FINAL REPORT

NACOE S26: Virtual WiM – Enriching WiM and Enhancing Decisions (2018–21)

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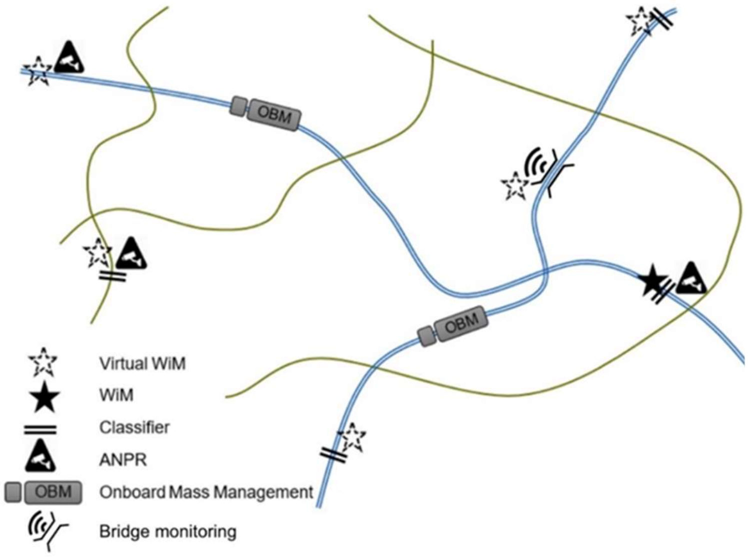
Summary

NACOE project S26, *Virtual WiM – Enriching WiM and Enhancing Decisions* identified opportunities for Queensland Department of Transport and Main Roads (TMR) to add value to investments by both TMR and the heavy vehicle transport industry. The project used recent developments in data analytics to link weigh-in-motion (WiM) data with other heavy vehicle datasets to generate new 'virtual WiM' or vWiM[1] datasets. The vWiM approach enhances data quality, coverage, accessibility, application, and value of TMR's existing WiM datasets (Figure S 1). The value of vWiM is generated through better evidence-based decisions relating to the $billions invested in transportation and infrastructure made every year while supporting safe productive access to TMR's infrastructure.

Figure S 1: vWiM leverages existing heavy vehicle data collection assets to enhance value, data quality, coverage and evidence-based decisions



The concepts of vWiM emerged while reviewing TMR's WiM systems, engaging with stakeholders, preparing a draft Strategic Asset Management Plan (SAMP) for WiM, and analysing 13 months of WiM focused on the load platforms, low loaders and cranes. These vehicles pose the largest risks to bridges. The vWiM concepts were further refined while integrating WiM data with other datasets including bridge monitoring, automatic number plate recognition (ANPR), GPS tracking of heavy vehicles (IAP), authority to operate (ATO), on-board mass management (OBM), and classifier data.

The project demonstrated the viability and value of vWiM concepts by extrapolating WiM data to more common classifier sites across Queensland. In addition, the viability of enhancing the quality of WiM mass data by comparing heavy vehicles of known mass in the traffic stream was demonstrated by integrating GPS tracking, OBM, and ATO data with WiM data. Similarly, bridge monitoring systems were also successfully calibrated using heavy vehicles in the traffic stream. Finally, a prototype tracking tool for Class 1 heavy vehicles was delivered which tracked load platforms posing the greatest risks to bridges through the network to provide a history of loading and inform access and asset management decisions.

The project recommends the adoption of the vWiM concepts and supporting a program of continual improvement. The program should target the quality, coverage, accessibility, and linking of datasets. Further development of the engineering and analytics to translate the data into information and knowledge are also necessary to support informed decisions that benefit the Queensland community.

[1] The concept of vWiM is to enhance the value, quality, accessibility and application of existing and emerging heavy vehicle data collection assets by interlinking these related datasets

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Keywords

WiM, virtual WiM, vWiM, data driven decisions, distilling, enriching, data analytics, adding value, risk informed decision making, continuous improvement, Class 1 heavy vehicles, tracking, data quality, optimising access, classifiers, ANPR.

Extended Summary

NACOE project S26, *Virtual WiM – Enriching WiM and Enhancing Decisions* identified opportunities for Queensland Department of Transport and Main Roads (TMR) to add value to investments by both TMR and the heavy vehicle transport industry. The project used recent developments in data analytics to link weigh-in-motion (WiM) data with other heavy vehicle datasets to generate new 'virtual WiM' or vWiM datasets. The vWiM approach enhances data quality, coverage, accessibility, application, and value of TMR's existing WiM datasets (Figure S 1). The value of vWiM is generated through better evidence-based decisions relating to the $billions invested in transportation and infrastructure made every year while supporting safe productive access to TMR's infrastructure.

The concepts of vWiM emerged while reviewing TMR's WiM systems, engaging with stakeholders, preparing a draft Strategic Asset Management Plan (SAMP) for WiM, and analysing 13 months of WiM focused on the load platforms, low loaders, and cranes. These vehicles pose the largest risks to bridges. The vWiM concepts were further refined while integrating WiM data with other datasets including bridge monitoring, automatic number plate recognition (ANPR), GPS tracking of heavy vehicles (IAP), authority to operate (ATO), on-board mass management (OBM), and classifier data. The practical applications and value of vWiM were highlighted during trials that integrated WiM and classifier data with multiple datasets[2].

Bridge monitoring identified that load platforms pose the largest risk to TMR's bridges, but these vehicles were not well represented in the WiM and classifier data (Figure S 2). Subsequent updates to WiM and classifier processing algorithms revealed a rich, previously hidden dataset of these and other heavy vehicles that are too wide for a single lane and consequently utilise multiple lanes to access the network.

Figure S 2: Updates to processing algorithms made wide and heavy loads 'visible' in TMR's WiM and classifier records

A prototype vWiM tracking tool, developed during this project, successfully tracked load platforms through the bridge network using their WiM and classifier 'axle spacing signatures' only. This increases the knowledge about the history of large loads crossing specific bridges and pavements, to inform bridge risk and support credible access decisions.

The project demonstrated the viability and value of extrapolating WiM data to more common classifier sites, thus leveraging WiM data across the state. A 'similarity statistic' was developed to determine the suitability of the extrapolations.

[2] The project explored the integration of WiM with classifier data, IAP (Intelligent Access Program telematics), OBM (On-Board Mass), ATO (Authority to Operate) and bridge monitoring data.

The viability of enhancing the quality of WiM mass data by comparing heavy vehicles of known mass in the traffic stream was demonstrated by integrating GPS tracking, OBM and ATO data with WiM data. Bridge monitoring systems were also successfully calibrated using heavy vehicles in the traffic stream.

This final report of NACOE S26, *Virtual WiM – Enriching WiM and Enhancing Decisions* provides further detail of the 4-year project. It recommends the adoption of the vWiM concepts of integrating multiple datasets and supporting a program of continual improvement. The program should target the quality, coverage, accessibility and linking of datasets. Further development of the engineering and analytics to translate the data into information and knowledge are also necessary to support informed decisions that benefit the Queensland community.

Aim

The overall aim of the project was to review the Queensland Department of Transport and Main Roads (TMR) WiM systems and to identify opportunities for improvement with an emphasis on technologies and systems that could improve input to the credible risk-informed management of the bridge stock.

Background

TMR works to optimise heavy vehicle access and benefit to the community accessing over 33,000 km of roads and 3,300 bridges. When determining access and planning outcomes, policy decision makers are regularly required to exercise judgment balancing productivity and risk (Figure S 3). Decisions must be made with an often-incomplete subset of information and knowledge available. This incomplete knowledge can lead to sub-optimal decisions and potentially uneconomic or unsafe utilisation of the network.

Figure S 3: Heavy vehicle access and planning decisions are a balancing act

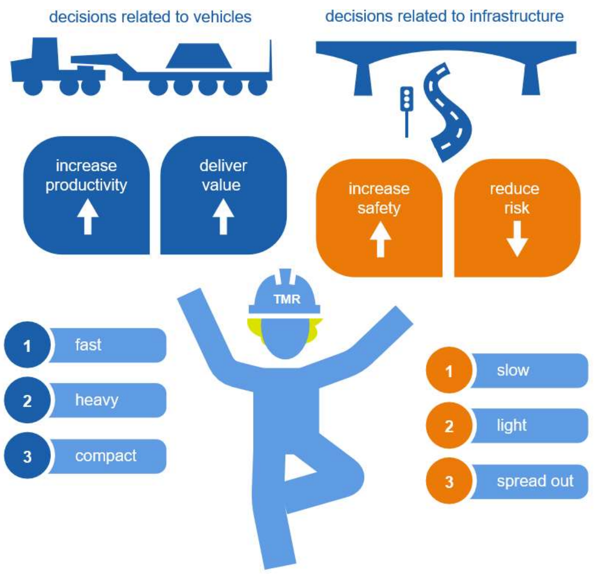
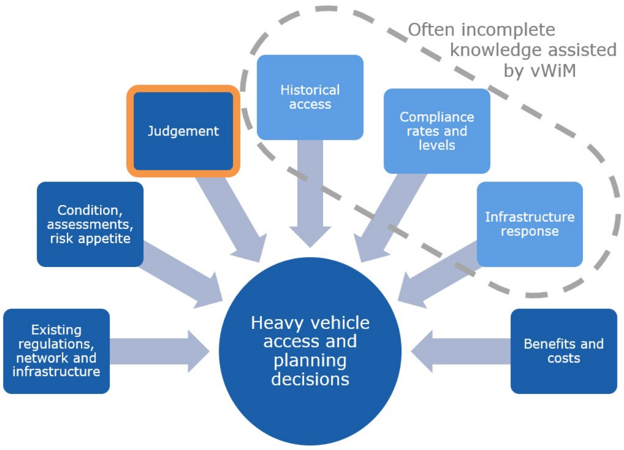


Figure S 4: Virtual WiM (vWiM) supports credible decision-making by providing factual evidence of current and historical access



Credible decisions are aided by accessible quality data and information. Decisions that are informed about the actual heavy vehicles accessing the network, compliance rates and how the infrastructure responds are more credible and respectful towards stakeholders and therefore more productive (Figure S 4). Developments in heavy vehicle data collection technologies and analytics are providing opportunities to improve these decisions and challenge in-built assumptions through the delivery of credible, accessible information about the heavy vehicles accessing the network.

Findings of the Project

TMR's WiM systems

Benchmarking TMR's WiM systems nationally concluded that TMR's systems are mature and would benefit from the generation of more accurate WiM data with less down time while reliably recording information on Class 1 heavy vehicles such as cranes, low loaders and load platforms. Approaches that may facilitate this outcome include:

- installing WiM stations in pavements with slow rates of deterioration to improve data quality over the life of the WiM station
- measuring ground contact width to improve the understanding of the loads and compliance levels of the Class 1 heavy vehicles
- improving data analytics to extract more knowledge from available data
- monitoring and continually improving the data quality.

Stakeholder engagement

The value and opportunity of WiM were discussed with stakeholders from the areas of Transport Planning, Portfolio Investment and Planning, Program Delivery and Operations and Engineering and Technology. Key observations from these discussions include:

- The outcomes that stakeholders are seeking from WiM include:
  - managing risk of vulnerable assets
  - informing the road manager
  - optimising return on investment
  - evidence based decisions
  - credibility of decisions
  - investment priorities
  - commodity movement
  - freight productivity and network access
  - freight task quantification
  - compliance management.
- There is a perception that WiM has limited value because the quality and availability of WiM data is often inadequate for enforcement purposes. This perception is inadequate in the contemporary context. Support for compliance management is just one of many roles WiM data can play underpinning evidence-based decision making and delivering value.
- WiM currently is not extensively used in decision-making. Network coverage, accessibility and inadequate quality contribute to this status. Greater utilisation of WiM will follow if these limitations are overcome. This is the case from planning to heavy vehicle operations, to pavement design and maintenance, bridge access management and risk assessments.
- The value proposition for WiM increases for all stakeholders as WiM data is integrated with other data, which include ANPR data, permit vehicle data, classifier data, OBM data, IAP data and ATO data. At present, on-board vehicle monitoring technologies are fitted to a small fraction of the heavy vehicle fleet.
- Bridge risk management using WiM is a key opportunity to inform stakeholders of the risks associated with the movement of the cranes, low loaders and load platforms across the network. While these vehicles represent the greatest risk to bridges, the least amount of information is known about them (as they were not previously visible in the WiM and classifier data stream).
- The transport industry knows more about what vehicles access the network than TMR. This is unacceptable.
- Classifiers are cost effective for vehicle classification, but WiM provides mass data as well and is helpful in validating access by innovative vehicles. WiM provides data about all vehicles whereas OBM only provides data from participating vehicles.

Strategic Asset Management Plan for WiM

The value proposition for WiM data is not well articulated globally because the focus is on collecting data to inform compliance rates rather than the optimal management of the road and bridge network and the heavy vehicles that provide transport services for the community.

The gross value added (GVA) to the Queensland economy by the transport, postal and warehousing industry was $15.3 billion in the year to June 2017 with approximately 45% of the workforce associated with road transport (TMR 2018)[3]. Similarly, TMR's annual expenditure on maintenance, preservation and operations is approximately $1 billion per year (TMR 2019).

Decisions relating $billions of investments in transportation and infrastructure are made every year. These decisions influence the productivity of transport, and associated industries as well as the wear of pavements and bridges and the risks of bridge collapses from overloading and fatigue. Better informed decisions, based on knowledge of the actual heavy vehicles operating on the network, will release value by supporting safe and productive access across TMR's existing infrastructure.

Increasing data analytics capabilities are transforming the accessibility of information derived from WiM and related data technologies. There are increasing opportunities for WiM and related technologies to support evidence-based decisions by TMR in its role as the road manager by informing credible risk-informed decisions to generate the optimal return on both TMR's and the transport industry's infrastructure.

The project generated a draft Strategic Asset Management Plan (SAMP) for TMR WiM to place WiM in the context of TMR's strategic plans, to articulate the value of WiM in informing better decisions and to develop a high-level plan for WiM going forward. The draft SAMP proposed a program of continual improvement and investment in data quality, accessibility and the application of WiM and related datasets over 10 years to respond to identified stakeholder needs. The draft WiM SAMP should be reviewed once TMR's organisation-wide SAMP is published in 2022. It is noted that the imperatives for productively and safely utilising the road network have further increased since the draft SAMP was prepared.

This report builds on the insights from the stakeholder feedback and the strategies of the draft SAMP to highlight opportunities, evaluate concepts and to develop prototype tools to point the way to extracting greater value from these datasets.

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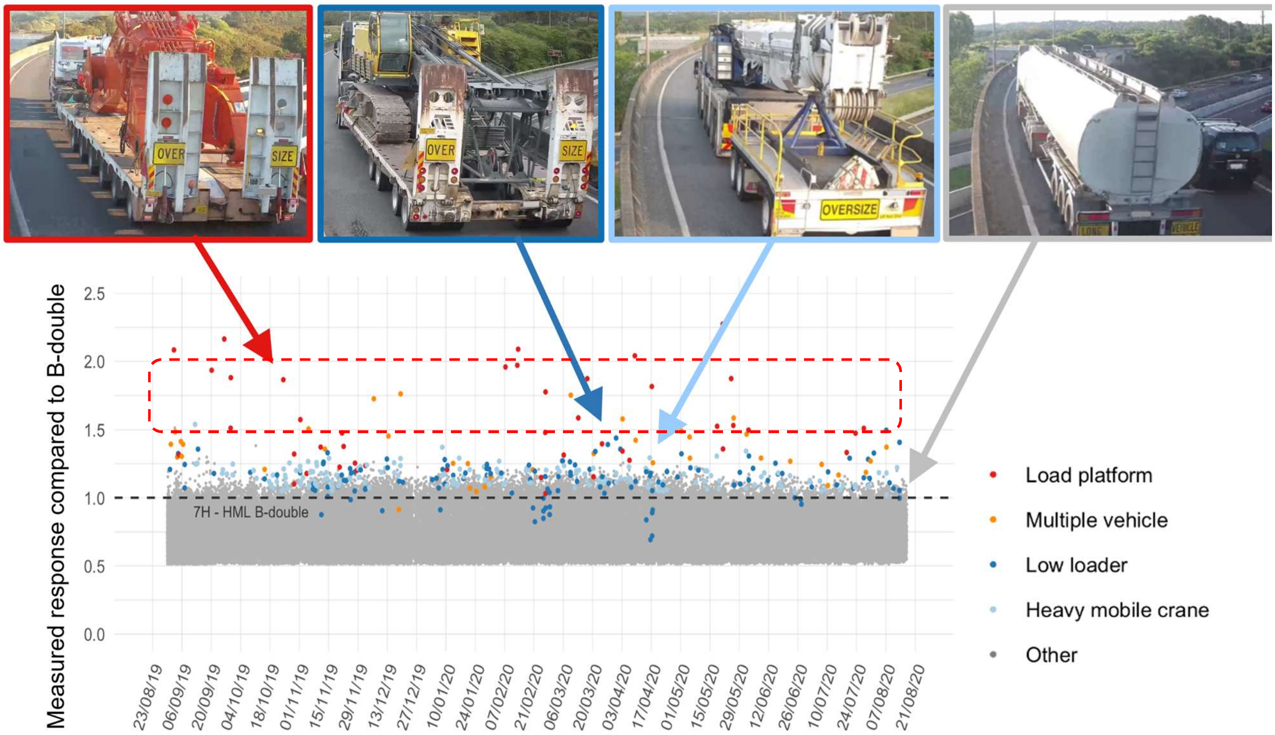
[3] Department of Transport and Main Roads, November 2018, Queensland Transport and Logistics Workforce Current and Future Trends Report, retrieved from https://www.tmr.qld.gov.au/-/media/busind/businesswithus/TLI-Connect/trends/qtlw-current-future-trends-report-2018.pdf?la=en

Cranes, low loaders, and load platforms

The largest vehicles on TMR's network, specifically Class 1 heavy vehicles such as load platforms, low loaders and cranes pose the greatest risk to bridges as illustrated in Figure S 5. Class 1 heavy vehicles are regularly observed in the bridge monitoring data stream but were not initially evident in the WiM and classified data. Enhancements to the data processing algorithms improved the visibility of Class 1 heavy vehicles in the data and provided the opportunity to better study these vehicles.

Figure S 5: Virtual WiM data from bridge monitoring has highlighted the importance of load platforms, low loaders, and cranes to bridge risk management



The collection of photos presented in Figure S 6 illustrate these load platforms, low loaders, and cranes traversing TMR's bridges.

Figure S 6: Load platforms, low loaders and cranes were a focus of this report as they represent the greatest risks to bridges

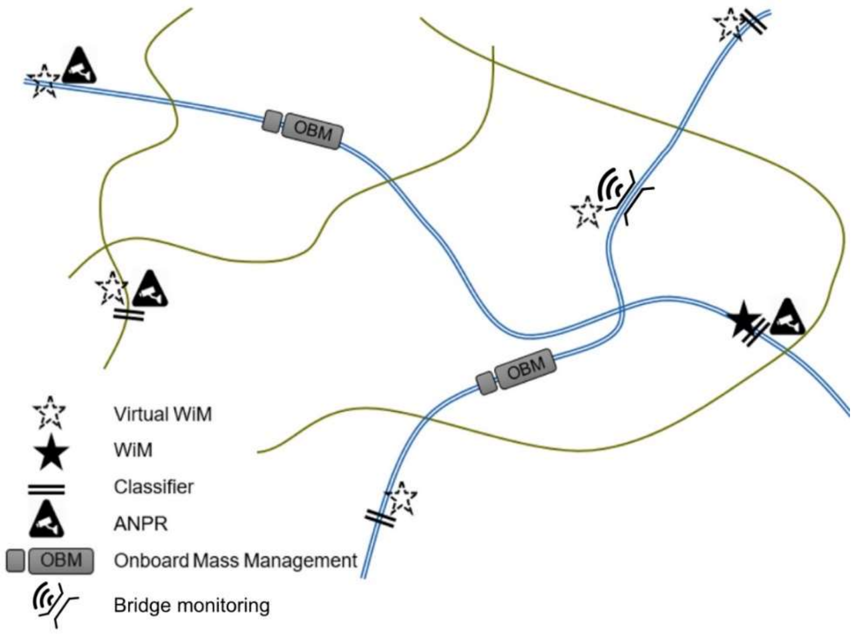
Dataset

The project sourced input from both WiM and classifier data collected over the period from 01/01/2019 to 09/02/2020. Across the Queensland network TMR has 60 WiM installations and 126 networked classifier installations. This project utilised data from 23 operational WiM installations and 97 networked classifier installations. The data set involved 28 million WiM and classifier records of vehicles similar to a semi-trailer and larger.

Virtual WiM

Virtual Weigh-in-Motion (vWiM) is an emerging concept targeted at enhancing data about the heavy vehicles that access the road network by firstly providing 'virtual[4]' WiM data and related information at locations without WiM data but with other assets such as classifiers or ANPR (Figure S 7). Secondly, vWiM enhances the credibility and application of heavy vehicle data by merging data subsets from different technologies (Figure S 7). vWiM increases the effective coverage and data quality of existing data collection infrastructure to provide a richer picture of heavy vehicle journeys and heavy vehicle characteristics.

Figure S 7: Virtual Weigh-in-Motion (vWiM) is an emerging concept leveraging existing heavy vehicle data collection assets to enhance value, data quality, coverage, and evidence-based decisions



vWiM analyses demonstrated that by merging WiM, classifier, bridge monitoring and OBM datasets, it is possible to:

- extend the coverage of WiM data by generating vWiM data at sites without WiM data such as classifier sites
- inform and monitor the infrastructure risk, and the credibility and effectiveness of access decisions
- identify load platforms based on their axle spacing footprint and track individual load platforms as they travel across the network, even without access to ANPR
- understand the characteristics of the actual vehicles accessing the network (as opposed to what is permitted) including:
  - when, where and how often they travel
  - their configuration, geometry, mass distributions and speed
  - structural impacts on bridges
- assess data quality and cross-validate multiple datasets to improve data quality.

