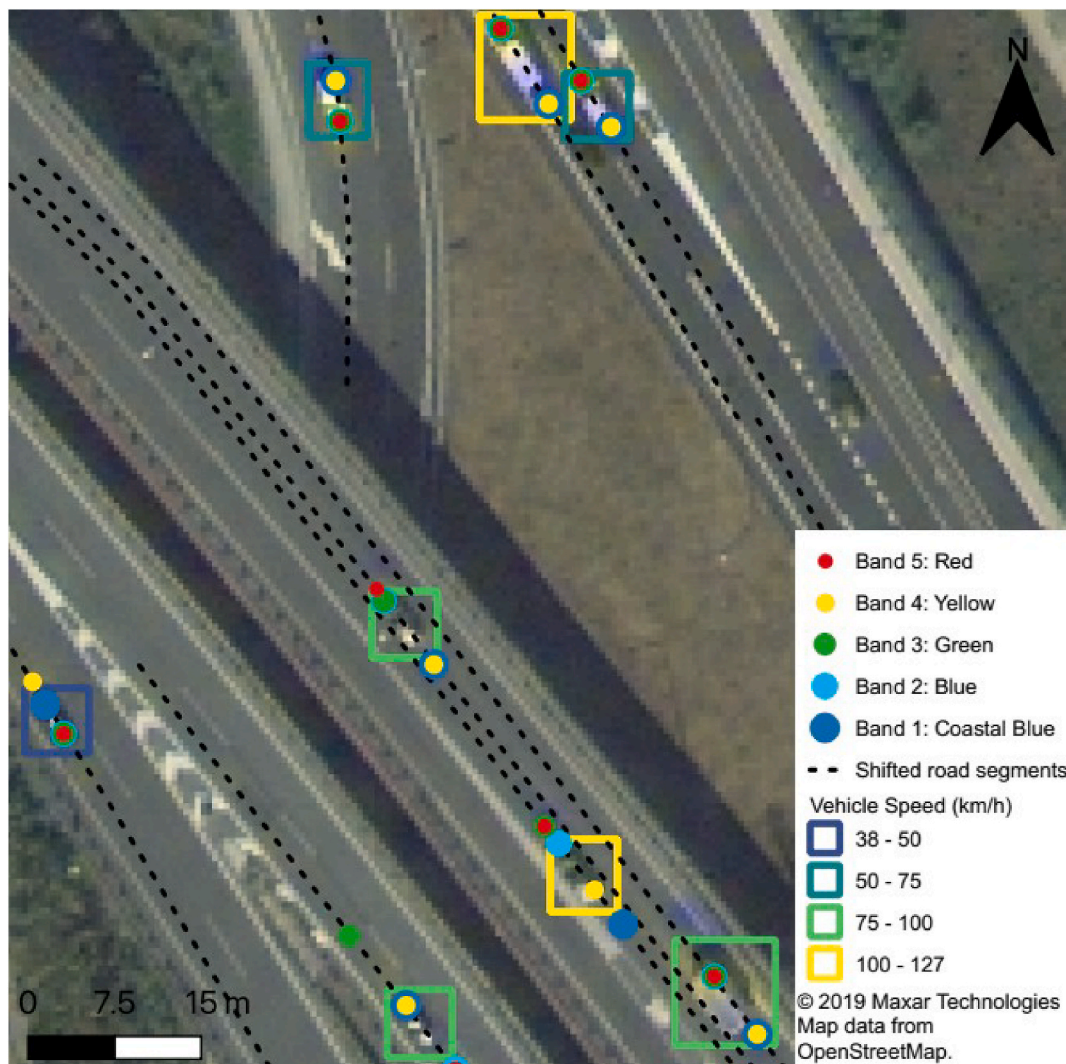


Fig. 4. Locations of the extracted spectral band pixels using the final vehicle speed method (Coastal Blue, Blue, Green, Yellow and Red) and the corresponding estimated vehicle speed (km/h) for vehicles travelling on a motorway.

pixel is not always selected by the different bands. Further examples are shown in Supplementary A.

2.2.4. Removing parked and erroneous vehicle detections

We developed methods to clean the processed data to detect and remove any parked (stationary) vehicles and erroneous vehicle detections. The methods and accuracy of the methods to remove parked and erroneous vehicle detections are provided in **Supplementary B**.

2.3. Evaluating satellite-derived vehicle speed estimates and road speed limits against data from Directions API

The satellite-derived vehicle speeds were evaluated against the Directions API road speeds. To enable comparison, the satellite-derived weighted average median vehicle speed was calculated for each of the 40 road segments in the Directions API data set. This was done by calculating the median speed of vehicles for each road segment in each satellite image, then calculating an average median vehicle speed for all satellite images through weighting the median vehicle speeds for each image by number of vehicles. The satellite-derived weighted average median vehicle speed was joined to the Directions API data set and assessed using Mean Bias (MB), Mean Gross Error (MGE), Normalised Mean Bias (NMB), Normalised Mean Gross Error (NMGE), Coefficient of determination (R^2) and Root Mean Square Error (RMSE). To compare the performance of satellite-derived vehicle speed estimates and road speed limits (i.e. default) from the Barcelona City Council ([Ajuntament de Barcelona, no date](#)), the road speed limits were assigned to each of the 40 road segments to create a data set and assessed using the metrics above.

3. Results

3.1. Vehicle speed

Vehicle speed was estimated for 128,206 moving and static vehicles on motorways, trunk, primary, secondary and tertiary roads in 10 satellite images covering the city of Barcelona. In Fig. 5 (and other examples in Supplementary C) most vehicle detections have speeds of less than 100 km/h, with two erroneous detections on the trunk road with an estimated speed of more than 150 km/h. There are some vehicles leaving the trunk road (left) which have lower speeds (less than 49 km/h) than other vehicles. There are also some detections with speeds of 0 km/h which are likely to be erroneous detections over road markings as there is not a junction in close proximity on the road. On the tertiary road (right), the majority of vehicles are parked, and this is reflected in the speed estimates, however, there are some parked vehicles with erroneous speeds of up to 150 km/h. All the moving vehicles on the tertiary road have realistic speeds of less than 50 km/h.

A box plot of estimated vehicle speed for each road type is shown in Fig. 6, where motorways and trunk roads have the highest median speeds, with average speeds of 69 km/h and 58 km/h respectively. Trunk roads have a broader range of speeds compared to motorways. Primary, secondary and tertiary roads have very similar median speeds with average speeds varying between 31 km/h and 35 km/h. Further, 75% of speeds are below 50 km/h and a large proportion have 0 km/h speeds (primary: 36%, secondary: 40% and tertiary: 43%).

3.2. Vehicle speed method performance

Fig. 7 and Table 2 shows the performance of the satellite-derived median weighted average vehicle speeds compared to the Directions API speed data set for the 40 segments across Barcelona. Overall, there is a good relationship between the satellite and Directions API data sets ($R^2 = 0.71$). The NMB shows that the median speed estimates are over predicted by about 4 %, and the NMGE value of 0.23 shows that there is some scatter and variability in the data set.

Fig. 8 shows the range of Directions API speeds for the 40 road segments and road speed limits. There were 29 road segments with speed limits of 50 km/h and these had Direction's API average speeds ranging from 13.5 to 49.3 km/h, with a mean of 21.6 km/h and RMSE of 29.4 km/h. There were 11 road segments with speed limits of 80 km/h, and these had satellite-derived average speeds ranging from 61.3 to 88.9 km/h, with a mean of 74.5 km/h and RMSE of 10.8 km/h. Overall, compared to the Directions API (benchmark) the road speed limits yielded an RMSE of 25.7 km/h, which is much larger (48%) than the satellite-derived vehicle speed RMSE of 13.4