[4] Virtual: not physically existing as such but made by software to appear to do so.

Estimating extreme bridge response to heavy vehicles from WiM data

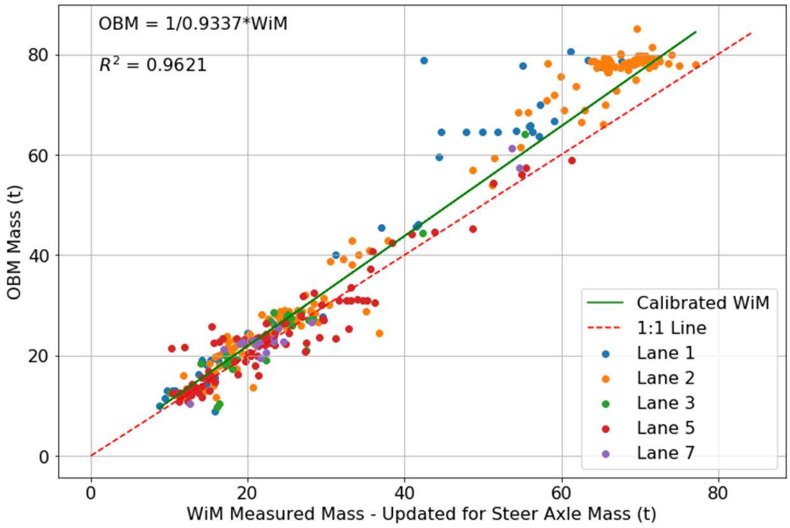
The axle loads and axle spacing reported by WiM systems and the measured responses of bridges to traffic provide an opportunity to determine the statistics of both the fatigue damage and the extreme response. These statistical summaries provide evidence to support risk-informed bridge assessments and to challenge the assumptions underpinning traditional code-based structural assessments. The statistical models of bridge responses to traffic have traditionally been focused on large bridges, however there is an opportunity to automate this process for short and medium span bridges to support the risk-informed management of TMR's ageing infrastructure of bridges.

Data integration and data quality

Studies involving the integration of WiM, classifier, ATO and OBM data as well as the camera and monitoring data from the Gateway Arterial Flyover (GAF) highlighted opportunities, including:

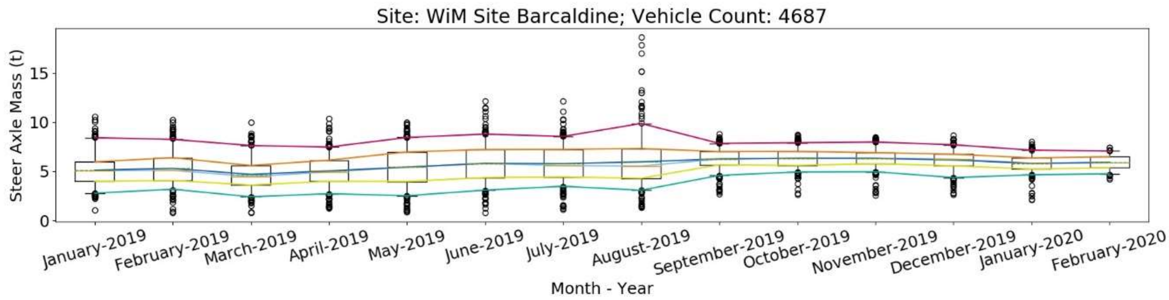
- Calibrating bridge monitoring and WiM systems using heavy vehicles identified in the traffic stream. This avoids traffic disruption and provides the opportunity to continually calibrate WiM and bridge monitoring systems to estimate axle group mass and gross combination mass (for example, refer to Figure S 8).

Figure S 8: Gross vehicle mass comparison between OBM data and WiM data



- Improving the detection rate of WiM and classifiers in identifying the load platforms and low loaders that pose the greatest risk to bridges. These vehicles are often wider than a lane and their ground contact widths vary along the length of the vehicle making them difficult to detect with traditional WiM algorithms, but readily detectable by bridge monitoring systems. Substantial progress was made during this project to 'stitch' multi-lane records together, with further improvements possible.
- Tracking load platforms across multiple WiM and classifier sites highlighted the opportunity to improve the quality of the axle spacing and axle group mass data by merging multiple records, inform the calibration accuracy of assets and build a historical database of these heavy loads crossing bridges along the route.
- Improving the accuracy of axle spacing determined by classifiers from ± 200 mm to ± 50 mm would enhance the classification of heavy vehicle types and help facilitate the live calibration of WiM and bridge monitoring systems. The surprisingly coarse axle spacing resolution evident, applies particularly to classifiers relying on one piezo sensor and loops rather than two piezo sensors and loops.
- Changing from simple averages to box and whisker plots of the steer axle mass of articulated vehicles to identify excessive variability within the data stream to better categorise data quality, support live calibration and continual improvement programs (Figure S 9).

Figure S 9: WiM monthly semi-trailer 123 configuration steer axle mass statistics

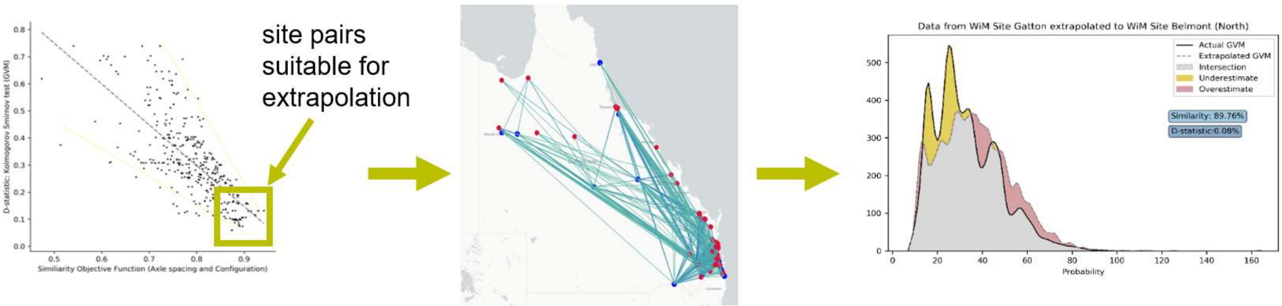


Extrapolating WiM data to classifier sites

The vWiM concept of extrapolating data from a WiM site and applying it at a site where there was only a classifier was investigated to establish if there was an opportunity to add value to the existing data collection infrastructure.

The systematic assessment of a site similarity statistic has revealed its potential in predicting sites with similar traffic and by extension WiM profiles. This statistic provides a novel method to determine if extrapolating WiM data to a classifier site is appropriate. The process undertaken is shown in Figure S 10.

Figure S 10: Process for extrapolating from WiM to classifier sites



Determine similarity (axle spacing data)

Identify similar sites (WiM + classifier)

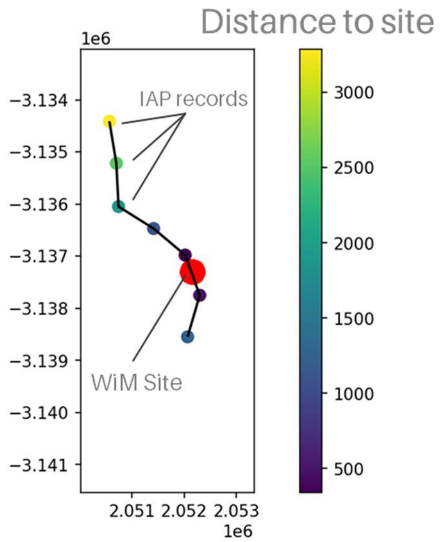
Extrapolate WiM to classifier sites

The extrapolation methodology was tested by extrapolating WiM data between WiM sites and comparing the extraoplated data (based on axle spacing similarity) with the actual WiM data. Not surpisingly, there was only a relatively small portion of the WiM stations where data extraoplation between sites was approporiate but because of the much larger number of classifier sites, it was found approporiate to extrapolate data from at least one of the WiM sites to at least one classifier site for more than 90% of the classifier sites.

The enhanced value of this extrapolation would be further increased by enhancing axle spacing and mass data quality. Extending traffic volume and WiM data through these statistical inference based methods can improve WiM data coverage across the network. This extrapolation is particularily relevant to pavement and bridge modelling where longer term WiM data is needed but often not avaliable.

Validating WiM calibrations using GPS tracking

Figure S 11: Integrating IAP with WiM via dead reckoning to facilitate updating WiM calibration



The emergence of GPS tracking of heavy vehicles (IAP data and telematics) in combination with ATO and on-board mass (OBM) data affords the opportunity to compare the mass measurements from two independent systems and potentially contribute to the regular updating of WiM system calibrations and the improvement in quality of WiM data. As part of a case study, WiM data collected at the Nudgee WiM site was compared against IAP telematics. Through comparison of the time, weight, and directional differences between IAP and WiM records, it was found that most anonymous WiM sightings could be matched to IAP records. This process relies on the easily transferrable method of dead reckoning (shown in Figure S 11), which can be extended to a wide range of other fleet telematics data sources.

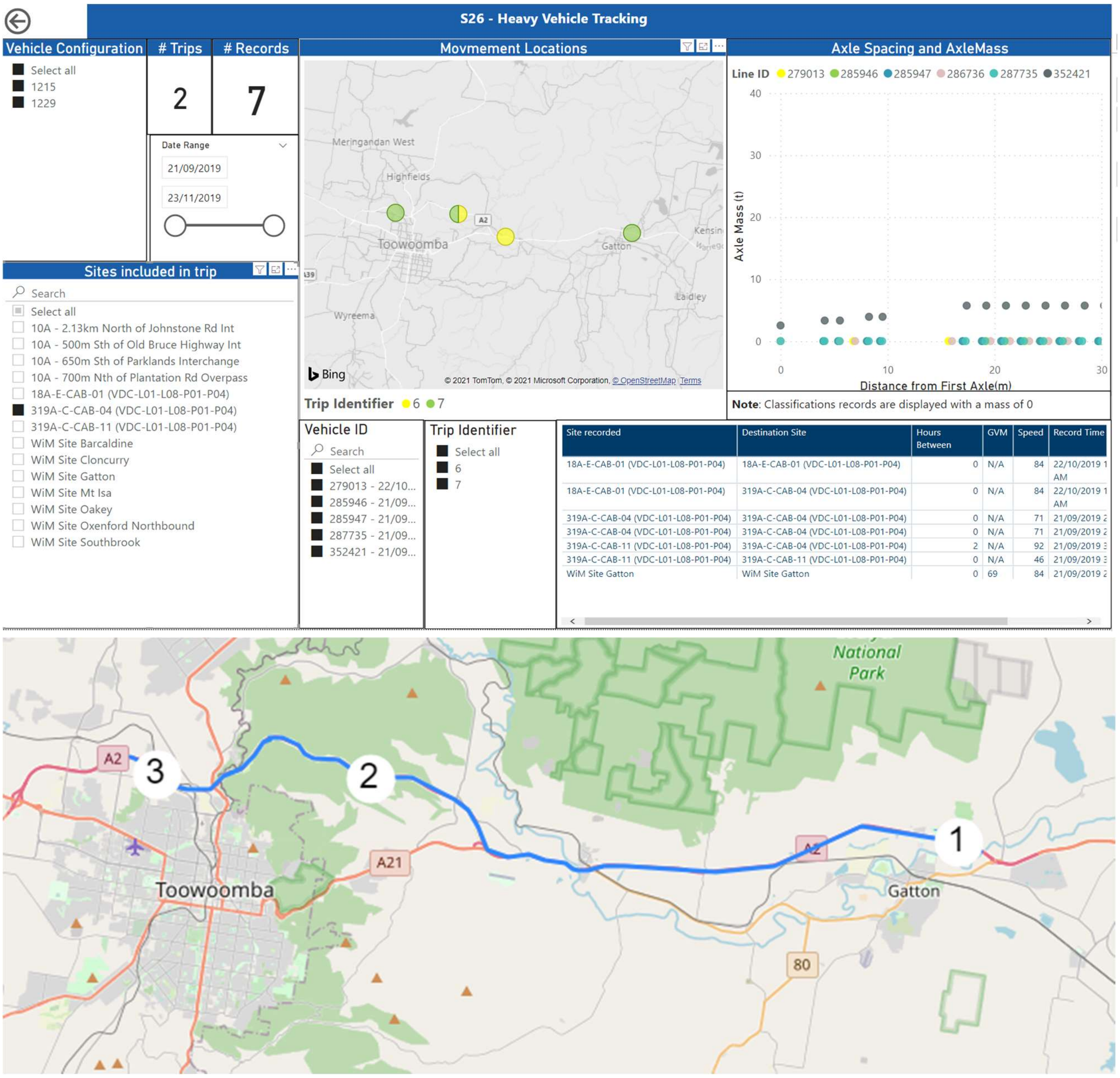
The value of WiM data is exponentially increased through data synthesis, whether IAP, ANPR or other datasets. Assisted tracking, where WiM records are matched to dedicated tracking systems, can supplement the value generated through tracking based on WiM and classifier 'axle spacing footprints' alone.

Tracking load platforms using WiM and classifier data

This project developed prototype tools to track uncommon Class 1 heavy vehicles, such as load platforms, through the network using only WiM and classifier data. These tools can track uncommon large vehicle movements through the network and thus provide the opportunity to build a database of the high-risk vehicles that have crossed bridges to inform the risk management of the bridge and enhance the credibility of access management and compliance management decisions.

Collectively, the tracking tools allow the user to find records of interest based on their configuration, mass, location and timings. If a record of interest is part of a trip, the locations and axle masses can be viewed for each paired site, as illustrated in Figure S 12.

Figure S 12: Tracking load platforms across multiple WiM and classifier sites to enhance knowledge of the vehicle and the performance of bridges they cross



Future considerations

Ten areas for future consideration are detailed based on the project's investigations.

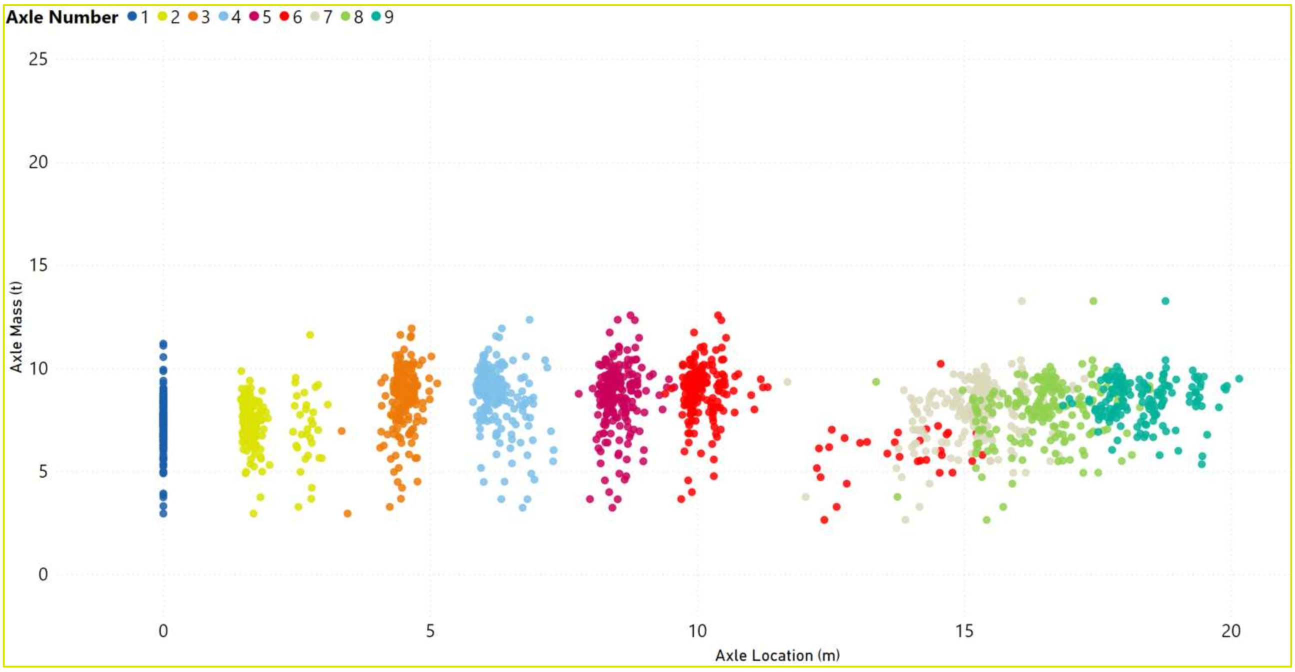
1. Axle Load Data

Ensuring quality axle load data over time (refer Figure S 9) lies at the core of the value proposition for WiM. Possible strategies for improving the axle load data measurements include valuing quality axle data highly and selecting WiM systems and sensors to provide value over the life of the sensors/system including regular road surface maintenance.

2. Axle Spacing

The spacing of the axles for heavy vehicles can act as a signature for the larger vehicles on the network and can help differentiate vehicle types, identify routes taken, identify vehicles that may be suitable for live calibration of WiM sites and to monitor compliance (Figure S 13). Some possible strategies for improving the accuracy of axle spacing and speed data include quantifying the variability in axle spacing through case studies, investigating the causes of variability in recording of the axle spacing and implementing a continual improvement program, possibly in conjunction with suppliers of WiM and classifier systems.

Figure S 13: Axle mass configuration for cranes with 6 or more axles

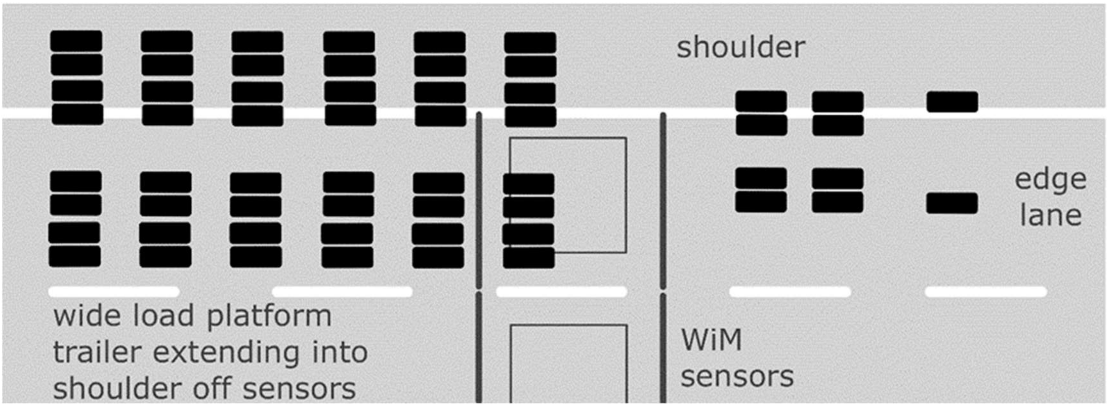


3. Coverage of Wide Vehicles

Pavement WiM and classifiers collect data for vehicles travelling in a lane, however wide vehicles such as low loaders and load platforms have a footprint that tends to straddle lanes or operate partly on the road shoulder. This means that while the detectors may collect data it may be inappropriate in terms of mass or configuration, leading to an underestimation of the actual loads on the road. When vehicles change lanes at WiM sites similar inaccurate inputs are provided. When vehicles are operating partly on the road shoulder, the mass operating on the shoulder is not recorded due to an absence of sensors located in the shoulder (Figure S 14). Even while vehicles such as prime movers may not straddle lanes, their trailers may do.

The correct understanding of mass and configuration of these vehicles is critical as these are the largest vehicles on the network and they represent the largest risks to bridges.

Figure S 14: The widest vehicles often run in the edge lane with tyres on the shoulder beyond the edge of the WiM sensors



Possible strategies for improving the coverage of wide vehicles include:

- upgrading algorithms to stitch together multi-lane WiM data (as was done for this project)

- extending the placement of sensors to include the shoulder
- considering the use of bridge WiM, where the whole bridge span is the sensor, ensuring that data is collected for all drivelines, even on the shoulder.

4. Ground Contact Width & Permits

Lateral distribution of axle loads within bridges due to permit vehicles such as low loaders and load platforms varies with the width of the ground contact. As ground contact width is currently not measured it is not possible to determine the lateral load distribution on bridge structural components and, subsequently, acceptable loads or if overloading of a structure is occurring. In addition, often the acceptable load per axle depends on the ground contact width and the number of wheels per axle.

Possible strategies to determine ground contact width and identify permit vehicles are to:

- investigate technologies such as the heavy vehicles being fitted with electronically readable devices containing the permit vehicle details to enable measured data to be tied to the permit
- trial technologies for measuring ground contact width, such as TIRTL, Lidar, laser and in-pavement sensors
- add sensors to measure, (i) ground contact width, (ii) the driveline of the truck and (iii) the number of tyres per axle.

5. Integration of ANPR Data with WiM

ANPR is important when using WiM as it supports vWiM, provides confirmation that the vehicle type and configuration are as recorded in the WiM records, tare mass information when linked to the registration to support mass and axle spacing calibration as well as supporting compliance. Possible strategies for improving the integration of ANPR with WiM data include:

- refining the integration of ANPR with WiM on multi-lane freeways
- trialling the use of emerging solar powered ANPR systems with 4G connectivity and CCTV capability, to facilitate the capture of number plates, CCTV and the ability to view still images of selected vehicles and their loading
- install front and rear facing systems where possible as well as ensuring that an angled view of the vehicle can be achieved, to allow for an identification of all the components of the configuration
- continue the development of the integration of ANPR with WiM in association with monitoring projects
- link ANPR, WiM and permit vehicle data sets.

6. Geographical Coverage of WiM

There are currently some portions of the road network where there are no WiM or classifier stations which transmit data back to the central data repository. These black spots in WiM or classifier stations include:

- urban freeways where vehicle sensing technologies that do not provide 'axle spacing signatures' (e.g. loops)
- highways where no WiM stations have been installed.