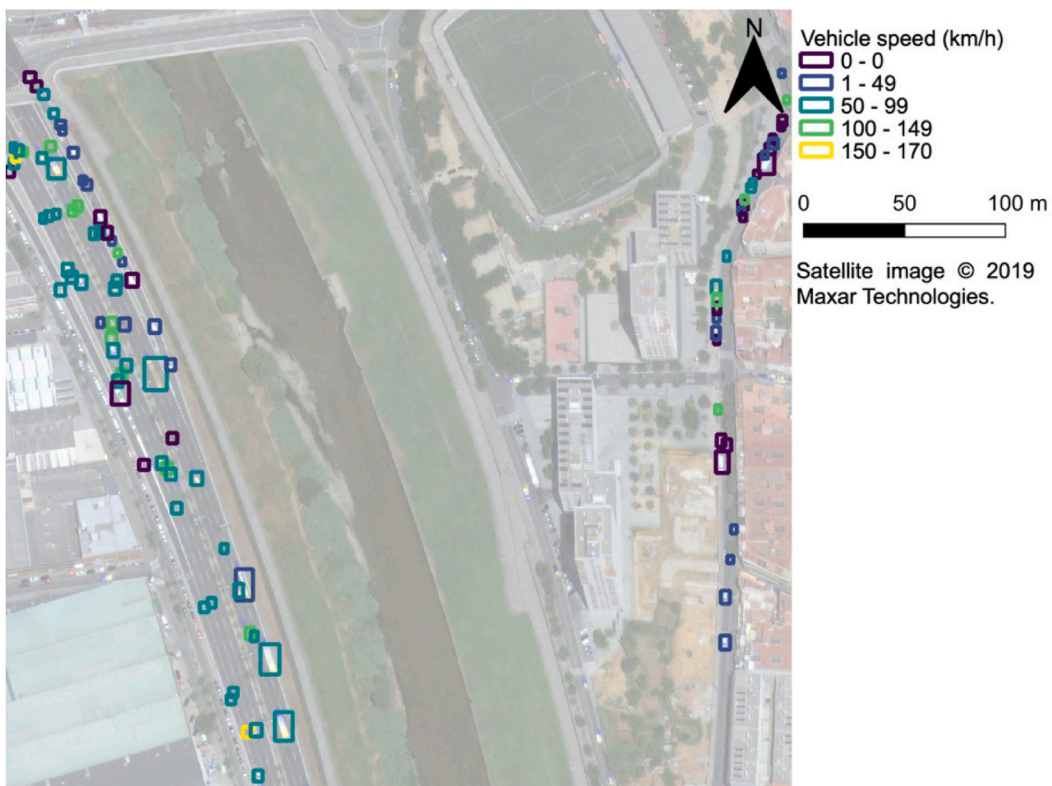


Fig. 5. Estimated vehicle speeds for detections in the final data set after the four cleaning steps, an example on trunk and tertiary roads.

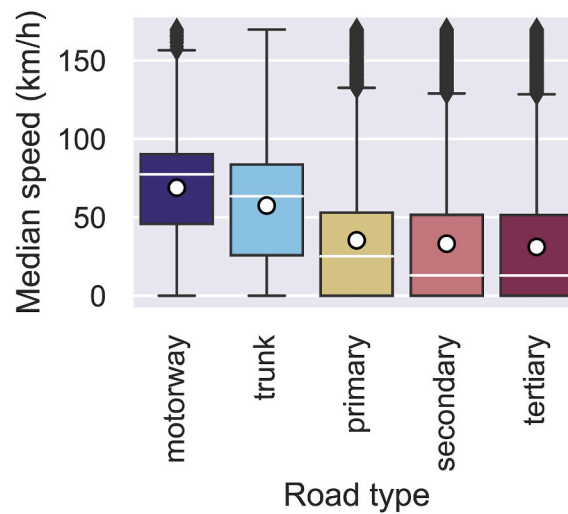


Fig. 6. Range of estimated satellite-derived vehicle speeds for each different road type. The median speed is represented by the white centre-line and the mean speed is represented with the white circle.

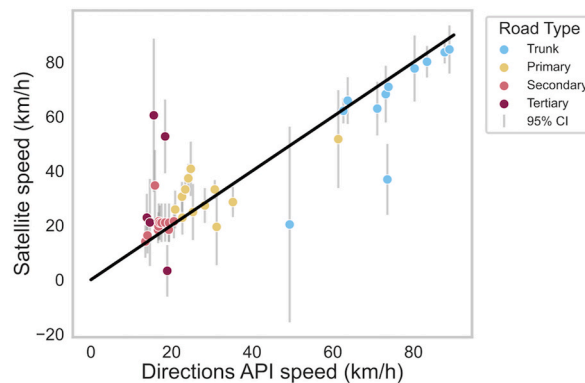


Fig. 7. Satellite-derived median weighted average vehicle speeds and the Directions API speed data set for 40 segments across Barcelona.

Table 2

Comparison between the satellite-derived median weighted average vehicle speeds and the Directions API speed data set for 40 segments across Barcelona.