Possible strategies for extending the geographical coverage of classifiers and WiM include

- updating classifiers to report data via telemetry
- installing WiM sites at critical locations
- progressing the concepts of virtual WiM. These vWiM concepts include integrating WiM and classifier data via 'axle spacing signatures' and or ANPR data to extrapolate WiM data to other locations on the network.

7. Bridge WiM

Bridge based WiM systems are not commonly used in Australia. It has the potential advantage of being more stable over time as less pavement maintenance is required. Advantages also include that the sensors generally are not installed in the road surface thus minimising traffic disruption during installation and eliminating the need to acquire and install new sensors when pavement upgrades are undertaken.

Additionally, the system and sensors are relocatable, the loads from all the wheels on wide loads are recorded and the guardrails are not required to prevent impacts with cabinets and ANPR cameras.

8. On-Board Mass (OBM) Measurement

On-board mass (OBM) measurement has been emerging for decades in parallel with WiM and is now becoming more common in Queensland. Data is currently available to TMR for a limited subset of heavy vehicles. As the heavy vehicle fleet is becoming increasingly sophisticated, there will likely be an increasing take-up of these technologies by transport companies.

Possible strategies relating to OBM and WiM include:

- Cease the collection of WiM and classifier data and rely on OBM and related technologies. From a bridge perspective this only works if all vehicles are fitted with OBM and all axle spacing and axle loads are reported.
- Utilise the OBM data to validate WiM station calibrations and support TMRs calibration of OBM data.
- Continue to use WiM and classifier data to ensure coverage of all vehicles.
- Merge the WiM, classifier and OBM datasets.

9. Bridge Response Monitoring

Bridge response monitoring provides both the performance data for components as well as the load model data for the traffic stream. Additional value is realised when the bridge-response monitoring data is integrated with other datasets such as ANPR, WiM, classifier, OBM, permit and ATO data.

Possible strategies for bridge response monitoring include continuing to integrate with other datasets to:

- inform structural behaviour
- monitor the changes in structural performance through time
- identify vehicles accessing the network and the responses they induce on structures
- support due diligence
- refine assessment load models to support risk and asset management
- safely extend lives of bridges, inform rehabilitation and improve utilisation of the bridge asset.

10. Uncommon Heavy Vehicle Tracking

Potential enhancements to track uncommon heavy vehicles such as load platforms and low loaders include:

- integration of the heavy vehicle network into the heavy vehicle matching algorithm
- mapping of potential heavy vehicle trips undertaken by vehicles
- integration with IAP to validate and improve tracking
- exploring methods to aggregate routing data of all vehicles which cross the same bridge.

From a bridge asset management perspective, tracking the largest of these vehicles through the network provides a history of access data to inform bridge capacity and risk assessments and enhance the credibility of decisions about access limits for routes.

Conclusions

The project investigated, found and demonstrated that there are increasing opportunities for WiM and related technologies to support evidence-based decisions by TMR.

Internal engagement, national and international reviews found the value proposition for WiM data is not well articulated because the value proposition focuses on compliance management and do not include the optimal management of the road and bridge network and the heavy vehicles that provide transport services for the community.

A draft Strategic Asset Management Plan (SAMP) for TMR WiM was developed. The draft SAMP proposed a program of continual improvement and investment in data quality, accessibility and the application of WiM and related datasets over 10 years to respond to identified stakeholder needs.

The load platforms, low loaders and cranes that pose the greatest risk to bridges across the network were investigated to understand their characteristics and to track them through the network to provide a loading history of large loads to inform access and asset management.

The applications and value of WiM expand with increasing data quality, data coverage, accessibility of data and transformation of data into information and knowledge.

While it is possible to extract value from imperfect data, it is also the case that some applications require improved quality and reliability of data. It was concluded that there are many means for improving data quality, including updating specifications for WiM and classifiers, continuous improvement of data post-processing with a network-level focus and live calibration of existing WiM sites (using vehicles of known and consistent mass, identified in the traffic stream).

Data coverage can be improved through strategic maintenance of existing WiM systems, identifying and addressing data black spots, using the WiM data extrapolation methods developed as part of this project to provide virtual WiM data at classifier sites, combining complementary datasets, incorporating the connection between WiM and other heavy vehicle data sources, including bridge monitoring, ANPR, IAP, ATO, OBM and classifier data. The more independent complementary data sources that can be effectively combined, the more opportunities and value that will arise.

This process of integration generates a completely new vWiM dataset that transforms the traditional view and value of WiM to support data-driven risk-informed decisions from planning to access management.

Recommendations

The project recommends the adoption of the vWiM concepts of integrating multiple datasets and supporting a program of continual improvement. The program should target the quality, coverage, accessibility and linking of datasets. Further development of the engineering and analytics to translate the data into information and knowledge are also necessary to support informed decisions that benefit the Queensland community.

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1. Introduction

1.1 Context

This is the final report of NACOE S26, Review of TMR WiM Systems and Strategies: Virtual WiM and Heavy Vehicle Tracking – Feasibility and Value. The project has spanned four financial years from 2018–19 to 2020–21.

The overall aim of the project was to review Queensland Department of Transport and Main Roads (TMR) weigh-in-motion (WiM) systems and to identify opportunities for improvement with an emphasis on technologies that could improve input to the risk-informed management of the bridge stock. Utilising 13 months of WiM and classifier data in conjunction with other datasets, the project sought to improve data quality and integration, and demonstrate practical applications of enhanced WiM data. In addition, a prototype tracking tool for Class 1 heavy vehicles was developed. Additional opportunities were also identified to further increase the value of WiM.

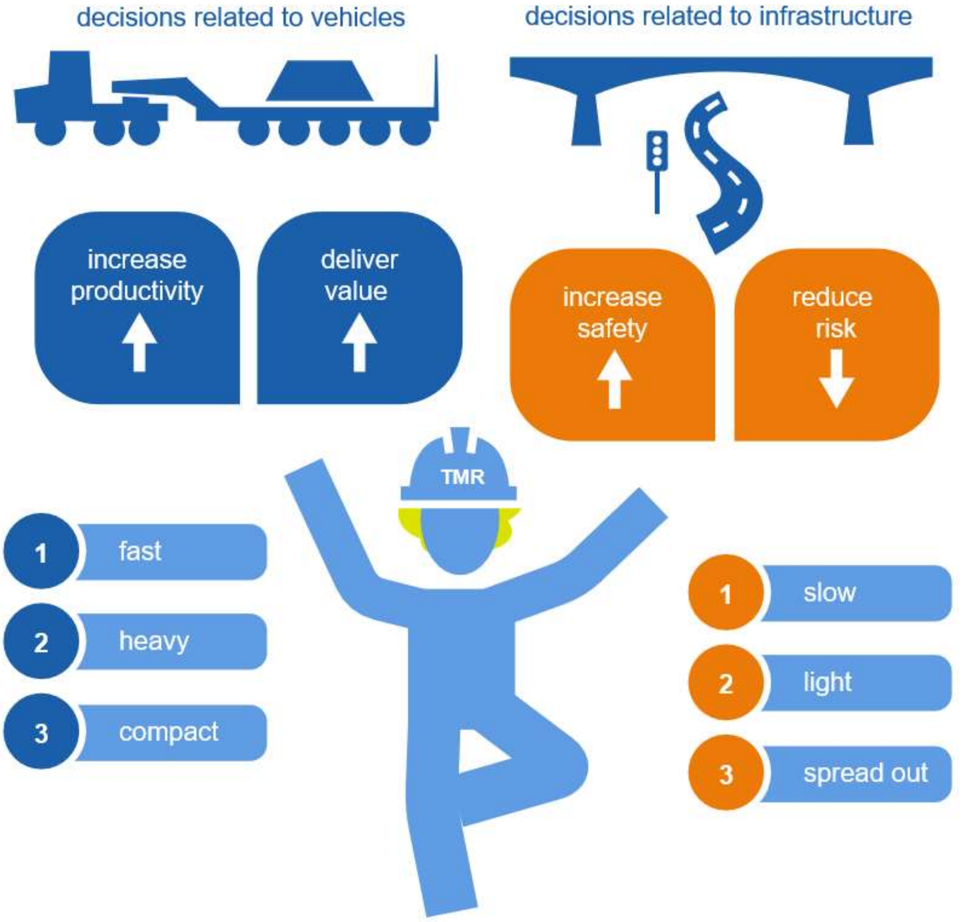
1.1.1 Bridges, WiM and the Network

TMR manages more than 33,000 km of state-controlled roads and 3,000 bridges. Approximately 10% of TMR's bridge assets are operating at less than Australian Standard margins (operational bridges). This presents significant cost, risk and performance issues for TMR transport network management. WiM technology can assist TMR in extending the lives of the operational bridges by quantifying and managing the heavy vehicle loads accessing the bridge network.

1.1.2 Evidence-based Decision Making

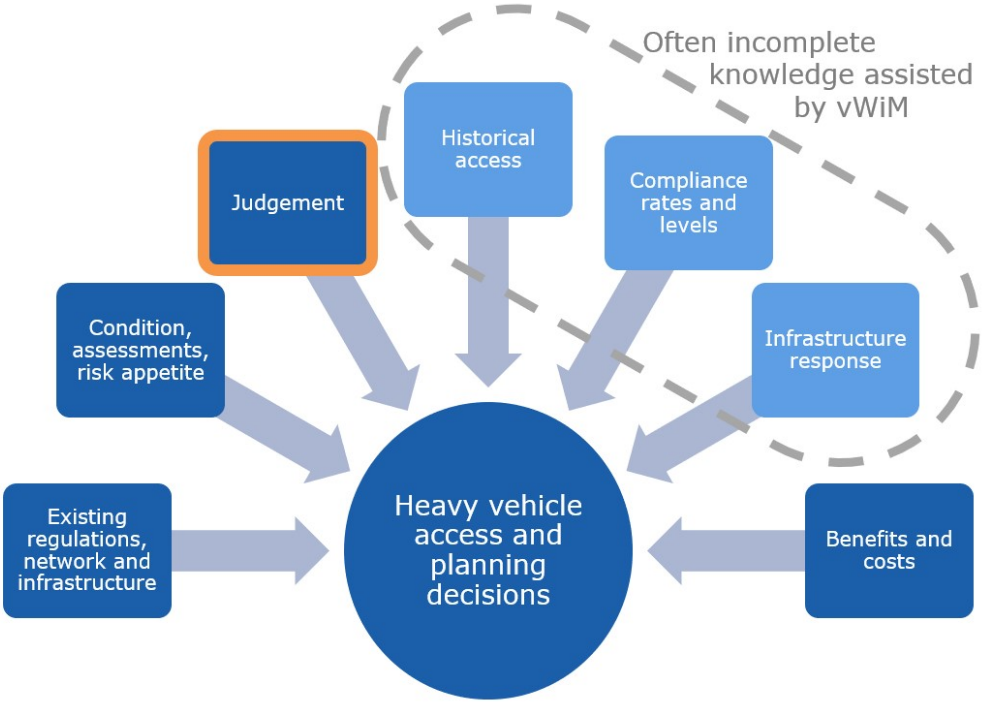
The Queensland economy is dependent on the transport efficiency of people and goods over its road network. The management of the road network by TMR is essential for Queensland. A key function of TMR is optimising heavy vehicle access to the $70 billion road network to benefit the Queensland community. When determining access and planning outcomes, decision makers are regularly required to exercise judgment balancing heavy vehicle productivity and economic development with infrastructure management and safety (TMR 2020). These competing drivers and inputs into the decisions associated with access and planning are summarised in Figure 1.1 and Figure 1.2.

Figure 1.1: Access and planning decision drivers



Evidence is drawn from a diverse range of sources to support these decisions, as illustrated in Figure 1.2. The light blue rectangles correspond to heavy vehicle data collected from weigh-in-motion, classifiers, bridge monitoring and imaging to support the heavy vehicle access decision making process.

Figure 1.2: Evidence is drawn from multiple sources to inform heavy vehicle access decisions



Access and planning decisions must be made with the (often incomplete) subset of information and knowledge available at a given time. This incomplete knowledge leads to sub-optimal decisions and potentially uneconomic or unsafe utilisation of the network.

Credible decisions are aided by accessible data with appropriate levels of confidence. Decisions that are informed about the actual heavy vehicles accessing the network are more credible and respectful towards stakeholders and therefore more productive.

Developments in heavy vehicle data collection and analytics (light blue shaded rectangles in Figure 1.2) are providing an opportunity to improve these decisions and challenge in-built assumptions through the delivery of credible, accessible information about the heavy vehicles accessing the network.

1.2 Aims and Objectives

1.2.1 Aims

The aim of this project is to enhance the value of WiM, classifier and other heavy vehicle data to inform bridge safety and decision making in relation to heavy vehicle network access and bridge management. The focus was on the largest heavy vehicles (Class 1 low loaders, load platforms and mobile cranes) as these vehicles represent the greatest risks to Queensland's bridges and the data available for these vehicles is limited.

1.2.2 Objectives

The objectives were:

1. to gather speed, axle spacing, axle group loads and geographical distribution of the low loaders, load platforms and cranes accessing the network
2. to review and enhance the visibility of low loaders and load platforms in the WiM and classifier data across the network
3. to determine if load platforms can be tracked through the network using WiM and classifiers alone
4. to develop a rationale for using classifier and WiM data to generate vWiM data at classifier stations
5. to ascertain the views of stakeholders on the value of vWiM.

1.3 Scope

The project analysed the WiM and classifier heavy vehicle data records for the TMR state road network in the period between January 2019 and February 2020. The project scope focused on load platforms, low loaders and cranes, and their attributes and behaviour on the network. The scope of activities included:

1. investigating load platform, low loader and crane attributes such as speed, configuration, axle spacing, and mass, and where they travel in the state:
2. investigating the potential for Virtual WiM to enhance the value of existing datasets:
    a. using WiM data to infer mass data for sites with only a classifier
    b. tracking large vehicles (such as load platforms) through the network using WiM and classifier data alone
    c. improving WiM/classifier data for wide low loaders and load platforms.

A related NACOE project, NACOE R103 *Virtual Weigh-in-motion and Queensland Freight Movement Study (2019–20)*, (Hore-Lacy et al. 2020), explored the concept of vWiM across the broader Queensland network and proposed a modular approach that would allow the vWiM system to be implemented sooner while scoping of the potential further advancements to improve accuracy.

1.4 Methodology

The methodology was as follows:

1. Review the literature to understand international experience with vWiM.
2. Collate 12 months of WiM and classifier data from available WiM and classifier sites in Queensland for heavy vehicles with 6 or more axles (Austroads Class 6+[5] heavy vehicles) and cranes.
3. Develop tools to explore, analyse and visualise WiM and classifier data.
4. Engage with stakeholders to identify and explore applications for the data.
5. Evaluate the reliability and levels of confidence in WiM and vWiM data.
6. Identify and trial methodologies for tracking load platforms through the network.
7. Document the characteristics and value of vWiM through a Strengths, Weaknesses, Opportunities and Threats (SWOT) analysis.

1.5 Report Outline

This report discusses the overall project findings as follows:

1. Introduction
2. Learnings of S26
3. Data Characteristics
4. Vehicle Classifications
5. Applications of Virtual WiM
6. Future Considerations
7. Appendices.

The Appendices provide the details of a range of investigations referenced in the report.

- Appendix A contains a list of definitions and terms used in this report.
- Appendix B contains a description of the project dataset.
- Appendix C contains a SWOT analysis of vWiM.
- Appendix D contains the details of stakeholder engagements undertaken as part of this project.

[5] *Austroads Class 6+ vehicles* or *Class 6+ vehicles* refer in this report to heavy vehicles with at least three axle groups.

2. Learnings of Project S26

Project S26 was undertaken over a period of four financial years from 2017–18 to 2020–21 and developed a number of learnings related to WiM. Each year of the project had different project teams and looked at different aspects of WiM. The aspects of WiM which were investigated were as follows:

1. Review of TMR WiM systems
2. Organisational context of WiM
    a. Stakeholder engagement
    b. Strategic Asset Management Plan for WiM
3. Analysis of WiM and classifier data
4. Complementary datasets and applications of vWiM.

2.1 Review of TMR WiM Systems

In the first year of S26, Zanardo and Heldt (2018) reviewed the current TMR WiM systems, to identify opportunities for improvement with the emphasis on technologies which could improve the inputs for risk-informed management of the bridge stock. This first year's work started with a review of the applications of WiM in regard to bridge management as well as the current WiM practices for Australia and New Zealand.

The review found that TMR had mature WiM systems which would benefit from the generation of more accurate WiM data more often across TMR's network of WiMs and to reliably record information on Class 1 heavy vehicles such as cranes, low loaders and load platforms. While Class 1 heavy vehicles are only a small portion of the heavy vehicle fleet, they pose the highest risks to bridges, with little to no reliable independent data available.

Of the identified technology, it was found that installing WiM stations in pavements with slow rates of deterioration would enable higher quality data to be collected more often. The measurement of ground contact width would improve the understanding of the loads of the Class 1 heavy vehicles of interest accessing the network.

2.2 Organisational Context of WiM

In the project's second year (2018–19), to enhance the value of WiM for TMR and provide organisational context, Heldt et. al. (2019) identified the existing value of TMR's WiM network and highlighted future values of an enhanced WiM network.

As TMR sought to better manage network outcomes, the usage of WiM data would become more significant over the medium term (10 years). This would correspond to a changing role for WiM, along with changing technologies, methodologies and organisational engagement. Development of a multi-department change strategy in relation to sourcing and using the data, including WiM data, could facilitate and expedite such change.

The traditional compliance focus for WiM is increasingly inadequate to define the emerging roles of WiM in decision making. There were strong common themes in relation to the future of desired WiM data across many parts of TMR. This would become increasingly true as TMR transitions towards a stronger emphasis on asset management, and as the limited coverage and reliability of WiM improves.

It was noted that WiM data was likely to become a more significant decision input from risk, performance and planning perspectives as well as in supporting compliance initiatives. Many of the developments required to meet this change required investment and engagement. It was difficult to quantify the value of WiM data in dollar terms, but there was evidence that WiM data already represented a strong value proposition under some specific circumstances.

The value of WiM data is enhanced when combined with other data sources and made more accessible. Earlier feedback noted that the development of appropriate TMR methodologies would be required for stakeholders to fully leverage the value of WiM data, including automated and semi-automated data analytics delivering information to support decision making.

As part of the identification of the organisational context, the project undertook several stakeholder engagements and also developed a draft Strategic Asset Management Plan (SAMP) which are outlined below.

2.2.1 Stakeholder Engagement

The value and opportunity of WiM was discussed with stakeholders from the areas of Transport Planning, Portfolio Investment and Planning, Program Delivery and Operations and Engineering and Technology. Key observations from these discussions include (Heldt et al. 2019, Eskew et al. 2021):

- The outcomes that stakeholders are seeking from WiM include:
  - managing risk of vulnerable assets
  - informing the road manager
  - optimising return on investment
  - evidence-based decisions
  - credibility of decisions
  - investment priorities
  - commodity movement
  - freight productivity and network access
  - freight task quantification
  - compliance management.
- The perception that WiM primarily supports enforcement, and since it is often not accurate enough for enforcement, it has limited value, is historic and inadequate in the contemporary context. Support for compliance management is one of many roles WiM data can play underpinning evidence-based decision making.
- WiM currently is not extensively used in decision-making. Network coverage, accessibility and inadequate quality contribute to this status. Greater utilisation of WiM will follow if these limitations are overcome. This is the case from planning to heavy vehicle operations, to pavement design and maintenance, bridge access management and risk assessments.
- The value proposition for WiM increases for all stakeholders as WiM data is integrated with other data, which include automatic number plate recognition (ANPR) data, permit vehicle data, classifier data, OBM data and IAP data. At present, on-board vehicle monitoring technologies are fitted to a small fraction of the heavy vehicle fleet.
- Bridge risk management using WiM is a key opportunity to inform stakeholders of the risks associated with the movement of the cranes, low loaders and load platforms across the network. While these vehicles represent the greatest risk to bridges, the least amount of information is known about them (as they were not previously visible in the WiM and classifier data stream).
- The transport industry knows more about what vehicles access the network than TMR. This is unacceptable.
- Classifiers are cost effective for vehicle classification, but WiM provides mass data as well and is helpful in validating access by innovative vehicles. WiM provides data on all vehicles whereas OBM only provides data from participating vehicles.

2.2.2 Strategic Asset Management Plan for WiM

The value proposition for WiM data is not well articulated globally because the focus is on collecting data to inform compliance rates rather than the optimal management of the road and bridge network and the heavy vehicles that provide transport services for the community.

The gross value added (GVA) to the Queensland economy by the transport, postal and warehousing industry is $15.3 billion in the year you June 2017 with approximately 45% of the workforce associated with road transport (TMR 2018)[6]. Similarly, TMR's annual expenditure on maintenance, preservation and operations is approximately $1 billion per year (TMR 2019). Despite this value and expenditure, WiM data is under-utilised, under-valued and under-loved.

Increasing data analytics capabilities are transforming the accessibility of information derived from WiM and related data technologies. There are increasing opportunities for WiM and related technologies to support evidence-based decisions by TMR in its role as the road manager by informing credible risk-informed decisions to generate the optimal return on both TMR's and the transport industry's infrastructure.

Following stakeholder engagement, the project generated a draft Strategic Asset Management Plan (SAMP) for TMR WiM. The draft SAMP proposed a program of continual improvement and investment in data quality, accessibility and the application of WiM and related datasets over 10 years to respond to identified stakeholder needs (Heldt et al. 2019). While the structure and place of these initiatives requires reconsideration as TMR publishes its organisation-wide SAMP in early 2022, the imperatives for the recommendations have only increased since they were prepared.

This report builds on the insights from the stakeholder feedback and the strategies of the draft SAMP to highlight opportunities, evaluate concepts and to develop prototype tools to point the way to extracting greater value from these datasets.

2.3 Analysis of WiM and Classifier Data

In the project's third year (2019–20), Eskew et. al. (2021) undertook an exploratory analysis of WiM and classifier data (from January 2019 to February 2020).

Several concepts to implement vWiM were developed and refined based on the consultation with stakeholders, which included:

1. combining multiple types of data to provide an enhanced understanding of heavy vehicle traffic and support bridge access and asset management (as exemplified by the monitoring of the Gateway Arterial Flyover)
2. combining WiM and classifier data to enable tracking for vehicles of interest across the network using only configuration and axle footprints. In many cases, measured mass at WiM sites along the trip taken provide mass information at the classifier sites where it was previously unavailable
3. extrapolating mass data from WiM sites to classifier sites with similar traffic, thereby providing an understanding of the expected mass of vehicles at additional locations without having to install new sensors.

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[6] Department of Transport and Main Roads, November 2018, Queensland Transport and Logistics Workforce Current and Future Trends Report, retrieved from https://www.tmr.qld.gov.au/-/media/busind/businesswithus/TLI-Connect/trends/qtlw-current-future-trends-report-2018.pdf?la=en

Using WiM and classifier data, the characteristics of Class 1 low loaders, load platforms and cranes were also explored. The range of dimensions, configurations and locations of operation were identified as part of the process. The following were observed:

1. Data interrogation rules could be developed to largely automate the sorting of WiM and classifier data by vehicle configuration with reasonable confidence, although some configurations were difficult to resolve as there were several possible alternative vehicle types.
2. Generally low loader and load platform data can be interrogated from WiM data with a reasonable level of confidence.
3. It is possible that OBM and ANPR data could be used to improve data confidence, but such data was not available for use.
4. Mobile crane data were found to have some discrepancies in the measured mass data compared to the ATO data.
5. It was possible to process WiM data such that reasonable estimates of WiM could be made at or extrapolated to classifier sites (vWiM).
6. It was feasible to track unusual load platforms through the network.

2.4 Complementary Data and Applications of vWiM

In the final year of project S26 (2020–21), Karl et al. (2021) built upon the findings of Eskew et al. (2021) and merged additional data sources to identify how these additional data could enhance the value of WiM. Utilising the same TMR's dataset of WiM and classifier data from the year 3 work, and with a particular focus on load platforms, low loaders and cranes, and their attributes and behaviour on the network, the following areas were investigated further:

1. ATO crane data to better understand discrepancies identified previously
2. use of the OBM data to benchmark WiM sites
3. investigation of the use of WiM to estimate extreme load effects moments (M), shears (V) and support reactions (R) to inform bridge risk management
4. extrapolation of WiM data to classifier locations
5. evaluation of ANPR data for WiM sites
6. vehicle tracking capability for Class 1 heavy vehicles.

It was estimated that 97% of classifier sites could benefit from GVM extrapolation from WiM sites.

PowerBI interfaces for visualising the detected trips were developed. These tools receive processed data from Python scripts, which output CSV files containing tracked trips, axle spacings and site locations. These tools allow the user to interactively view the axle mass and axle spacings at sites where the vehicle was detected.

In combining complementary datasets, the project found that vWiM could be used to provide increased value to asset managers within TMR. Applications of vWiM investigated which could deliver value to TMR included:

1. combining multiple types of data to provide an enhanced understanding of heavy vehicle traffic and support bridge access and asset management
2. combining WiM and classifier data to enable vehicles of interest to be tracked across the network using configuration and axle footprints alone. In many cases measured mass at WiM sites along the trip taken provide mass information at the classifier sites where it was previously unavailable
3. extrapolating mass data from WiM sites to similar classifier sites providing an understanding of the expected mass of vehicles at additional locations without having to install new sensors
4. comparing known parameters between different sites to assess if their traffic is similar, to better understand where data can be expanded to gain additional insights.

3. Data Characteristics

3.1 Introduction

This section provides insights into the data collected by classifiers and WiM sites around the state using the project dataset as an example[7]. The focus on Class 1 heavy vehicles, which is detailed in Section 3.2, provided the context for the investigations of the potential insights related to Class 1 heavy vehicles from the WiM data (Section 3.3) and classifier data (Section 3.4).

3.2 Identifying Low Loaders and Load Platforms

Bridge monitoring identified the importance of understanding the bridge risks associated with low loaders and load platforms and confirmed that these were under-represented in the WiM and classifier data (Eskew et al. 2021).

Figure 3.1: Load platforms (left) and low loaders (right) are heavy and wide and it is important to understand the risk they pose to bridges

Low loaders and load platforms are uncommon, exhibit unusual vehicle configurations, often occupy multiple lanes and have higher axle loads and gross vehicle mass compared to freight vehicles, refer to Figure 3.1 for examples. These attributes make them difficult to reliably detect with pavement-based systems setup to collect data for the vast majority of vehicles that travel within their lane. Consequently, many of these vehicles are often labelled as erroneous in the WiM and classifier database. Zanardo and Heldt (2018)

[7] An overview of the project dataset (Jan 2019 – Feb 2020) can be found in Appendix B.

recommended the measurement of ground contact width (GCW) low loaders and load platforms. The number of tyres on each axle also affects the axle loads accepted by road agencies.

The width of wide low loaders and load platforms, which often occupy multiple lanes, also means that these vehicles appear in the WiM records as vehicle fragments travelling in adjacent lanes. Refinements to the post-processing algorithms stitched these fragments back together for this study, but further developments by WiM manufacturers to positively identify these vehicles would be welcome. These refinements yielded the previously hidden Class 1 dataset discussed below.

3.3 WiM Data

WiM sites record data on vehicles as they pass over the sensors. As a vehicle passes over the sensors, the following information is recorded:

- time and location of the record
- lane
- configuration
- vehicle speed
- spacings between individual axles
- gross vehicle mass (GVM)
- axle group mass.

TMR has over 60 WiM sites, however, only a subset of these is operational at any given time. The work in this project utilised WiM data from 23 sites rated as having an accuracy of Class C or above per MRTS203 (TMR 2020b). Zanardo and Heldt (2018) identified that TMR would benefit from 'more accurate WiM data more often' across the state.

This section identifies and discusses WiM site variation in configuration, axle spacing and axle mass measurements and measurement accuracy. To develop a better understanding of the limitations of WiM data quality, an assessment of the level of confidence which could be placed in conclusions drawn from the data was undertaken.

3.3.1 Statistics of Semi-trailer Steer Axle Mass

A common metric used to evaluate WiM data accuracy, is by an evaluation of the steer axle mass of a heavy vehicle, under the principle that these values are generally not influenced by the cargo being carried. TMR utilises vehicles with a '123' configuration as their baseline, which have steer axle masses commonly known to range between 5 to 6 t and a tight distribution. As part of the benchmarking, the following were undertaken:

- network investigation
- site specific statistical investigation.

Network investigation

Previous analysis of the axle group masses for 123 configuration vehicles (semi-trailers) in Queensland's WiM data was performed by Vanderstaay (2006). Vanderstaay determined the steer axle mass, laden and unladen tandem axle mass, and laden and unladen tri axle mass for the 123 configuration vehicles.

The project calculated the same axle group mass values from the 123 configuration records of the Austroads class 6+ supplied dataset within 0.1 t, shown in Figure 3.2. The axle group mass median values from Vanderstaay (2006) and the Austroads class 6+ vehicle dataset are shown in Table 3.1. The close match between values (less than 10% variation) provided an indication that the 123-configuration data from the supplied dataset was typical of TMR's network heavy vehicle traffic and that the steer axle masses were relatively consistent over time.

Figure 3.2: Distribution of 123 vehicle axle masses -- Austroads class 6+ dataset (2019–20)

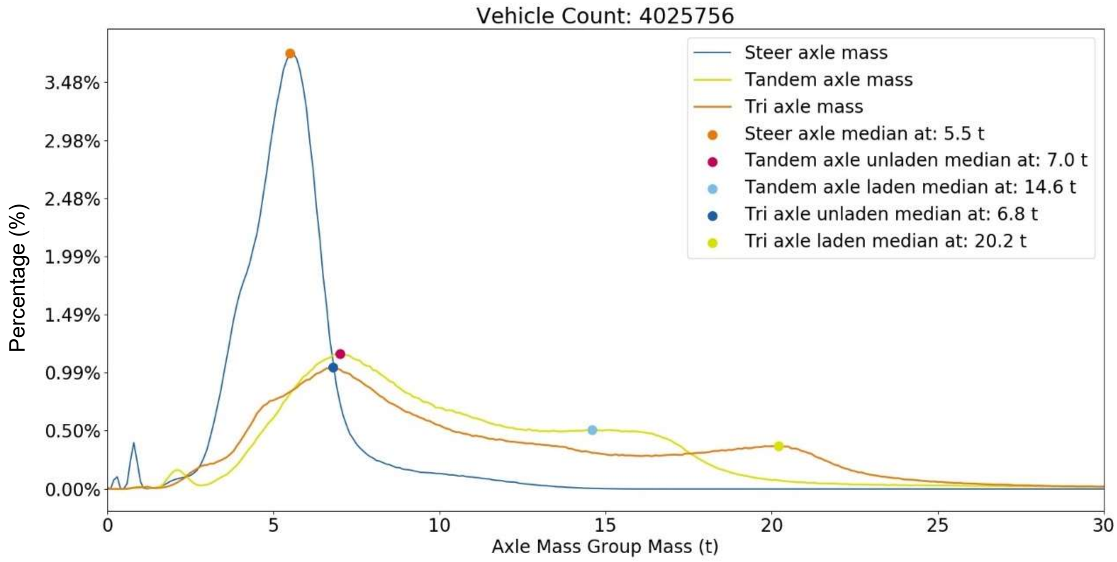


Table 3.1: Comparison of median axle group masses of 123 configuration vehicles

Source	Median steer axle mass (t)	Median tandem axle group mass (t)		Median tri- axle group mass (t)	
		Unladen	Laden	Unladen	Laden
Vanderstaay (2006)	5.4	6.7	15.7	6.7	19.2
Austroads class 6+ dataset (TMR 2019–20)	5.5	7.0	14.6	6.8	20.2

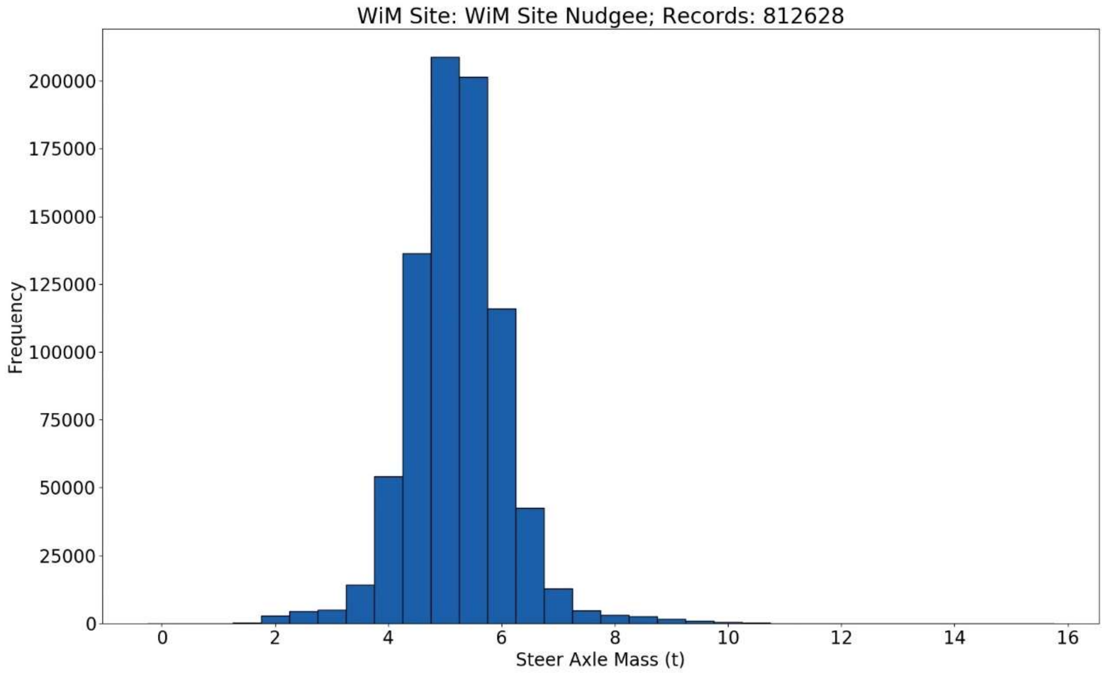
Site-specific statistical investigation

The consistency between the steer axle mass statistics for 123 configuration vehicles between the Vanderstaay paper (2006) and the project dataset support the use of steer axle masses for 123 vehicles to assess the quality and reliability of WiM data. The steer axle masses from supplied data for each WiM site were analysed over a period (one month), using the following steps:

1. The Austroads Class 6+ project dataset (Appendix B) was filtered to only include the records for vehicles with a 123 configuration.
2. Records were grouped by WiM site and by month of recording.
3. For each WiM site during each month, the mean, median, 25% quartile, 75% quartile and ± 2 standard deviations were calculated for the steer axle masses.

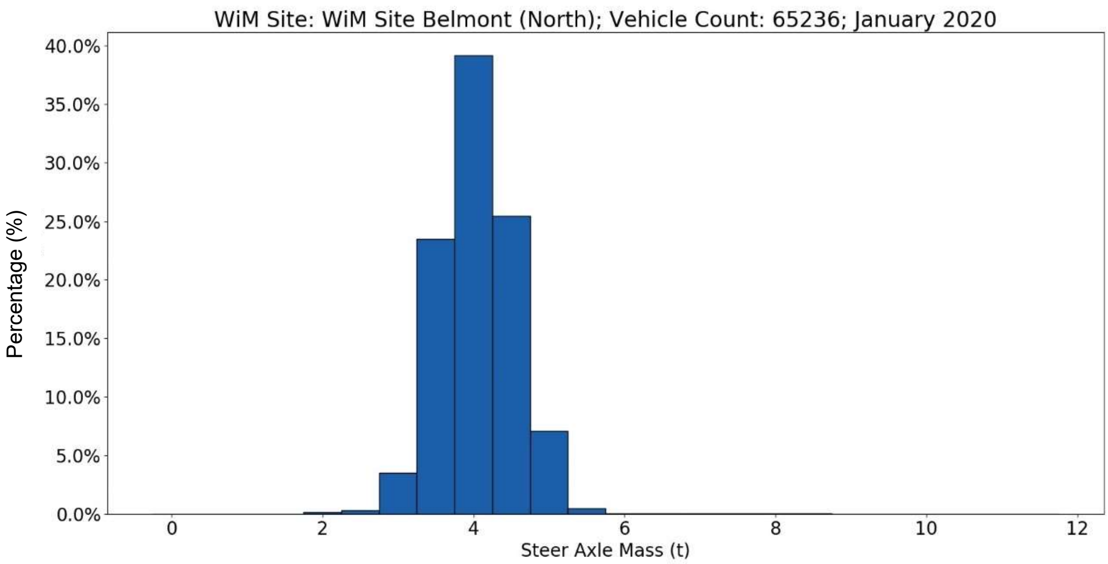
It is assumed that the steer axle masses for the 123 vehicle configurations should be relatively consistent over time, as illustrated in Table 3.1. When a WiM site is providing data which confidently represents the expected traffic it is reasonable to expect the 123 steer axle mass data to present as a normal distribution with tight tails with a mean around 5 to 6 t, such as the distribution shown in Figure 3.3.

Figure 3.3: Expected 123 steer axle mass distribution



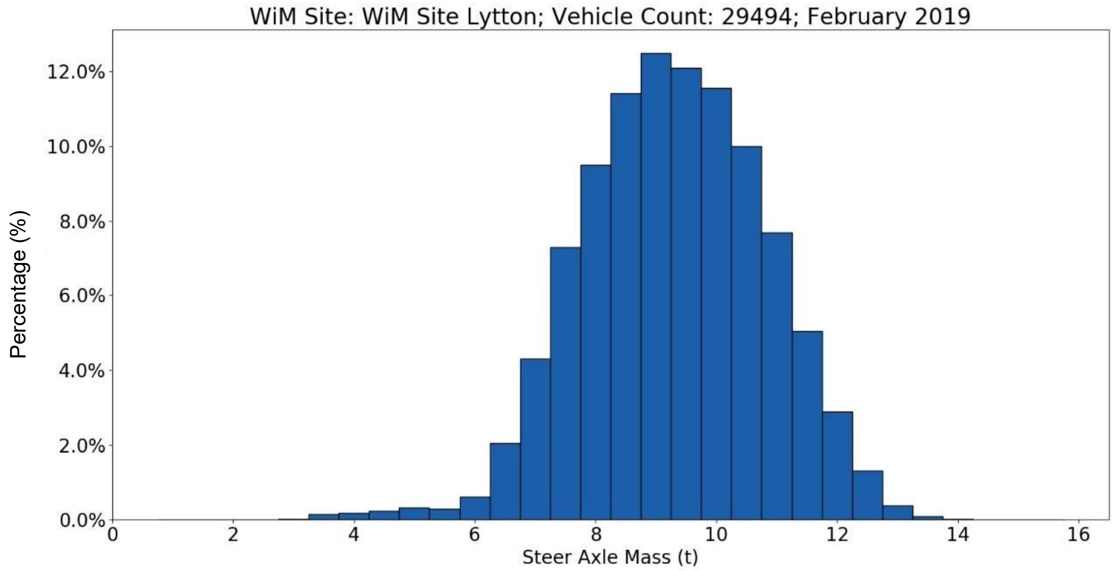
In the event of accuracy concerns of a site's calibration, it can be expected that the mean 123 steer axle masses will be lower or higher. An example of a distribution with a lower mean is shown in Figure 3.4.

Figure 3.4: 123 steer axle mass distribution with calibration concerns



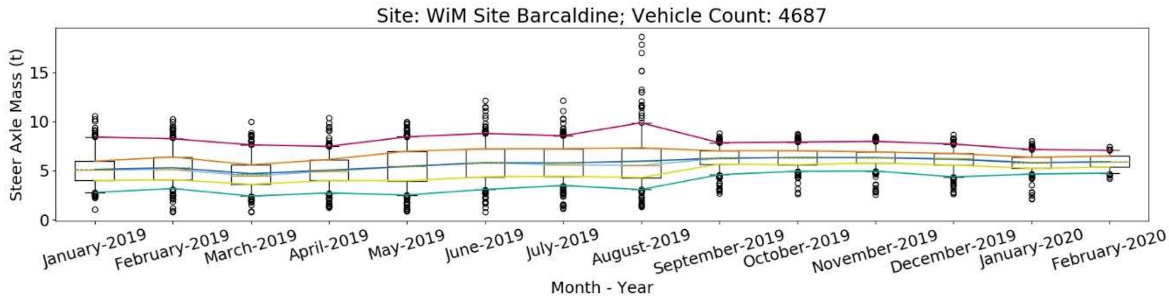
When the 123 steer axle mass data is not normally distributed with tight tails it may indicate that traffic is not normally distributed, that there are errors in the WiM data capture, or there have been changes in quality within the analysed month. An example dataset without a tight distribution is shown in Figure 3.5.

Figure 3.5: Unexpected 123 steer axle mass distribution



The project chose to assess if the 123 steer axle mass distribution was as expected. To accomplish this, box and whisker plots were created for the 123 steer axle masses for each month at each WiM site. An example is shown in Figure 3.6, additional plots at each site can be found in Appendix B. This shows the monthly mean (dark blue), median (light blue), 25% quartile (yellow), 75% quartile (orange) and ± 2 standard deviations (or 5% and 95% bounds) respectively (maroon and aqua). The black circles document the records that are outside the 5% and 95% bounds. These statistical parameters are also presented in a tabular form. These statistical parameters were chosen to assess whether each month of WiM was normally distributed and within the expected ranges with suitably tight tails.

Figure 3.6: Barcaldine WiM site monthly 123 steer axle statistics



	Mean	Median	25% Quartile	75% Quartile	2σ below mean	2σ above mean
January-2019	5.13	5.07	3.99	5.97	2.78	8.43
February-2019	5.30	5.11	4.08	6.39	3.18	8.26
March-2019	4.69	4.47	3.61	5.60	2.41	7.63
April-2019	5.05	4.95	3.99	6.14	2.73	7.48
May-2019	5.43	5.43	3.98	6.98	2.52	8.45
June-2019	5.82	5.82	4.37	7.22	3.09	8.80
July-2019	5.79	5.58	4.44	7.24	3.48	8.56
August-2019	5.97	5.54	4.30	7.33	3.08	9.88
September-2019	6.27	6.26	5.67	7.02	4.59	7.85
October-2019	6.34	6.34	5.61	7.04	4.94	7.92
November-2019	6.33	6.34	5.78	6.91	4.96	7.99
December-2019	6.16	6.23	5.57	6.75	4.37	7.71
January-2020	5.80	5.84	5.24	6.37	4.65	7.16
February-2020	5.91	5.92	5.37	6.49	4.76	7.08

When reviewing the box and whisker plots, seasonal variability was observed in the 123 steer axle masses at some sites, with larger masses recorded in the hotter summer months and smaller masses in the colder winter months. The seasonal variability can be clearly seen in the 2 bands (the 25–75% quartile band as well as the 5–95% band). Seasonal variations in environmental conditions can affect the sensors installed within the pavements. Culway type sensors are less susceptible to change in temperature, being installed on the soffit of culverts where temperatures are more stable. Some newer loggers include temperature sensors to account for temperature variation. However, accurate temperature correction requires multiple calibrations which capture the range of operating temperatures.

More concerning though are the black dots outside of the 5–95% band. These indicate extremely low or high steer axle masses which are most likely erroneous and likely to be considered as implausible records for the steer axle mass (see especially records in Aug 2019, Figure 3.6). The existence of these dots outside the 5–95% band most likely indicates the need for recalibration of the WiM and these dots reduced significantly by Sept 2019, possibly through calibration.