	MB (km/h)	MGE (km/h)	NMB	NMGE	RMSE (km/h)	R ²
Directions API	1.3	8.4	0.04	0.23	13.4	0.71

km/h.

4. Discussion

4.1. Summary

We developed a method to estimate vehicle speed of vehicle detections in WV2/3 satellite imagery across Barcelona. The estimated satellite-derived average speed for the different road types, varied from 69 km/h on motorways to 31 km/h on tertiary roads. The satellite-derived estimates compared to the Directions API data set yielded an RMSE of 13.4 km/h compared to RMSE of 25.7 km/h from using road speed limit (i.e., the default proxy for vehicle speed).

4.2. Comparison with the Directions API

The comparison between the satellite vehicle speed estimates and the Directions API data set as the measurements (i.e., dependent

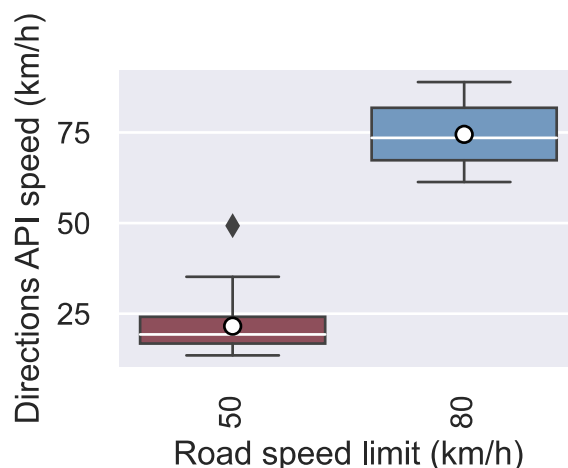


Fig. 8. Directions API speeds by road speed limits for the 40 road segments across Barcelona.

variable) produced good results ($R^2 = 0.71$ and $NMGE = 0.23$). The NMB (0.04) value suggests that on average the satellite estimates were 4% higher than the Directions API. The Directions API requests were routed along a road different to the requested road if there were disruptions on a route or projected to take longer than a different route. As these “wrong routes” were removed, the Directions API data set used to validate the satellite-derived vehicle speeds may be biased towards faster speeds. Therefore, whilst this comparison is useful in understanding whether the satellite data set produces similar results to the Directions API, there are uncertainties in both data sets and comparison was only conducted on 40 segments on 14 roads. Future work on evaluating the Directions API route requests data with ground-based traffic measurements would be beneficial to quantify the uncertainty in the Directions API data set.

The Directions API speeds are considerably lower (mean speed 21.6 km/h) on roads with speed limits of 50 km/h and were on average 5 km/h slower on roads with speed limits of 80 km/h. The Direction’s API speeds yielded values of RMSE of 13.4 km/h compared with satellite-derived estimates, compared to an RMSE of 25.7 km/h for road speed limits for the 40 road segments. The lower speeds on inner-city roads with a 50 km/h speed limit may reflect the impact of traffic congestion and traffic calming measures (e.g. traffic lights) on vehicle speed. The comparison highlights the importance of methods to estimate vehicle speeds and the potential large bias using road speed limits as a proxy input variable for vehicle speed in models. Furthermore, road speed limits nor average vehicle speeds for roads capture the variability in vehicle speed and dynamics (i.e. acceleration and deceleration) along road sections, which have an important impact on vehicle emissions (Panis et al., 2006).

4.3. Comparison of vehicle speed method with other studies

This study used the OSM road network to extract the locations of moving vehicles. Previous studies have subset the imagery to roads to reduce the search area in which to identify vehicles, to reduce the impact of noise and other objects on the method to estimate vehicle speed. This has been done in various ways such as manually digitising roads (Marchesi et al., 2012), using a road mid-line data set with corresponding road width measurements (Gao et al., 2014), to an elaborate image segmentation method to extract roads (Salehi et al., 2012). In most cities, accurate road mid-lane data sets do not exist, and even rarer do corresponding road widths. In Salehi et al. (2012)’s paper, whilst their method has the potential to be applied to imagery across other cities and areas, they commented on the difficulties of extracting roads from satellite imagery due to the spectral similarity of roads and buildings. In this study, to limit the impact of noise in the image on the vehicle speed estimation, initial work was completed on images subset to a 5 m buffer square around the detection. However, it became clear during method development that the search area was not sufficiently narrow as vehicles in neighbouring lanes influenced the vehicle movement extraction. This would have still been an issue if the image was reduced to the road surface, as it would have included all the road lanes on a road. The method in this study identified the nearest road in the OSM roads network, and shifted the nearest road to the vehicle detection centroid so that the spectral values could be extracted along the road segment. This method effectively removed a large amount of noise and other objects such as other vehicles, buildings and vegetation from the search area.