Bridge live load models are interested in estimating extreme loads as well as understanding the typical live load and so an understanding of the accuracy of the estimates of extreme axle loads is important. The outliers in the Figure 3.3 histogram and Figure 3.6 box and whisker plots highlight the challenge of not achieving good results across the spectrum of load levels. From this perspective, the data in Figure 3.6 for February 2020 is excellent but the data leading up to an apparent intervention in August/September 2019 is of much lower quality. Similar patterns can be seen in additional plots in Appendix D of Eskew et al. (2021).

Greater attention to and monitoring of the black dots (outliers), combined with temperature compensation for known seasonal variation impacts on WiM records can be used to improve the quality of the data from WiM sites, which would therefore meet the vision of 'better data more often' thereby providing bridge engineers greater confidence in estimating extreme loads using WiM data.

3.3.2 Evaluation of WiM Data

The benchmarking analysis showed it is possible to assess the quality of WiM data over time using the statistical parameters of the 123 steer axle mass. With this understanding, a method was developed to assess the level of confidence that the data represented the actual traffic. Due to inherent variation in steer axle mass, the method for assessing confidence used threshold values aiming to replicate the accuracy levels for WiM sites defined in MRTS203 *Provision of Weigh-in-Motion System* (TMR 2020b).

Subsequently, WiM data could be filtered, using similar principles, identifying the records within the vehicles of interest dataset inspiring specified levels of confidence. While the use of this filter does not guarantee the accuracy of an individual record, it provides an understanding of the level of confidence inspired by the data from the site at the time the record was captured. Even if the sensors measure axle group loads with perfect accuracy, individual records must be treated with some degree of caution due to potential sources of variation in load including acceleration and braking, lane changes, debris on the road near the sensors and the possibility of wheels running in the shoulder off sensors. Outliers may also represent extreme events which should be considered due to the risk of deterioration to the network and should not be ignored but analysed separately and with due care.

Using confidence filters can improve the plausibility of the observed (WiM data) and expected mass. The level of required confidence in the data is dictated by the specific use case and different use cases require varying levels of confidence. While it is possible to extract value from imperfect data, it is also the case that some applications require improved quality and reliability of data.

The project revealed that it would be possible, based upon the described statistical measurements, to distinguish whether or not the 123 steer axle mass distributions exhibited:

- a normal distribution with tight tails and a mean around 5 to 6 t
- a normal distribution with a lower or higher mean
- a non-normal distribution or a normal distribution without tight tails.

Assessing the distribution of 123 steer axle masses per month allowed the project to estimate the confidence inspired by data from a specific WiM site during a particular period. The low loader and load platform datasets could be filtered to obtain records from temporal periods where the confidence inspired by the data was acceptable. As WiM sites are already assigned accuracy classes based on their performance during calibration (as described in Appendix B), the confidence levels developed aimed to approximate these WiM accuracy levels repeatably. The development of the WiM data confidence levels and the application of these levels to the Austroads Class 6+ dataset are described below.

WiM data confidence levels

Based on the statistical investigation of the 123 steer axle masses, the project determined that it would be possible to assess whether the data from a WiM site over a temporal period could be confidently relied upon as representative of the expected traffic at the site. The project used the statistical parameters shown in Table 3.2 to assess the confidence in the data at a WiM site over a temporal period. These parameters provide an indication of the data mean and distribution shape.

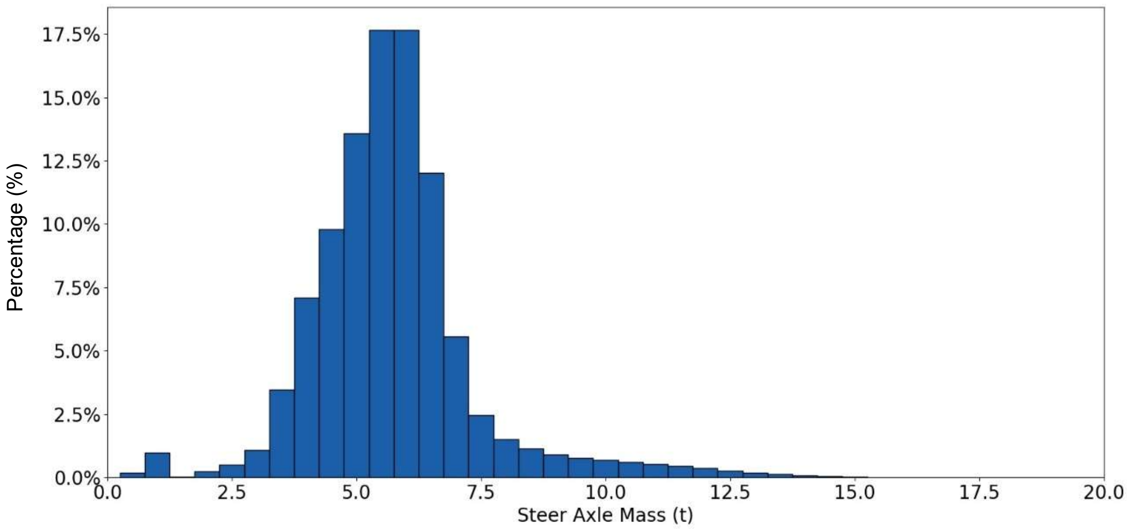
Table 3.2: WiM site confidence parameters

Parameter	Purpose
123 steer axle mass mean	Assess if the 123 steer axle mass data is generally within the expected range.
123 steer axle mass 25% and 75% quartiles	Assess if the 123 steer axle mass distribution has tight tails.
Difference between 123 steer axle mass mean and median	Assess if the 123 steer axle mass is of a normal distribution.

Each statistical parameter is assessed, by comparing it to confidence threshold values, to determine if the data confidently represented the expected traffic during each calendar month. The confidence thresholds for the mean and 25/75% quartiles were set as those values for the 123 steer axle masses from the entire Austroads Class 6+ dataset, based upon the assumption that the majority of the WiM data could be confidently relied upon. The distribution exhibited by the Austroads Class 6+ 123 steer axle masses is shown in Figure 3.7.

The mean and 25/75% quartiles of the full Austroads Class 6+ 123 steer axle masses were 5.48 t, 4.58 t and 6.11 t respectively.

Figure 3.7: Austroads class 6+ 123 steer axle mass distribution



The accuracy of mass readings at WiM sites are known to vary and this is measured at calibration, assigning classes A, B and C according to the accuracy of individual axle, axle group and gross vehicle mass measurements. The confidence thresholds were extended considering the axle group accuracy ranges providing the basis of the class A, class B and class C confidence levels. For the mean to median ratio, a constant 10% variation limit was imposed, based upon the class A axle group accuracy. The thresholds for each confidence level are described in Table 3.3.

Table 3.3: WiM site confidence limits

Parameter	Austroads Class 6+ 123 steer axle mass dataset statistic	Class A confidence limit	Class B confidence limit	Class C confidence limit
Axle group accuracy	--	± 10%	± 15%	± 20%
123 steer axle mass mean	5.48 t	4.98–6.03 t	4.77–6.30 t	4.57–6.58 t
123 steer axle mass 25% quartile	4.58 t	4.16 t	3.98 t	3.82 t
123 steer axle mass 75% quartile	6.1 t	6.71 t	7.02 t	7.32 t
Difference between 123 steer axle mass mean and median	--	10%	10%	10%

For each WiM site and calendar month, the calculated statistical parameters of the 123 steer axle mass were compared to the respective confidence thresholds for each parameter.

Considering a potential use case which requires data quality of at least Class B accuracy, the data can be assessed as Confident, Calibration Concerns, or Unconfident (as defined in Table 3.4) relative to that target accuracy class by comparing the 123 steer axle masses to the Class B Confidence limits outlined in Table 3.3. Similarly, a use case which has a lower requirement for accuracy may consider more of the data to be 'Confident' or one requiring the higher accuracy may consider fewer sites to be 'Confident'.

Table 3.4: WiM site reliability classifications

Classification	Basis	Meaning
Confident	All parameters within Table 3.3 limits.	The 123 steer axle mass distribution was normal with short tails, as shown by the low mean to median ratio and quartile values within the defined bounds, with the average steer axle mass within a range of values demonstrating the accuracy of the site calibration. The data can be confidently used to represent the expected network traffic.
Calibration Concerns	Mean and/or quartile values outside of Table 3.3 limits, mean to median ratio under limit.	The 123 steer axle mass possibly has a similar distribution as the expected network traffic, with the steer axle mass distributions of the expected normal distribution with short tails, but the mean steer axle mass is outside the expected values. This would indicate that the site calibration may no longer be accurate, however the recorded data is otherwise not erroneous.
Unconfident	Mean and median difference outside of Table 3.3 limits or no data recorded.	The 123 steer axle mass likely has an unexpected distribution, with the steer axle mass distribution not exhibiting the expected normal distribution with short tails, as shown by the large mean to median ratio and/or wide quartile values. This designation is not designed to identify the cause or speak to the quality of the data, only indicate that the data within does not reliably represent the expected traffic on the network.

WiM data confidence

The previously defined data confidence evaluation was performed on the Austroads Class 6+ dataset at each site and calendar month. The classifications are provided in Figure 3.8 to Figure 3.10. Using the data classified as 'confident', the mean tandem axle masses from the 123 vehicles are compared to the values determined by Vanderstaay (2006) and from the full Austroads Class 6+ vehicle dataset in Table 3.5.

Table 3.5: Confident dataset 123 steer axle mass statistical comparison

Source	Per cent of WiM dataset	Steer axle mass mean (t)	Tandem axle group mass median (t)		Tri- axial group mass median (t)	
			Unladen	Laden	Unladen	Laden
Vanderstaay (2006)	N/A	5.4	6.7	15.7	6.7	19.2
Austroads Class 6+ dataset (TMR 2019–20)	100%	5.5	7.0	14.6	6.8	20.2
Class A confidence subset of dataset	52%	5.5	7.1	16.0	6.8	20.4
Class B confidence subset of dataset	65%	5.5	7.0	15.9	6.8	20.4
Class C confidence subset of dataset	77%	5.4	7.1	15.1	6.8	20.0

Figure 3.8: Austroads class 6+ class A confidence assessment

Legend	
Confident	(blue)
Calibration Concerns	(orange)
Unconfident	(yellow)
Missing Data	(grey)

WiM / Month	Jan-19	Feb-19	Mar-19	Apr-19	May-19	Jun-19	Jul-19	Aug-19	Sep-19	Oct-19	Nov-19	Dec-19	Jan-20	Feb-20
WiM Site Barcaldine	Calibration Concerns	Calibration Concerns	Calibration Concerns	Calibration Concerns	Calibration Concerns	Calibration Concerns	Calibration Concerns	Calibration Concerns	Calibration Concerns	Calibration Concerns	Calibration Concerns	Calibration Concerns	Confident	Confident
WiM Site Belmont (North)	Confident	Confident	Confident	Confident	Confident	Confident	Calibration Concerns	Calibration Concerns	Calibration Concerns	Missing Data	Calibration Concerns	Calibration Concerns	Calibration Concerns	Calibration Concerns
WiM Site Belmont (South)	Confident	Confident	Confident	Confident	Confident	Confident	Confident	Confident	Confident	Missing Data	Calibration Concerns	Calibration Concerns	Calibration Concerns	Calibration Concerns
WiM Site Boggabilla	Confident	Confident	Confident	Confident	Confident	Confident	Confident	Missing Data	Missing Data	Missing Data	Missing Data	Missing Data	Missing Data	Missing Data
WiM Site Burpengary	Missing Data	Missing Data	Missing Data	Missing Data	Missing Data	Calibration Concerns	Missing Data	Missing Data	Missing Data	Missing Data	Missing Data	Missing Data	Missing Data	Missing Data
WiM Site Calcium	Confident	Confident	Missing Data	Missing Data	Confident	Confident	Confident	Confident	Confident	Confident	Confident	Confident	Calibration Concerns	Calibration Concerns
WiM Site Capella	Calibration Concerns	Calibration Concerns	Missing Data	Calibration Concerns	Missing Data	Calibration Concerns	Calibration Concerns	Calibration Concerns	Calibration Concerns	Calibration Concerns	Calibration Concerns	Calibration Concerns	Calibration Concerns	Calibration Concerns
WiM Site Cloncurry	Missing Data	Missing Data	Missing Data	Missing Data	Missing Data	Confident	Confident	Confident	Calibration Concerns	Calibration Concerns	Calibration Concerns	Calibration Concerns	Confident	Calibration Concerns
WiM Site Freestone	Calibration Concerns	Confident	Calibration Concerns	Calibration Concerns	Calibration Concerns	Calibration Concerns	Calibration Concerns	Calibration Concerns	Confident	Calibration Concerns	Calibration Concerns	Calibration Concerns	Calibration Concerns	Calibration Concerns
WiM Site Gatton	Confident	Confident	Confident	Calibration Concerns	Calibration Concerns	Calibration Concerns	Calibration Concerns	Calibration Concerns	Calibration Concerns	Confident	Calibration Concerns	Calibration Concerns	Calibration Concerns	Confident
WiM Site Hemmant	Calibration Concerns	Calibration Concerns	Calibration Concerns	Confident	Confident	Confident	Confident	Confident	Confident	Calibration Concerns	Calibration Concerns	Calibration Concerns	Missing Data	Missing Data
WiM Site Hotham Ck southbound	Calibration Concerns	Calibration Concerns	Calibration Concerns	Missing Data	Missing Data	Missing Data	Missing Data	Missing Data	Missing Data	Missing Data	Missing Data	Missing Data	Missing Data	Missing Data
WiM Site Lytton	Missing Data	Calibration Concerns	Calibration Concerns	Calibration Concerns	Confident	Confident	Confident	Confident	Missing Data	Missing Data	Missing Data	Missing Data	Missing Data	Missing Data
WiM Site Middle Creek	Unconfident	Missing Data	Missing Data	Missing Data	Missing Data	Missing Data	Missing Data	Missing Data	Missing Data	Missing Data	Missing Data	Missing Data	Missing Data	Missing Data
WiM Site Mt Isa	Missing Data	Missing Data	Missing Data	Missing Data	Missing Data	Calibration Concerns	Calibration Concerns	Calibration Concerns	Calibration Concerns	Calibration Concerns	Calibration Concerns	Unconfident	Unconfident	Unconfident
WiM Site Narangba	Unconfident	Unconfident	Unconfident	Calibration Concerns	Calibration Concerns	Calibration Concerns	Calibration Concerns	Missing Data	Missing Data	Missing Data	Missing Data	Missing Data	Missing Data	Missing Data
WiM Site Nudgee	Confident	Confident	Confident	Confident	Calibration Concerns	Calibration Concerns	Calibration Concerns	Calibration Concerns	Confident	Confident	Confident	Confident	Calibration Concerns	Calibration Concerns
WiM Site Oakey	Calibration Concerns	Calibration Concerns	Calibration Concerns	Calibration Concerns	Calibration Concerns	Calibration Concerns	Calibration Concerns	Calibration Concerns	Calibration Concerns	Calibration Concerns	Calibration Concerns	Calibration Concerns	Calibration Concerns	Missing Data
WiM Site Oxenford northbound	Unconfident	Unconfident	Unconfident	Unconfident	Unconfident	Unconfident	Unconfident	Unconfident	Missing Data	Unconfident	Unconfident	Calibration Concerns	Calibration Concerns	Calibration Concerns
WiM Site Southbrook	Calibration Concerns	Calibration Concerns	Calibration Concerns	Missing Data	Missing Data	Confident	Confident	Confident	Confident	Calibration Concerns	Calibration Concerns	Confident	Confident	Confident
WiM Site Townsville Port Access Road	Calibration Concerns	Calibration Concerns	Calibration Concerns	Calibration Concerns	Calibration Concerns	Confident	Confident	Missing Data	Missing Data	Missing Data	Missing Data	Missing Data	Missing Data	Missing Data
WiM Site Tugun	Confident	Confident	Confident	Confident	Confident	Confident	Confident	Confident	Confident	Confident	Confident	Confident	Missing Data	Missing Data

Figure 3.9: Austroads class 6+ class B confidence assessment

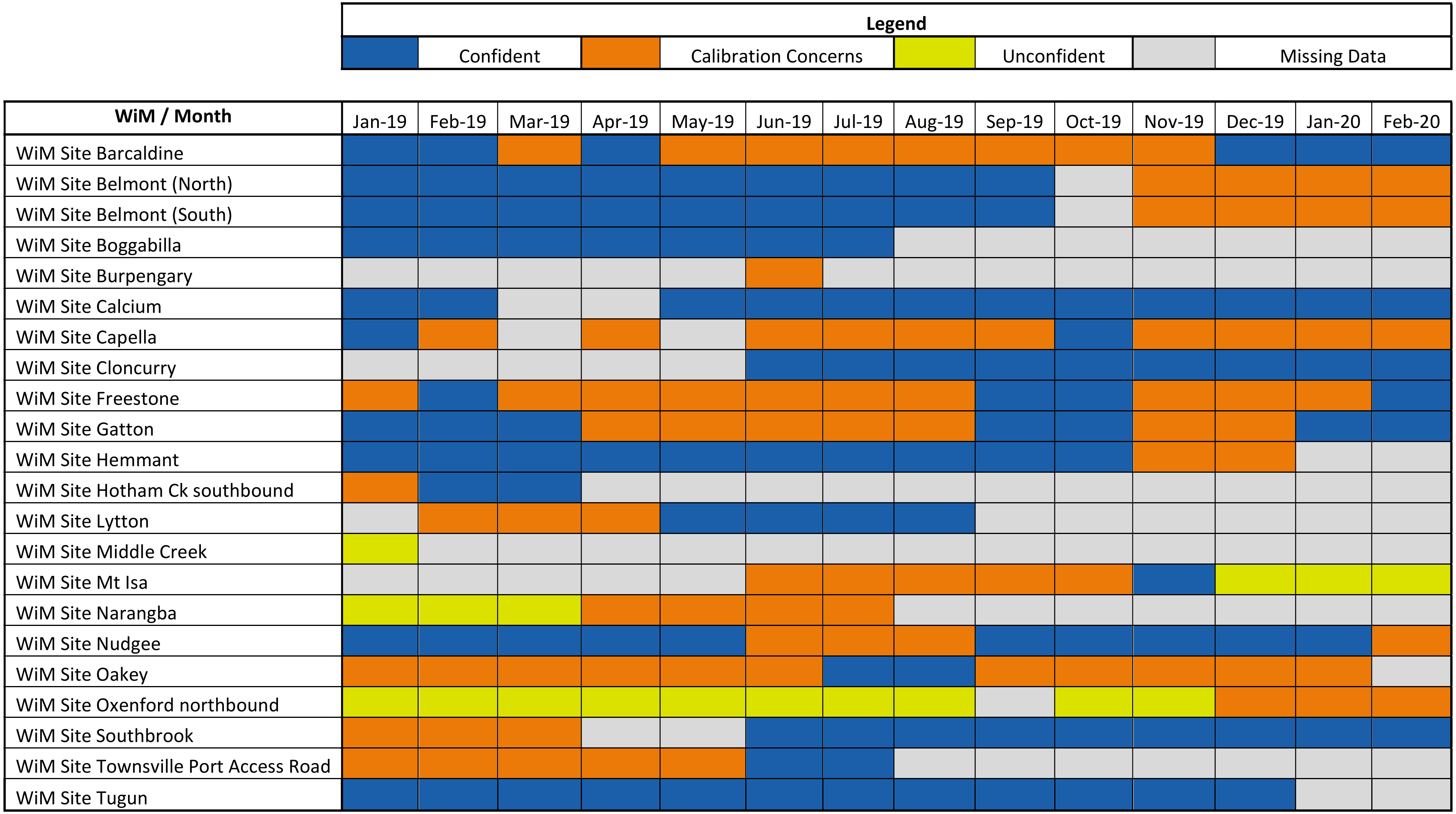


Figure 3.10: Austroads class 6+ class C confidence assessment

Legend: Confident (blue) | Calibration Concerns (orange) | Unconfident (yellow) | Missing Data (grey)

WiM / Month	Jan-19	Feb-19	Mar-19	Apr-19	May-19	Jun-19	Jul-19	Aug-19	Sep-19	Oct-19	Nov-19	Dec-19	Jan-20	Feb-20
WiM Site Barcaldine	Confident	Confident	Calibration Concerns	Confident	Confident	Confident	Confident	Calibration Concerns	Confident	Confident	Confident	Confident	Confident	Confident
WiM Site Belmont (North)	Confident	Confident	Confident	Confident	Confident	Confident	Confident	Confident	Confident	Missing Data	Calibration Concerns	Calibration Concerns	Calibration Concerns	Calibration Concerns
WiM Site Belmont (South)	Confident	Confident	Confident	Confident	Confident	Confident	Confident	Confident	Confident	Missing Data	Calibration Concerns	Calibration Concerns	Calibration Concerns	Calibration Concerns
WiM Site Boggabilla	Confident	Confident	Confident	Confident	Confident	Confident	Confident	Missing Data	Missing Data	Missing Data	Missing Data	Missing Data	Missing Data	Missing Data
WiM Site Burpengary	Missing Data	Missing Data	Missing Data	Missing Data	Missing Data	Confident	Missing Data	Missing Data	Missing Data	Missing Data	Missing Data	Missing Data	Missing Data	Missing Data
WiM Site Calcium	Confident	Confident	Missing Data	Missing Data	Confident	Confident	Confident	Confident	Confident	Confident	Confident	Confident	Confident	Confident
WiM Site Capella	Confident	Confident	Missing Data	Confident	Missing Data	Calibration Concerns	Calibration Concerns	Confident	Confident	Confident	Confident	Confident	Confident	Confident
WiM Site Cloncurry	Missing Data	Missing Data	Missing Data	Missing Data	Missing Data	Confident	Confident	Confident	Confident	Confident	Confident	Confident	Confident	Confident
WiM Site Freestone	Calibration Concerns	Confident	Confident	Calibration Concerns	Calibration Concerns	Calibration Concerns	Calibration Concerns	Calibration Concerns	Confident	Confident	Confident	Confident	Confident	Confident
WiM Site Gatton	Confident	Confident	Confident	Confident	Calibration Concerns	Calibration Concerns	Calibration Concerns	Calibration Concerns	Confident	Confident	Confident	Confident	Confident	Confident
WiM Site Hemmant	Confident	Confident	Confident	Confident	Confident	Confident	Confident	Confident	Confident	Confident	Confident	Confident	Missing Data	Missing Data
WiM Site Hotham Ck southbound	Calibration Concerns	Confident	Confident	Missing Data	Missing Data	Missing Data	Missing Data	Missing Data	Missing Data	Missing Data	Missing Data	Missing Data	Missing Data	Missing Data
WiM Site Lytton	Missing Data	Calibration Concerns	Calibration Concerns	Calibration Concerns	Confident	Confident	Confident	Confident	Missing Data	Missing Data	Missing Data	Missing Data	Missing Data	Missing Data
WiM Site Middle Creek	Unconfident	Missing Data	Missing Data	Missing Data	Missing Data	Missing Data	Missing Data	Missing Data	Missing Data	Missing Data	Missing Data	Missing Data	Missing Data	Missing Data
WiM Site Mt Isa	Missing Data	Missing Data	Missing Data	Missing Data	Missing Data	Confident	Confident	Confident	Confident	Confident	Confident	Unconfident	Unconfident	Unconfident
WiM Site Narangba	Unconfident	Unconfident	Unconfident	Calibration Concerns	Calibration Concerns	Calibration Concerns	Calibration Concerns	Missing Data	Missing Data	Missing Data	Missing Data	Missing Data	Missing Data	Missing Data
WiM Site Nudgee	Confident	Confident	Confident	Confident	Confident	Confident	Confident	Confident	Confident	Confident	Confident	Confident	Confident	Confident
WiM Site Oakey	Calibration Concerns	Calibration Concerns	Calibration Concerns	Calibration Concerns	Calibration Concerns	Confident	Confident	Confident	Confident	Calibration Concerns	Calibration Concerns	Calibration Concerns	Calibration Concerns	Missing Data
WiM Site Oxenford northbound	Unconfident	Unconfident	Unconfident	Unconfident	Unconfident	Unconfident	Unconfident	Unconfident	Missing Data	Unconfident	Unconfident	Calibration Concerns	Calibration Concerns	Calibration Concerns
WiM Site Southbrook	Calibration Concerns	Calibration Concerns	Confident	Missing Data	Missing Data	Confident	Confident	Confident	Confident	Confident	Confident	Confident	Confident	Confident
WiM Site Townsville Port Access Road	Calibration Concerns	Confident	Confident	Calibration Concerns	Calibration Concerns	Confident	Confident	Missing Data	Missing Data	Missing Data	Missing Data	Missing Data	Missing Data	Missing Data
WiM Site Tugun	Confident	Confident	Confident	Confident	Confident	Confident	Confident	Confident	Confident	Confident	Confident	Confident	Missing Data	Missing Data

3.3.3 Key Findings

The results of the analysis of the 123 steer axle masses revealed:

- The 123 steer vehicles have not significantly changed mass profile since 2006, supporting their use as a long-term metric for estimating WiM accuracy and confidence.
- Seasonal variability in the mass readings is evident at certain WiM sites.
- It is easy to observe from statistical parameters (mean, median and quartiles) when the steer axle masses:
  - follow the expected values and distribution
  - follow the expected distribution shape but with values which had been shifted higher or lower (indicating sensors drifting out of calibration)
  - did not follow the expected distributions (may indicate poor data quality).
- The existence of records (black dots) outside of the 5–95% band most likely indicate the need for recalibration of the WiM site while the seasonal variations in the 25–75% and 5–95% bands provide opportunities for temperature compensation based on known seasonal effects on WiM data at the specific site.
- 123 vehicle steer axle mass can be used to assess the confidence inspired by data collected at a WiM site over a period of time.
- The confidence assessment can be used to filter the data to provide increased confidence in subsequent analyses of vehicles of interest such as low loaders and load platforms or for specific use cases.

As bridge engineers are interested in estimating extreme loads to inform assessments, there is considerable opportunity to improve WiM data at the extreme loads, by paying greater attention to and monitoring of the outliers (black dots in Figure 3.6), combined with temperature compensation for known seasonal variation impacts on WiM records. This recommendation would result in 'better data more often' and improve the confidence bridge engineers have in WiM data.

3.4 Classifier Data

Like WiM sites, classifiers record vehicles passing a point on the road. The same information is recorded at classifiers as at WiM sites except mass is not recorded. As a vehicle passes over the sensors, the following information is recorded:

- time and location of the record
- lane
- configuration
- vehicle speed
- spacings between individual axles.

In this report, the term 'classifier data' refers to the classifier portion of the data from both classifier and WiM sites.

3.4.1 Identifying Vehicles of Interest within Classifier Data

One of the initial challenges with the classifier data was the identification of the Class 1 vehicles of interest. Logical rules were developed based on a review of Heavy Vehicle National Laws (HVNL) and internal access assessment procedures, to identify low loaders, load platforms and cranes within the larger datasets.

The project dataset includes 27,000,000 Austroads Class 6+[8] vehicles of which 393,500 were identified as low loaders or load platforms including 45,779 WiM records after application of data quality filters to remove records where confidence in the data is low[9]. Filtering the raw Austroads Class 6+ data, in this way for vehicles of interest, reduced the size of the working dataset (approximately 2% of the total dataset) facilitating simpler data manipulation and analysis.

An evaluation of classifier data, to identify the vehicles of interest is provided in the following section. This looked at:

- axle spacing measurement accuracy
- axle spacing impact on configuration
- axle spacing accuracy impact on classification
- incorrect configuration.

Axle spacing measurement accuracy

The axle spacings for larger heavy vehicles can act as a signature, which are important to identify and understand their impact on the network as they are often carrying larger loads. The axle spacing measurement accuracy plays a big role in being able to accurately identify this individual footprint, as the more accurate the measurement, the more confidence that it is the same vehicle at another location. If it is known where the vehicle has been it is possible to identify the potential impact the vehicle may have had on the infrastructure it has crossed.

While investigating the accuracy of the axle spacing measurements, a review was conducted on the spacing thresholds used to identify separate axle groups. As per the Austroads vehicle classification system (Austroads 2006), adjacent axles are considered to be part of the same group if they are ≤ 2.1 m from each other. However, during this investigation the project noted deviations from this rule at some sites. To investigate the axle group spacing rules for each WiM and classifier site, the project identified the maximum axle spacing between two adjacent axles within any axle group and the minimum axle spacing between axles of different groups for each site. This allowed the project to establish the axle group cut-off rule at each site. Many sites had rules which, based upon the available data, conformed to the Austroads axle group rule (e.g. *14C Ch 17.22 – West Hughenden* or *WiM Site Gatton*). However, some sites had noted axle group thresholds higher (e.g. *WiM Site Lytton* or *180 m West of Macgregor Street*) or lower (e.g. *WiM Site Hemmant* or *South of Progress Rd on the Ipswich Motorway*) than those prescribed by Austroads.

The minimum axle spacing between 2 axle groups, maximum axle spacing within an axle group and the axle group threshold rule implied by the records are displayed in Table 3.6 for a sample of sites representing:

- axle group thresholds lower than the Austroads rule
- axle group rules conforming to the Austroads rule (axle group cut-off of ≤ 2.1 m)
- axle group thresholds higher than the Austroads rule.

Axle group rules are coded into the site data loggers and pre-determined in the data received by TMR, however the axle groupings can also be re-calculated directly from the axle spacing data in a post-process.

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[8] *Austroads Class 6+ vehicles* or *Class 6+ vehicles* refers in this section to heavy vehicles with at least three axle groups.

[9] Records with speeds greater than 150 km/h, axle spacings less than 1 m, and periods when steer-axle masses of semi-trailers were far from the expected range were removed.

Table 3.6: Representation of types of axle group cut-off rules

Classifier and WiM sites	Minimum axle spacing between 2 axle groups (m)	Maximum axle spacing within a group (m)	Axle group cut-off rule (m)	Relation to Austroads axle group rule
WiM Site Hemmant	2.01	2	≤ 2.01	Lower
WiM Site Belmont (south)	2.01	2	≤ 2.01	Lower
WiM Site Belmont (north)	2.01	2	≤ 2.01	Lower
South of Progress Rd on Ipswich Motorway	2.07	2.06	< 2.07	Lower
17B-20 m E of Acacia Ave (PS) Loop/Piezo	2.09	2.08	< 2.09	Lower
14C Ch 17.22 – West Hughenden	2.1	2.09	< 2.1	Conforming
WiM Site Gatton	2.1	2.09	< 2.1	Conforming
WiM Site Nudgee	2.1	2.09	< 2.1	Conforming
14E Ch 6.33 – 2.7 km west of Int 14E/78A	2.1	2.09	< 2.1	Conforming
15B Ch 50.9 km (west of Gunpowder Int)	2.1	2.09	< 2.1	Conforming
WiM Site Barcaldine	2.1	2.09	< 2.1	Conforming
5807 Ch 4.88 km – south of Julia Creek	2.11	2.09	< 2.11	Conforming
30 m north of Tallebudgera Creek Overflow	2.11	2.09	< 2.11	Conforming
180 m west of Macgregor Street	2.11	2.1	≤ 2.1	Conforming
WiM Site Lytton	2.31	2.3	≤ 2.3	Higher
WiM Site Boggabilla	2.31	2.3	≤ 2.3	Higher
WiM Site Hotham Ck southbound	2.31	2.3	≤ 2.3	Higher
WiM Site Tugun	2.35	2.3	≤ 2.3	Higher

Axle spacing impact on configuration

The definitions in Table 3.7 are used throughout the document, for further details refer to Appendix A.

Table 3.7: Common terms

Term	Definition
Austroads class 6+	A vehicle with ≥ 3 axle groups and ≥ 3 axles. *Refer to* Figure A.1 *for more details.*
Classification	The type of vehicle which is identified (e.g. truck, crane, truck and dog, low loader, load platform, B-double, etc.) based on a vehicle classification scheme, e.g. the Austroads 1994 12-bin vehicle classification scheme (Austroads 2000), HVNL classification scheme.
Classifier	In this report, the term 'classifier data' refers to the classifier portion of the data from both classifier and WiM sites.
Configuration *(of a vehicle)*	A string representing the number of axles in each successive **axle group** of a vehicle **combination**. (e.g. '1223')
Combination	A group of vehicles consisting of a motor vehicle such as a **prime mover** or rigid truck towing one or more other vehicle units such as a **semi-trailer** or trailer. *Source: National Heavy Vehicle Regulator (NHVR) (2016a).*
Vehicle type	The common language description of the vehicle (e.g. truck, crane, truck and dog, low loader, load platform, B-double, etc.), closely aligned to a vehicle classification scheme.

The configuration of a record represents the number of axles in each axle group. Variations in axle spacing accuracy and axle group rules impact the calculated configuration for a record. Examples of incorrectly identified crane configurations, based on manufacturer specifications, using the variations in axle spacing accuracy are shown in Table 3.8. A number of inconsistencies in the recorded configurations were identified in the supplied dataset. Subsequently the configurations were re-calculated for each record using the axle spacing data and the Austroads classification rules. While this did not address errors associated with measurement errors, it did address concerns regarding varying axle group rule cut-offs implemented at different sites.

Table 3.8: Effect of measurement accuracy tolerance on the configuration

Crane	Axle spacing 1 (m)	Axle spacing 2 (m)	Axle spacing 3 (m)	Axle spacing 4 (m)	Axle spacing 5 (m)	Axle group rules	Potential configurations based upon axle group rules and tolerances
LIEBHERR LTM1090 all-terrain crane	2.54	1.65	2.44	1.65	-	*Axle group spacing cut-off*: < 2.1 m, < 2.3 m	122 or 14
Demag AC 205 all-terrain crane	1.7	2.0	1.65	–	–	*Axle group spacing cut-off*: < 2.1 m	22 or 4
LIEBHERR LTM 1160 all-terrain crane	2.85	1.7	2	1.7	1.7	*Axle group spacing cut-off*: < 2.1 m	15 or 123

Note: Assumed axle spacing tolerance of ± 200 mm.

Additionally, it was noted during the project's stakeholder engagement that low loaders, load platforms and cranes can have retractable axles. If a vehicle travels over a classifier or WiM site with an axle retracted, that would impact its classification and configuration.

Impact of axle spacing measurement tolerance on vehicle classification

The effect of axle spacing measurement tolerance on the classified configuration was investigated to better understand how improving the accuracy of axle spacing measurements may impact classification. Vehicle counts for common low loader and load platform configurations are shown in Table 3.9, determined using two different axle spacing measurement tolerances. These are:

1. the nominal ± 200 mm measurement tolerance used by TMR
2. a tighter tolerance of ± 100 mm.

Changing the assumed axle spacing tolerance from ± 200 mm to ± 100 mm reduced the total count of vehicles of interest (low loaders and load platforms) by 66% ($\frac{n_{200}-n_{100}}{n_{100}}$). This demonstrates that the axle spacing measurement accuracy impacts the interpretation of the data. Better understanding of the measurement accuracies enables improved analysis of the datasets and increases the value of the data for certain use cases.

Table 3.9: Effect of axle spacing measurement tolerance on low loader and load platform vehicle counts

Configuration	Vehicle count for ± 200 mm tolerance	Vehicle count for ± 100 mm tolerance	% difference ($\frac{n_{200}-n_{100}}{n_{200}}$)
125	1,501	814	−46%
1,225	1,318	630	−52%
225	540	276	−49%
126	1,112	754	−32%
1,226	335	167	−50%
127	1,200	777	−35%
1,227	456	291	−36%
128	712	448	−37%
1,228	152	85	−44%
129	236	146	−38%
1,229	14	13	−7%

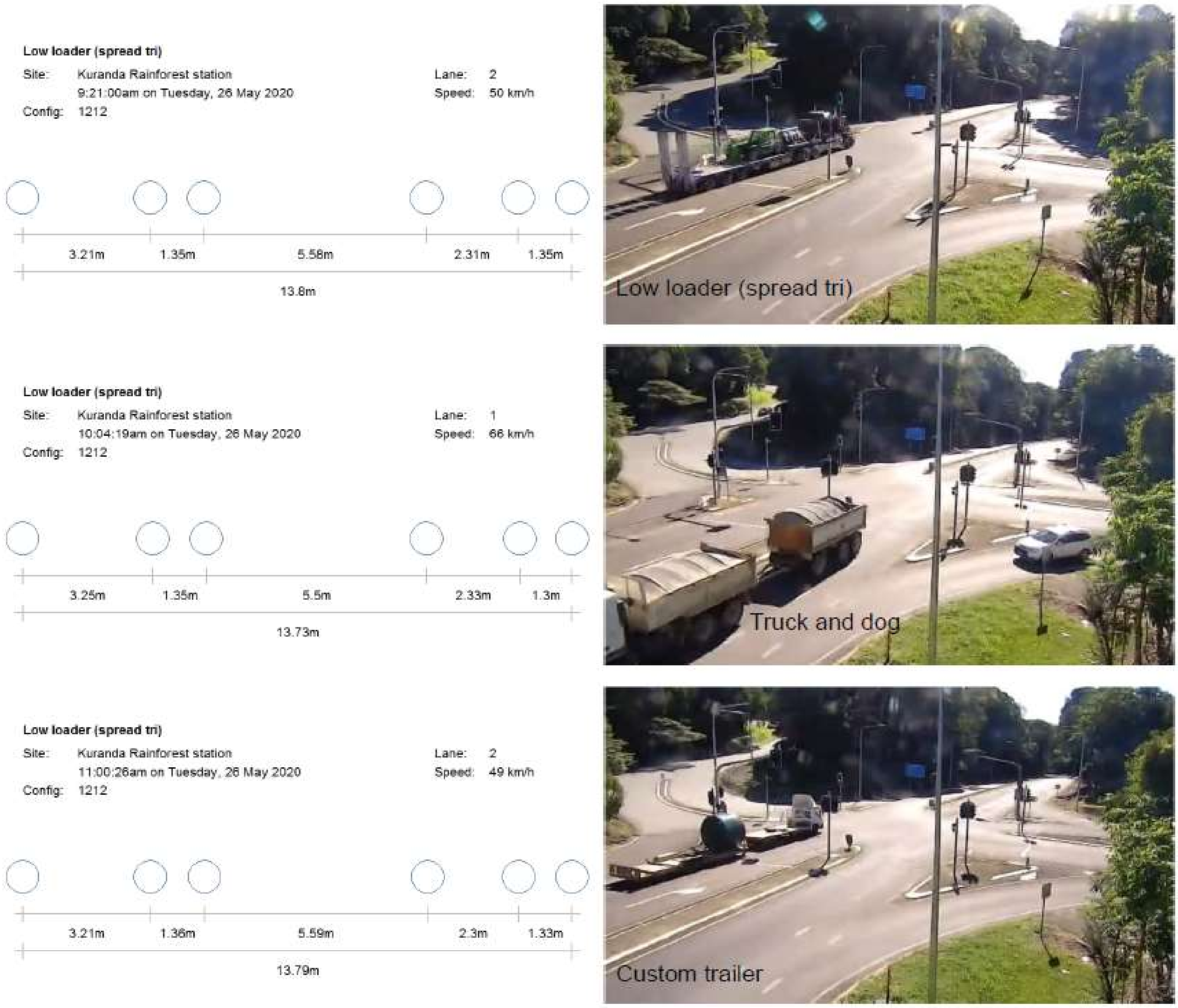
Configuration	Vehicle count for ± 200 mm tolerance	Vehicle count for ± 100 mm tolerance	% difference $\left(\frac{n_{200}-n_{100}}{n_{200}}\right)$
120	422	316	−25%
1,220	219	162	−26%
12A	48	44	−8%
All	8,265	4,923	−40%

Incorrect vehicle classification

While the project's procedure for identifying the configuration in a record improved the accuracy of identifying vehicles of interest, errors were still noted throughout the dataset. Different vehicle types (refer to Appendix A for definition) can have the same configurations and spacing, which means distinguishing vehicle groups using axle spacing rules can be challenging. An example of the potential for incorrect classification is shown in Figure 3.11. Each of the three vehicles have nearly indistinguishable axle spacing geometries and were classified as low loaders. However, through analysis of available photos from a nearby camera, it was noted that only one of the records was a low loader, with the other two records identified as a truck and dog and a custom trailer. These incorrect classifications are likely common throughout the low loader dataset for vehicles without a dolly, with lower frequency amongst the rarer load platform configurations.

The use of ground contact width would add another axis which would help to improve the differentiation of vehicles, depending on the accuracy of the measurements.

Figure 3.11: Inaccurate vehicle type identification using configuration and axle spacing rule



The project noted that at the Tugun WiM, the axle spacing measurements had a resolution of ± 50 mm (i.e. measurements would be 2.30 or 2.35 m but not in-between). This occurrence seemed to be isolated to this site.

3.4.2 Evaluation of Classifier Data

WiM and classifier data were analysed and reviewed to understand their applications and limitations. The technical specification for WiM sites (MRTS203 TMR 2020b) calls for an accuracy of ± 15 mm on axle spacing. Conversely there is no similar requirement currently specified for classifiers (MRTS251 TMR2017), which requires > 95% accuracy on the classification of vehicles using Austroads vehicle types. Operationally TMR assumes an accuracy of ± 200 mm due to variability of axle spacing data between classifier and WiM datasets.

Inconsistencies were identified in configurations automatically computed by the proprietary installations, which appear due to differences in the logic implemented in the data loggers. To ensure consistency, configurations were re-calculated based on Austroads vehicle classification rules (Austroads 2006), such that axles were grouped if they were ≤ 2.1 m from each other.

3.4.3 Key Findings

The project investigated the accuracy of the axle spacing measurements and configurations, and explored the possibility of identifying vehicles of interest using classifier data. Key findings from this investigation included:

- Axle spacing accuracy operationally ranges by ± 200 mm. Additionally, not all WiM and classifier sites report configurations in accordance with the Austroads axle group rules. By re-calculating the configurations from the measured axle spacings, the project was able to improve consistency in the configurations in the dataset.
- Low loaders and cranes were noted as having near identical axle spacing geometries to other types of vehicles, highlighting the value of combining video footage with the WiM and classifier data.
- The presence of retractable axles on the vehicles of interest could lead to incorrect configurations for records.

While incorrectly identified configurations exist within the vehicles of interest datasets, the project acknowledged the issues and developed the conclusions with this in mind. Future work should be devoted to improving the axle spacing measurement accuracy. Doing so will increase the number of potential applications of the data and improve the identification and characterisation of vehicles of interest. Applications and findings from the analysis of the classifier data from Class 1 heavy vehicles are discussed further in Section 4.

3.5 Summary

By improving WiM data processing, TMR has increased visibility of low loaders and load platforms on its network for the first time. The project team was provided access to the improved dataset and the classifier and WiM data were analysed.

Classifier data

Axle spacing measurement and configuration accuracy was investigated, and the possibility of identifying vehicles of interest using classifier data was explored. It was found that in practice the axle spacing accuracy is approximately ± 200 mm. Additionally, not all WiM and classifier sites use the Austroads axle group cut-off rules (≤ 2.1 m). The project was able to address concerns with varying axle group rules through re-calculation of axle groups and configuration using measured axle spacings, improving the identification of vehicles. Filters were also developed to identify vehicles of interest from the larger WiM and classifier datasets including low loaders, load platforms and cranes.

WiM data

An analysis of WiM steer axle mass data from 123 vehicle configurations was undertaken. It was found that steer mass profiles have not changed much since 2006. Seasonal variability and black dot outliers were found in the dataset. It was noted that calibration for temperature compensation and the use of the black dot outliers as an indication of the need to re-calibrate the WiM would result in 'better data more often' for TMR and bridge engineers specifically who are interested in the extreme loads.