Previous studies have used a wide range of methods to extract vehicle speed estimates from remote sensing imagery. For example, studies have looked at temporal change-detection based methods such as Salehi et al. (2012) study that used PCA to identify the locations of vehicles in the MS1 and MS2 sensors on WV2, Bar and Raboy (2013) study used a spectral and spatial (SNS) approach to detected moving vehicles in WV2 images and Marchesi et al. (2012) study used a region growing image segmentation algorithm to extract moving vehicles from Coastal Blue and Blue band images. Whereas Gao et al. (2014) study used a change detection index (ERGAS) to measure the spectral difference between composite MS1 and MS2 normalised images and a 5×5 pixel sized window to scan for moving vehicle locations and used SNS on various spectral bands to extract the moving vehicle locations. However, whilst these studies estimate vehicle speed in WV2/3 imagery, they cannot be used to compare the accuracy of the results shown in this work, as none of the previous papers have evaluated their vehicle speed estimates due to no available evaluation data sets. Instead, these

papers have compared their estimates to road speed limits.

Furthermore, it is difficult to compare the results to the wider literature since previous studies have been over much smaller scales, with this study being unique in tackling an entire city. For example, [Gao et al. \(2014\)](#)'s method was applied to a few roads in San Francisco on one image captured on a Sunday afternoon on highway and suburban road segments, identifying less than 250 vehicles. In [Salehi et al. \(2012\)](#)'s paper, they apply their method to two small sections of a multi-lane highway in New Brunswick, Canada covering a total of 272 vehicles. After narrowing the search area to the road surface, both studies have a relatively noise-free image scene, with vehicles that are moving at speeds fast enough to be visible across the different spectral bands. Whereas, in Barcelona images suffer from shadow, narrow streets, vegetation, buildings and similar looking objects such as bins and road markings. In addition, [Gao et al. \(2014\)](#)'s study used a 5×5 pixel sized window to scan for moving vehicle locations, and whilst this is possible on a data set of 241 vehicles, it is unlikely to be scalable to over 1 million detections, such as the Barcelona data set presented here. Additionally, these studies are applying these methods to first identify the vehicle and then estimate the vehicle speed, whereas in this work the vehicles have been identified using object detection and the vehicle speed method is used in part to remove parked and erroneous vehicles.

4.4. Limitations

The vehicle speed method relies on the multi-spectral bands. However, the literature states that there may be big spectral differences between the bands which may impact accuracy ([Gao et al., 2014](#)). Previous studies investigated the accuracy of different spectral band combinations, and whilst not directly comparable due to different methods used, they found that Coastal Blue - Blue, Yellow - Green, and Near Infrared 1 - Near Infrared 2 band combinations had similar accuracy ([Gao et al., 2014](#)). Our vehicle speed method used four different combinations of the multi-spectral bands to limit this impact. Additionally, during method development it was found that the Green band was influenced by vegetation, the Red band influenced by buildings, with all spectral bands influenced by vehicles of the corresponding colour and shadow. Therefore, through calculating the median speed from the four band combinations, the method attempted to limit the spectral signatures of other features in the environment such as shadow, vegetation and buildings, and vehicle colour on the speed method. Future work could investigate the Near Infrared 1 and 2 bands to assess their suitability for the vehicle speed method.

Another limitation was the 2 m resolution of the MS sensors on the WV2/3 satellites used in the vehicle speed estimation method. To estimate vehicle speed, the pixel spectral values were extracted from the 2 m resolution imagery at a sampling distance of 1 m along the shifted road network and therefore, the lower limit of vehicle speed estimates for a moving vehicle is 12.5 km/h. In the Directions API data set, only one road segment (Carrer de Bilbao) had estimated speeds of less than 12.5 km/h for 16.5% of route requests. The difference in estimated road segment speed from the Directions API and satellite methods was 2.3 km/h (a 15% overestimation of speed). This highlights that there may be some overestimation of satellite-derived average speed estimates for road segments, but it is likely to be for a small proportion of the road network and proportion of the API extracts for the roads where this is the case.