As a result, the project:

1. benchmarked the WiM records using 123 vehicle configuration steer axle masses
2. developed filters based on the benchmarked WiM accuracy to isolate records deemed to represent the actual heavy vehicle traffic stream with confidence.

The additional processes undertaken in the classifier and WiM data above enabled (i) increased confidence in the WiM data collected at a WiM site over a period of time and consequently (ii) increased confidence in the derived low loader and load platform datasets. Applications and findings from the analysis of the classifier data from Class 1 heavy vehicles are discussed further in Section 4.

4. Characteristics of Class 1 Heavy Vehicles

4.1 Introduction

This section utilises the WiM dataset described in Section 3 to investigate and report the characteristics of Class 1 Heavy Vehicles. It builds upon the analysis and filters detailed in Section 3 which increased the confidence in the WiM and classifier data and enabled improved sorting of vehicles of interest from the WiM and classifier datasets used in this project.

The high risk posed by low loaders, load platforms and heavy mobile cranes to structures on the TMR road network necessitates additional risk management activities specifically for these vehicles. However, limited operational data has historically been available on these vehicles of interest aside from the permit applications and data collected by transport inspectors. This has led to decisions being made without access to good field information about the actual vehicles accessing the network compared to the permit applications.

4.2 Data Filters

With the improvements to the WiM processing algorithms as described in Section 3, a filtered WiM and classifier dataset is available for these vehicles of interest. An analysis was undertaken for three groups of vehicles, specifically low loaders, load platforms and cranes (Sections 4.3, 4.4 and 4.5). The following sections provide a summary of the findings for each group of vehicles based on the quality data subsets discussed in this section.

Data filters were established to extract low loaders, load platforms, and cranes from the datasets. In addition, vehicles with 123 configurations were extracted to facilitate data quality considerations.

To extract the relevant data, filters were developed to:

- extract a subset of the data that satisfied the quality requirements for a specific application from the Austroads Class 6+ vehicles dataset
- extract low loader and load platform records from the Austroads Class 6+ vehicles dataset
- extract vehicles with a 123 configuration from the Austroads Class 6+ vehicles dataset
- extract crane records from the full WiM and classifier datasets.

The low loader, load platform and crane datasets were interrogated using filters based upon key parameters to support the investigations undertaken in this project. These filters are discussed and reported in Section 4.2.2 and in Eskew et al. (2021). The details of the key filters identified within this section include:

- GVM
- steer axle mass
- 'A' distance
- WiM data confidence
- site type (WiM or classifier)
- speed
- configuration
- vehicle characteristics
- time range
- axle spacing
- vehicle count.

4.2.1 Approach

The data filters used to interrogate the data are detailed below.

Gross combination mass (GCM)

To improve the understanding of vehicle GCMs likely to cause damage to assets on the road network, filters were developed in the data visualisations. As classifiers record a GCM value of 0, GCM was also used as a filter between classifier and WiM records.

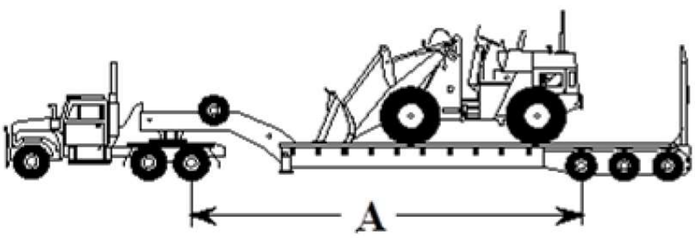
Steer axle mass

For low loaders, load platforms and '123' semitrailers (but not mobile cranes), the steer axle mass for specific combination vehicles was found to be relatively consistent, regardless of vehicle loading. This makes it a key metric for evaluating the quality of WiM records. A range of steer axle masses were used as filters to the dataset throughout this project.

'A' distance

For low loaders, the 'A' distance, or the length between the centreline of the last axle of the prime mover and the first axle of trailer (or last axle of the dolly and the first axle of the trailer where a dolly is present) as indicated in Figure 4.1, limits the total mass limit for the vehicle (HVNL Multi-State Class 1 Load Carrying Vehicles Mass Exemption Notice 2016 Amendment Notice 2019 (No. 1)). The mass restrictions assist in managing the risk of failure of road structures associated with carrying the large indivisible loads. This project calculated the 'A' distance for low loaders and load platforms from the WiM and classifier data based upon their measured axle spacings. Filters were developed for the data visualisation based upon the calculated 'A' distance values.

Figure 4.1: 'A' distance for a low loader



Source: HVNL Multi-State Class 1 Load Carrying Vehicles Mass Exemption Notice 2016 Amendment Notice 2019 (No. 1).

WiM data confidence

Data confidence is a metric developed during this project to evaluate if the mass data from a WiM station confidently represented the expected heavy vehicle traffic at a site over a period of time, based upon the steer axle mass of 123 vehicle configuration records at the site. Based on the WiM confidence a filter was developed, as described below.

Analysis of the 123 steer axle masses at WiM sites provided an assessment of the project's confidence in the data reflecting the expected traffic over time. This information was utilised to develop a confidence data filter for the low loader and load platform dataset. The filter excluded data from WiM sites collected during months classified as 'Calibration Concerns' or 'Unconfident', per Table 3.5.

Site type (WiM or classifier)

The data recorded at individual WiM or classifier sites varied based upon accuracy, vehicle traffic and other factors. Filters were therefore developed to isolate records based upon site type, site accuracy, and for specific sites on the network.

Speed

Vehicle speed impacts the dynamic amplification of the load over a structure, potentially causing increased deterioration of roadways. Filters were developed to isolate a range of recorded speeds, to better understand the relationship between travel speed and other characteristics such as vehicle type.

Configuration

Different types of vehicles, as identified by their configurations, exhibit different behaviours on the network. A filter was developed to identify the records related to specific configurations and allow for an interrogation into how the different types of vehicles utilise the road network.

Vehicle characteristics

This project identified various low loader and load platform vehicle characteristics, including:

- steer axle type – single or tandem axles
- dolly type
- trailer axles.

From the crane database, the project identified make and model of crane based upon the developed crane classification rules (see Appendix N, Eskew et al. 2021).

Time range

Heavy vehicle traffic, and the cargo carried, can depend on the time of day and/or time of year. Additionally, some WiM sensors can be impacted by changing environmental factors such as temperature. Filters were therefore developed to isolate records based upon a range of dates and times.

Axle spacing

The minimum axle spacing of low loaders and load platforms in accordance with the Heavy Vehicles National Laws is 1.2 m. Based upon this information, a filter was developed to remove records with an axle spacing of under 1.0 m, with a 0.2 m variation allowed to account for variations in measurement accuracy.

Vehicle count

The number of identified vehicles required to develop findings was identified based on the use of the data. This was particularly relevant for configurations, where configurations with minimal records were indicators of outliers (excluded from the general data analytics due to their rarity across the network) or erroneous data. Filters were developed to exclude configurations which did not meet the minimum record count requirements.

4.2.2 Application

Low loader and load platform vehicle records were extracted and quality filtered from the supplied Austroads Class 6+ dataset based upon their axle spacings as defined in Heavy Vehicles National Laws (NHVR 2016b). The algorithm used to extract these records included an axle spacing tolerance of ± 0.2 m to allow for the measurement accuracy range. The data was filtered based on the similarities between the WiM and classifier datasets. Due to classifiers not measuring axle mass, this was not used as a filter criterion.

Crane records were extracted from the full WiM dataset using an algorithm based upon configuration, similar to the filter used for low loaders and load platforms. To filter light vehicles out of the analysis any vehicle less than 20 t GVM was excluded. Filter criteria were developed for specific crane models found in the Intelligence Access Program (IAP) crane register based upon axle spacings identified from the relevant manufacturers' specifications. Overall, 83 crane axle spacings were incorporated, further information can be found in Appendix N of Eskew et al. (2021).

4.2.3 Observations

A review of the filtered dataset determined that:

- Some rigid truck and dog vehicles have been included in the dataset as low loaders due to their similar configuration (1222) and axle spacing. There is no way of reliably separating these two groups using configuration and axle spacing alone.
- Many 4 axle twin-steer rigid trucks were identified as cranes due to similarities in their axle spacings (models TADANO GT550/E-1 and GT550/E-2, LINKBELT HTC86100, GROVE TMS9000E, and KATO NK500, NK550 and SL-700R). These crane models were not included in the crane dataset to limit the pollution of the results by the twin-steer rigid truck records.
- The records from the classifier 5807 Ch 4.88 km – south of Julia Creek were excluded as observed data quality was low (see Appendix E.4 of Eskew et al. 2021).

In order to remove additional outlying low loader and load platform records individual records with steer axle masses outside of ± 2 standard deviations (5% – 95%) of the 123-steer axle mass mean (3.34 to 8.51 t), adjusted based upon the confidence class, were excluded. For each confidence class this filter equated to:

- Class A Confidence: 3.04 to 9.36 t
- Class B Confidence: 2.90 to 9.79 t
- Class C Confidence: 2.78 to 10.21 t.

The additional filter was utilised to provide further confidence that the supplied records reflect the expected low loader and load platform traffic at the WiM site and exclude outliers and erroneous data. It was found that the low loader and load platform vehicles steer axle masses are generally similar to those of the 123 configuration vehicles, as shown by the similarity in mean steer axle masses in Table 4.1. Therefore, using the 123-steer axle mass ± 2 standard deviations was deemed to be acceptable for developing limits for the low loader and load platform steer axle masses.

Table 4.1: Confidence dataset 123 steer axle masses comparison for configurations with over 200 records

Configuration	Austroads class 6+ dataset		Class A Confidence		Class B Confidence		Class C Confidence	
	Steer axle mass mean (t)	Record count	Steer axle mass mean (t)	Record count	Steer axle mass mean (t)	Record count	Steer axle mass mean (t)	Record count
123	5.48	4,025,756	5.47	2,167,825	5.47	2,709,837	5.43	3,162,876
1222	5.97	52,868	5.89	27,378	5.89	34,189	5.80	41,470
1212	5.41	21,207	5.33	10,770	5.24	13,309	5.18	14,996
12222	6.35	12,808	6.10	5,857	6.13	7,896	6.06	9,850
124	5.32	16,880	5.40	10,953	5.43	13,057	5.42	14,325
1221	5.78	5,412	5.84	2,543	5.81	3,200	5.74	4,013
2222	5.58	346	–	–	4.84	205	4.81	240
125	6.23	453	–	–	5.95	246	6.08	308
1225	5.85	301	–	–	5.87	212	5.95	244
127	6.55	286	–	–	–	–	6.31	226
12221	6.54	211	–	–	–	–	–	–
126	6.30	325	–	–	6.27	249	6.33	286

Application of the described filter created a 'confident' dataset, which provides increased confidence in the outcome of specific use cases reflecting expected loads from low loader and load platform vehicles. The Confidence filters reduced the original low loader and load platform WiM records (112,319) as follows:

- Class A Confidence: 58,879 records (52%)
- Class B Confidence: 73,479 records (65%)
- Class C Confidence: 86,959 records (77%).

4.3 Low Loaders

Low loaders are prime movers hauling a trailer with a deck no more than 1.2 m above the ground, which may or may not include a dolly (Appendix A, Eskew et al. 2021). These vehicles carry indivisible loads on TMR's network and are lower to the ground so they can provide increased clearance to the undersides of structures.

WiM and classifier data for the low loaders was sorted from the larger datasets. Using the information from all available sites across the network, analyses were performed using the data filters identified in Section 4.2 and the result summarised in this section.

4.3.1 Truck and Dogs Incorrectly Identified as Low Loaders

In this project, vehicles were classified based upon their axle footprints. Due to the similarities between the axle spacing between certain low loader configurations and truck and dog vehicles, a large number of truck and dogs are likely to have been included in the low loader dataset, as discussed in the incorrect vehicle classification subsection of Section 3.4.1. The potential inclusion of truck and dogs, particularly for low loaders without dollies, should be accounted for when drawing conclusions from the analyses that follow.

4.3.2 Configurations

The configuration generally dictates the cargo type and volume of cargo the vehicle carries as well as how it operates on the network. The different configurations classified as low loaders by the project are displayed in Figure 4.2 and Figure 4.3. Most of the 380,000 identified low loaders were of the configurations 1222, 1212, 12222, 124, 1221 or 2222. The filter for combinations containing low loader or low-loader-like trailers focused on the front part of the vehicle (allowing for prime movers, with or without dollies) followed by a low loader trailer. Consequently, some longer configurations may represent other vehicle types with indistinguishable axle spacing geometry or records containing a low loader followed closely by another vehicle with the classifiers failing to split the following vehicle from the leading vehicle.

Figure 4.2: Low loader configurations – configurations with a frequency over 1

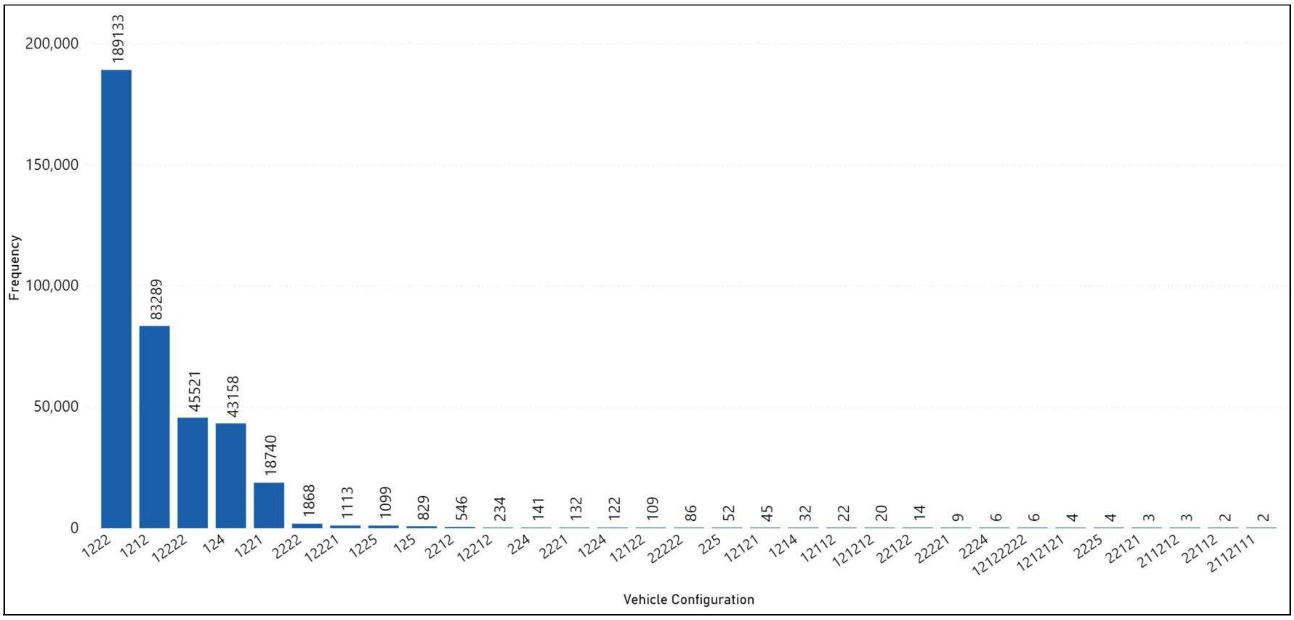
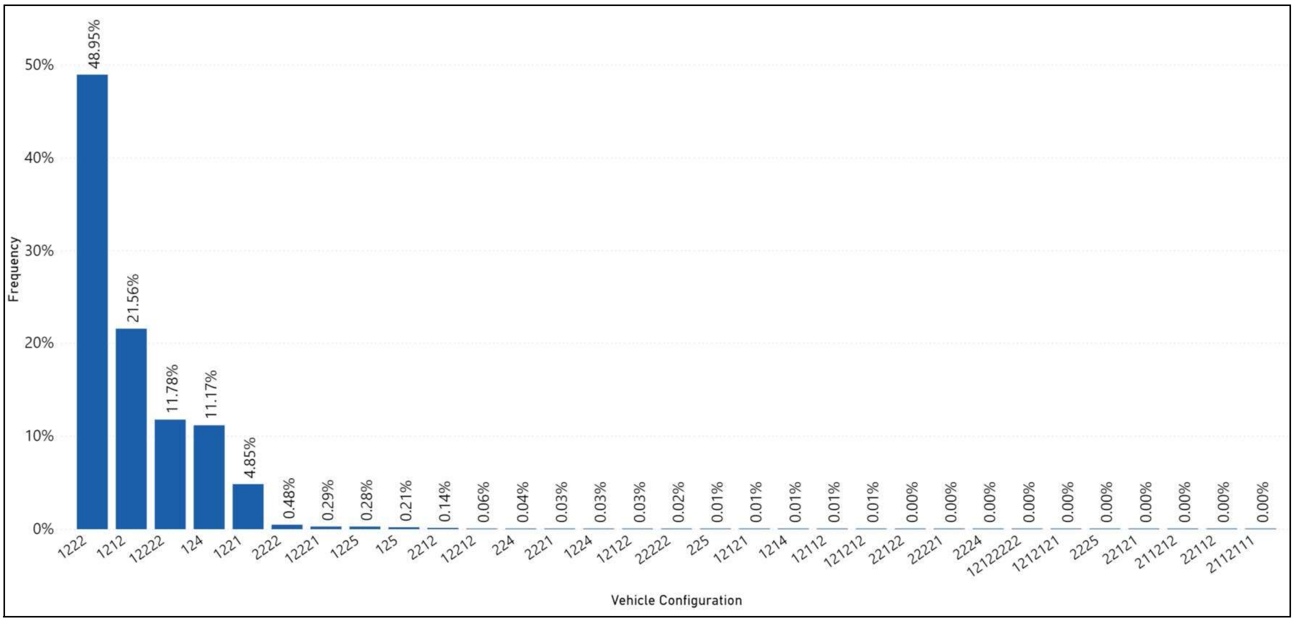


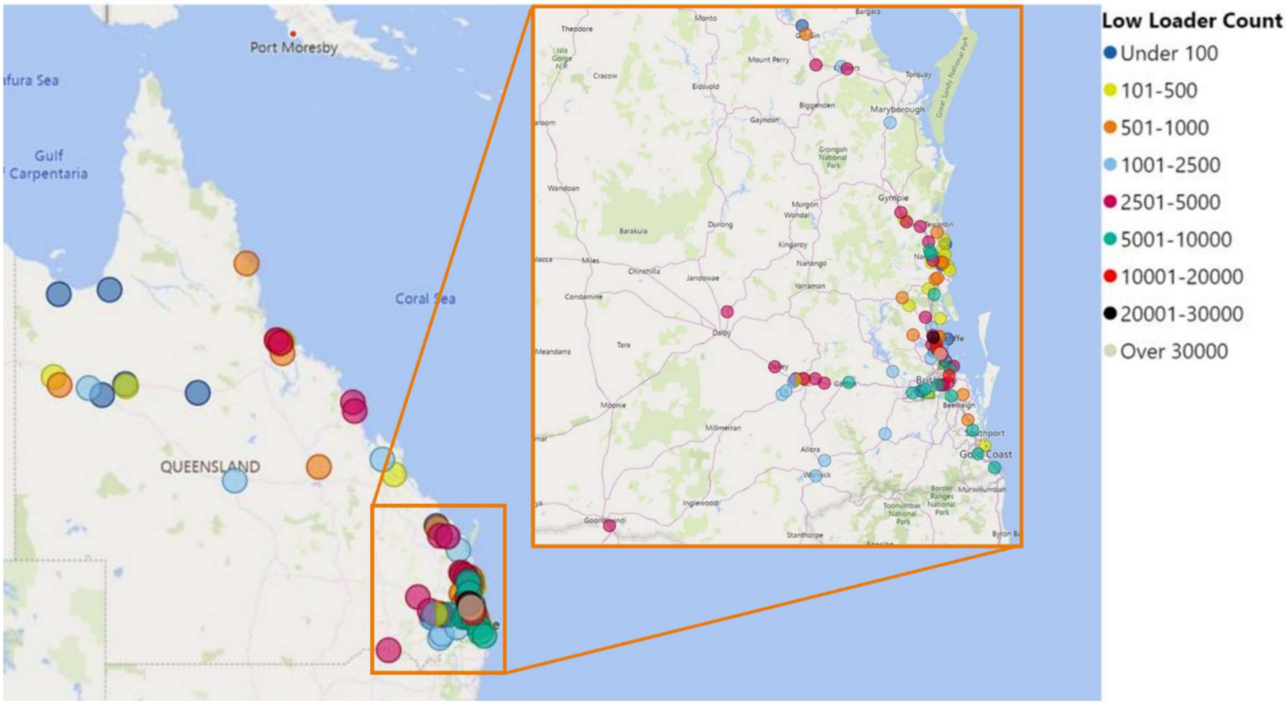
Figure 4.3: Low loader configurations by percentage – configurations with a frequency over 1



4.3.3 Spatial Occurrences

A key question posed to the project regarding the low loaders was ‘*where are they*?’. To address this question, the project investigated the locations where the low loader records occurred. The map in Figure 4.4 shows the locations of the WiM and classifier sites, with the colour of each marker indicating the number of low loader records identified between 01/01/2019 and 09/02/2020. The sites with the highest density of low loader records occur in South East Queensland, near Brisbane. Away from Brisbane there were sites with between 2,501 and 5,000 records near Townsville and Mackay. The remaining sites had under 2,500 low loader records each.