The vehicles in the satellite imagery were detected using DL OD algorithm YOLO which had an F1 score of 0.74, precision of 0.69 and recall of 0.79 ([Sheehan et al., 2023](#)). These metrics show that approximately 31% of the vehicles identified in the satellite imagery were erroneous and 21% of vehicles in the imagery were not identified. To reduce the influence of erroneous detections on the method, data cleaning steps were conducted to remove erroneous and parked vehicles detections from the vehicle speed data set (outlined in Section 2.2.4. and Supplementary B). The average number of vehicles on a road segment is 586 (varying between an average of 38 vehicles on tertiary roads to 753 on primary roads). Taking away an assumed 30% of detections which may be in error due to the performance of the DL OD method, there are still a substantial number of vehicle speed estimates to estimate the average speed by road.

For the comparison with the Directions API speeds, the satellite-derived median weighted average vehicle speeds were calculated for the 40 road segments. The average number of vehicles on the road segments used to calculate the satellite-derived median weighted average vehicle speeds ranged from 38 for tertiary roads to 753 for primary roads (trunk roads = 652, secondary roads = 345). Therefore, we have some confidence that we are able to estimate the average speed of a road link from the available satellite-derived vehicle speeds.

A further limitation is the relatively small number of satellite images (10 images collected during the period 2017–2019) collected in time compared to the Directions API (every hour over seven months: August 2021–February 2022 inclusive), with none of them being contemporaneous. Ideally, the timing of the images would correspond to the same hours of the API estimates. We are unable to assess the implications of this in the performance of the methodology at present. In future work we will look to make improvements to this aspect of the methodology.

Finally, cities are complex environments and there are limitations when using satellite imagery, which can obstruct vehicles from view, the variety of road types, road layout and the number of parked vehicles. In this study we used a limited number of satellite images, captured at the same time of day (11 a.m.) to produce average speed estimates for roads. These points make developing a method to estimate vehicle speed, that works in all situations challenging. The methods tested and developed throughout this study have attempted to tackle these different aspects.

5. Conclusions

We have presented novel methods for using satellite (or aerial) imagery to estimate the vehicle speed at the city scale. Satellite imagery offers a global data set, enabling traffic speed data to be estimated road by road, with up to daily resolution from an archive of imagery. As noted in this study, there are many challenges to overcome in developing methods to use satellite imagery to detect vehicle

speeds and produce speed data across a connected road network as input to environmental models. Despite these challenges, the performance of the method presented here is promising and warrants further work in geographically contrasting locations.

CRediT authorship contribution statement

Annalisa Sheehan: Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Formal analysis, Data curation. **Andrew Beddows:** Writing – review & editing, Supervision, Methodology. **John Gulliver:** Writing – review & editing, Supervision, Methodology. **David C. Green:** Writing – review & editing, Supervision, Methodology, Conceptualization. **Sean Beevers:** Writing – review & editing, Supervision, Methodology, Funding acquisition, Conceptualization.

Ethical Statement for Remote Sensing Applications: Society and Environment

Hereby, I Annalisa Sheehan consciously assure that for the manuscript ‘Estimating road vehicle speed from high-resolution satellite imagery for environmental applications: a case study of Barcelona’ the following is fulfilled.

- 1) This material is the authors’ own original work, which has not been previously published elsewhere.
- 2) The paper is not currently being considered for publication elsewhere.
- 3) The paper reflects the authors’ own research and analysis in a truthful and complete manner.
- 4) The paper properly credits the meaningful contributions of co-authors and co-researchers.
- 5) The results are appropriately placed in the context of prior and existing research.
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I agree with the above statements and declare that this submission follows the policies of Remote Sensing Applications: Society and Environment as outlined in the Guide for Authors and in the Ethical Statement.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.rsase.2025.101507>.

Data availability

Two data sets are freely available from Zenodo: <https://doi.org/10.5281/zenodo.13737577.1>

Average satellite-derived vehicle speeds estimated for each OSM road link in Barcelona (excluding service, living streets and residential roads).2)

Google Directions API route requests for 40 road segments across Barcelona.

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