Figure 4.4: Density of low loader records at WiM and classifier sites within dataset



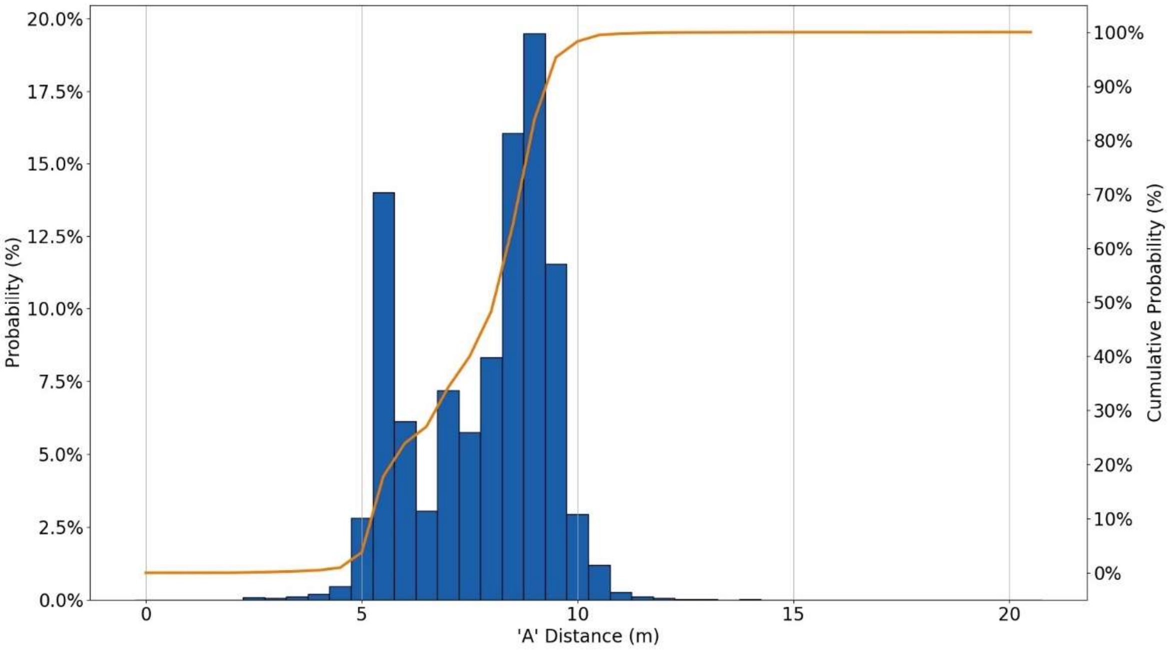
4.3.4 'A' Distance

According to the HVNL the allowable GCM of low loaders in Queensland is generally limited by the mass limit on the structure, road or up to 59.5 t (60 t with a complying steer axle). The 59.5 t limit is reduced for low loaders by 1 t for every 0.3 m increment of 'A' distance under 6.0 m (HVNL Multi-State Class 1 Load Carrying Vehicles Mass Exemption Notice 2016 Amendment Notice 2019 (No. 1)).

For this project the 'A' distance was calculated as the distance from the back axle of the prime mover to the first axle of the low loader, or if the vehicle included a dolly as the back axle of the dolly to the first axle of the low loader (refer Figure 4.1).

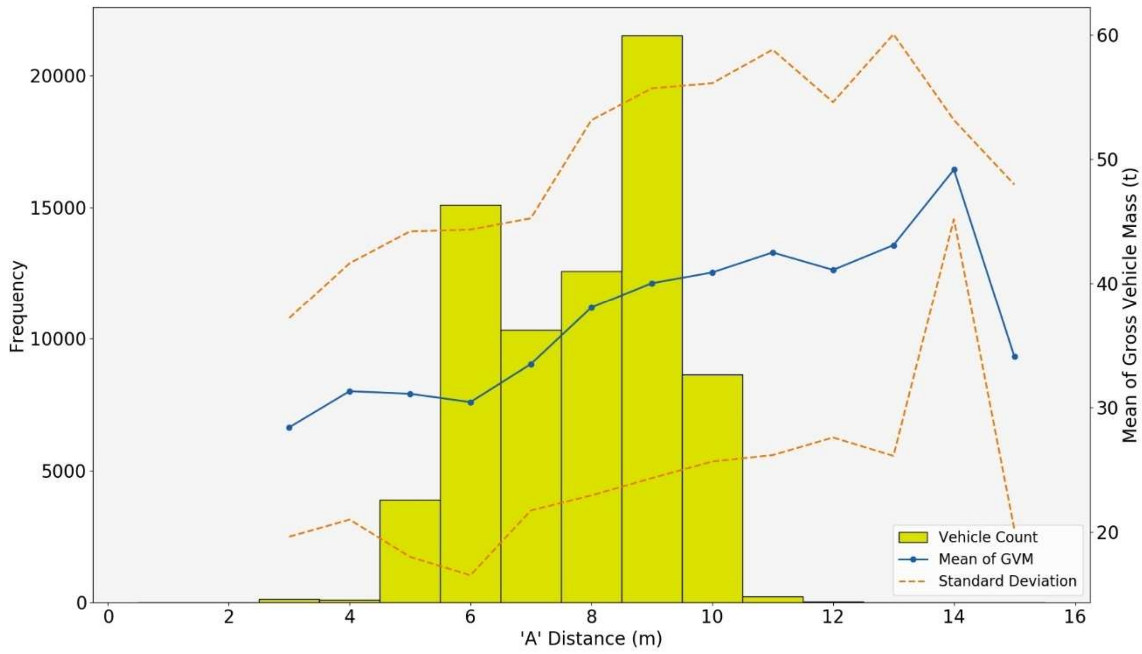
The 'A' distances for low loaders, in 0.5 m bins, are shown in Figure 4.5, where the blue bars are the distributions of records (left scale) and the orange line is the cumulative distribution (right scale).

Figure 4.5: Low loader 'A' distance histogram and corresponding cumulative distribution



As the 'A' distance governs the low loader GCM limit and the effects induced in bridges, the project investigated if there was a relationship between GCM and 'A' distance. Figure 4.6 shows that there is a slight increase in mean GCM with increasing the 'A' distance. Of the 72,504 class B confidence low loaders identified, 26% (19,100) had a recorded 'A' distance under 6 m, and so are subject to reduced GCM limits. Only 0.2% (132) of those vehicles had a recorded GCM over 59.5 t. Given bridge risk management is concerned about extreme events as well as the average, continuing to monitor 'A' distance is valuable.

Figure 4.6: Confidence B low loader 'A' distance by GCM



4.3.5 Temporal Traffic

The project analysed the low loader records for any temporal patterns by breaking the records down into the day of week (Figure 4.7) and hour of day (Figure 4.8). As was expected, most of the vehicles are noted as traveling during the weekday and between 6 am and 6 pm.

Figure 4.7: Low loaders by day of the week – percentage

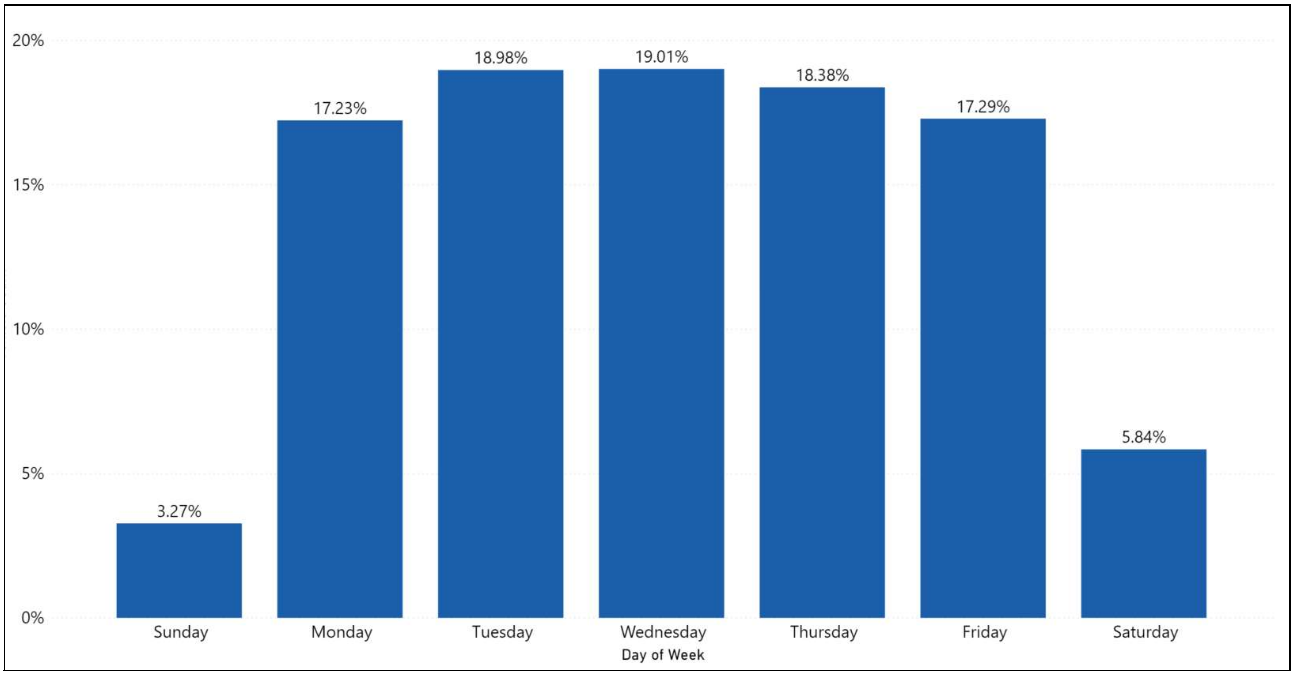
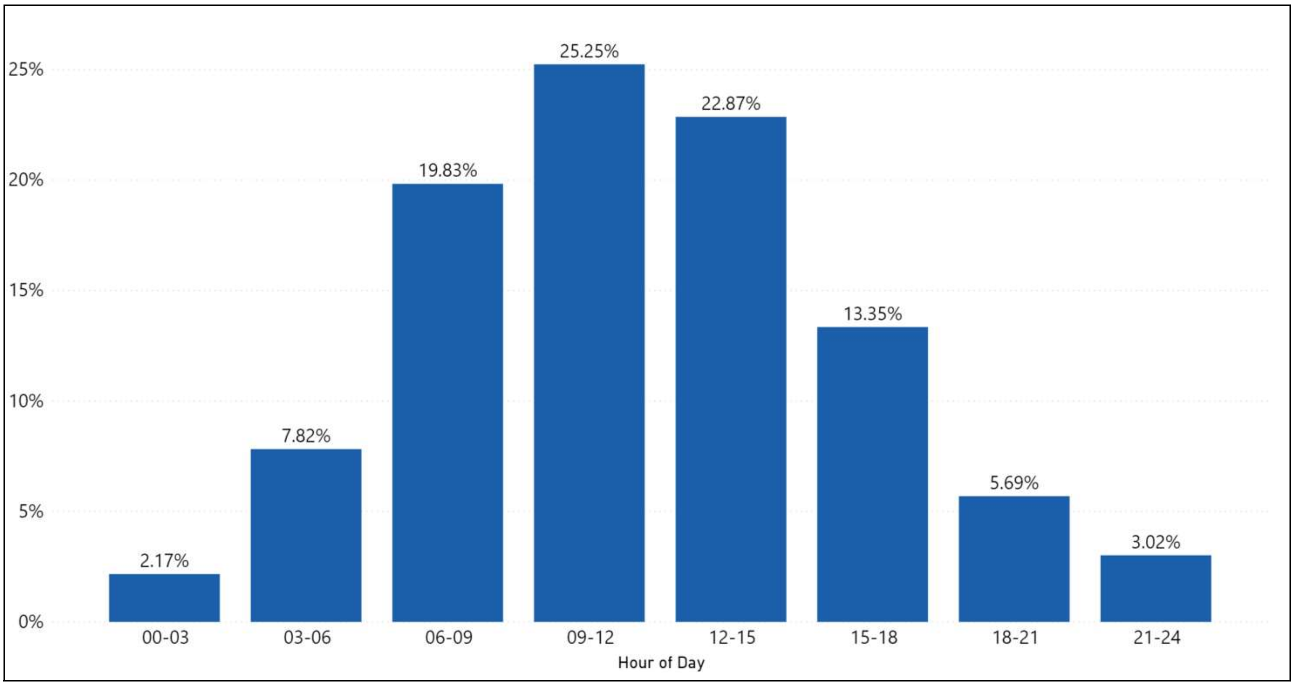


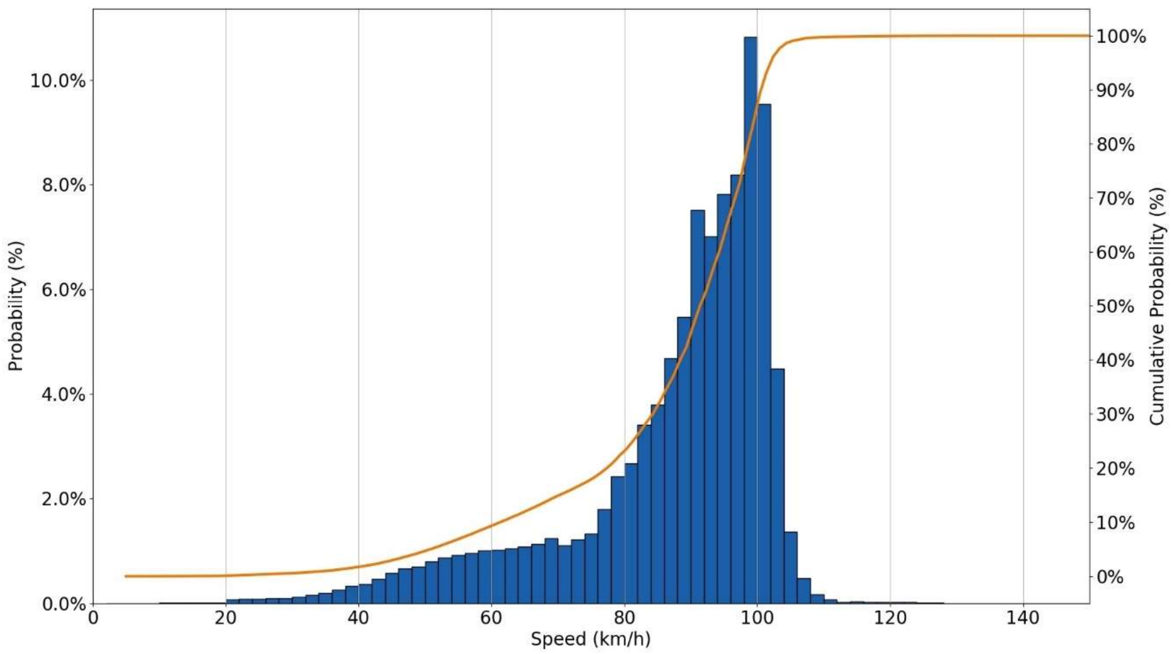
Figure 4.8: Low loaders by hour of the day – percentage



4.3.6 Vehicle Speed

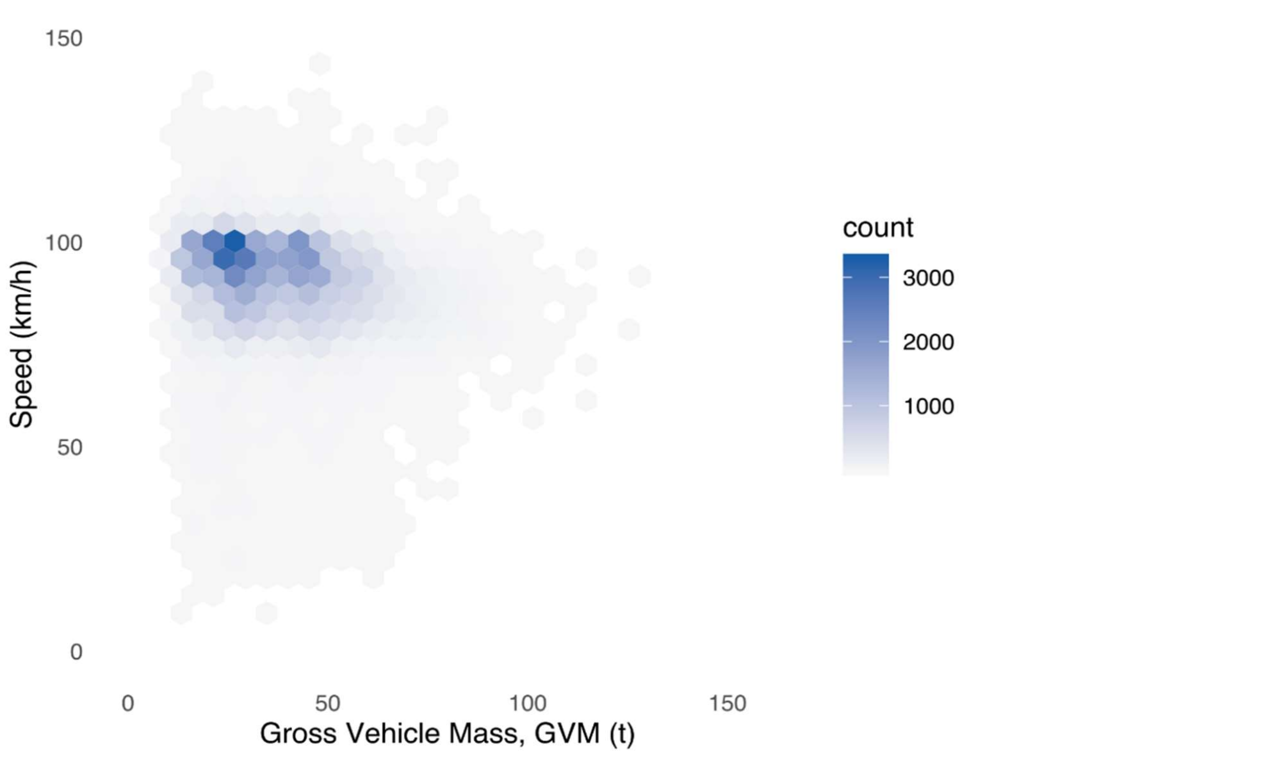
Analysis of the travel speed of the low loaders revealed that approximately 85% of the low loaders recorded speeds between 70 and 110 km/h. As the speed limits of these roads were typically 80 or 100 km/h, it can be inferred that most low loaders will travel at the speed dictated by traffic. A histogram and the cumulative distribution of the recorded low loader vehicle speeds are presented in Figure 4.9, where the blue bars are the histogram and the orange line is the cumulative distribution.

Figure 4.9: Low loader vehicle speed histogram – cut off at 150 km/h



As safety and the dynamic effect a vehicle has on a structure or pavement is influenced by its mass and speed, the project investigated the correlation between these two parameters. The recorded GCM was plotted against the vehicle speed for low loaders from the class B confidence dataset, as shown in Figure 4.10. The highest density of vehicle records tends to exist about the 90 to 100 km/h speed reading, regardless of GCM. This indicates that low loaders will generally travel at the speed limit regardless of their loads.

Figure 4.10: Low loader speed by Gross Vehicle Mass (GVM)

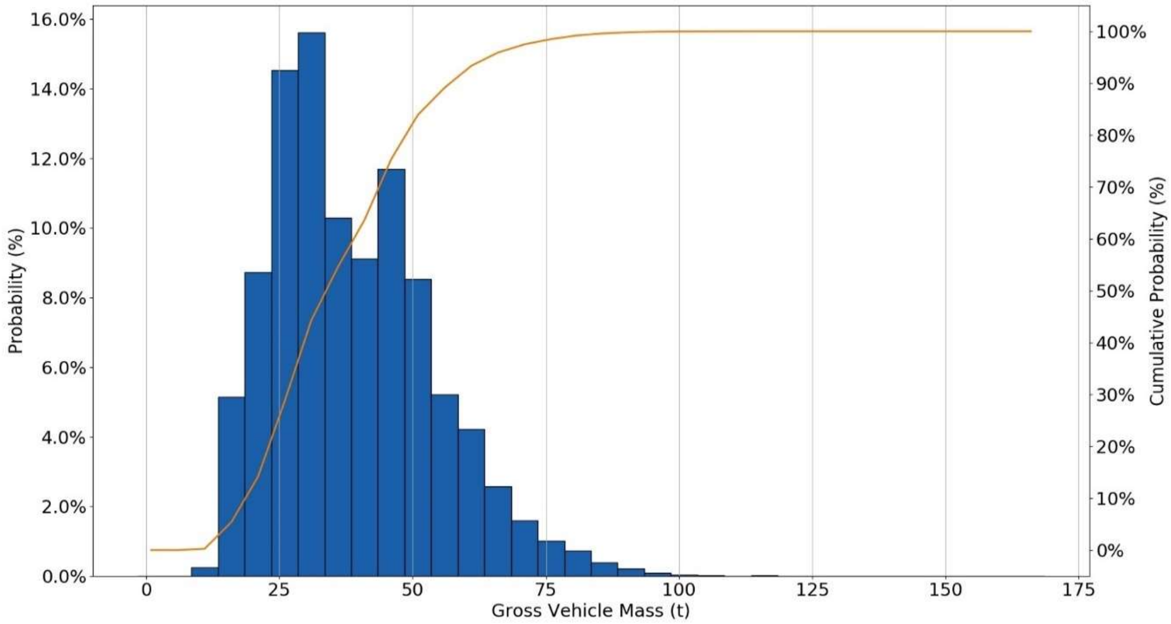


4.3.7 Gross Vehicle Mass

According to the HVNL, the allowable GCM of low loaders in Queensland is generally limited by the mass limit on the structure, road or up to 59.5 t (60 t with a complying steer axle) (HVNL Multi-State Class 1 Load Carrying Vehicles Mass Exemption Notice 2016 Amendment Notice 2019 (No. 1)). The project investigated the low loaders with a class B confidence to assess compliance, as shown in Figure 4.11.

The project determined that approximately 90% of the low loader records were below the 60 t limit. Taking into consideration the ± 10% GVM error allowance for class B sites and on the basis that the majority of WiM sites used in the analyses were class B confidence, the limit increases to 66 t. The project found that 96% of vehicles were recorded as below the 66 t limit. While the general finding would be to note that on average 10% of the vehicles exceeded the 60 t limit, it would be reasonable to assert that even after the likely errors were taken into account, at least 4% of the low loaders were likely to have been non-compliant.

Figure 4.11: Confidence B low loader GVM statistics

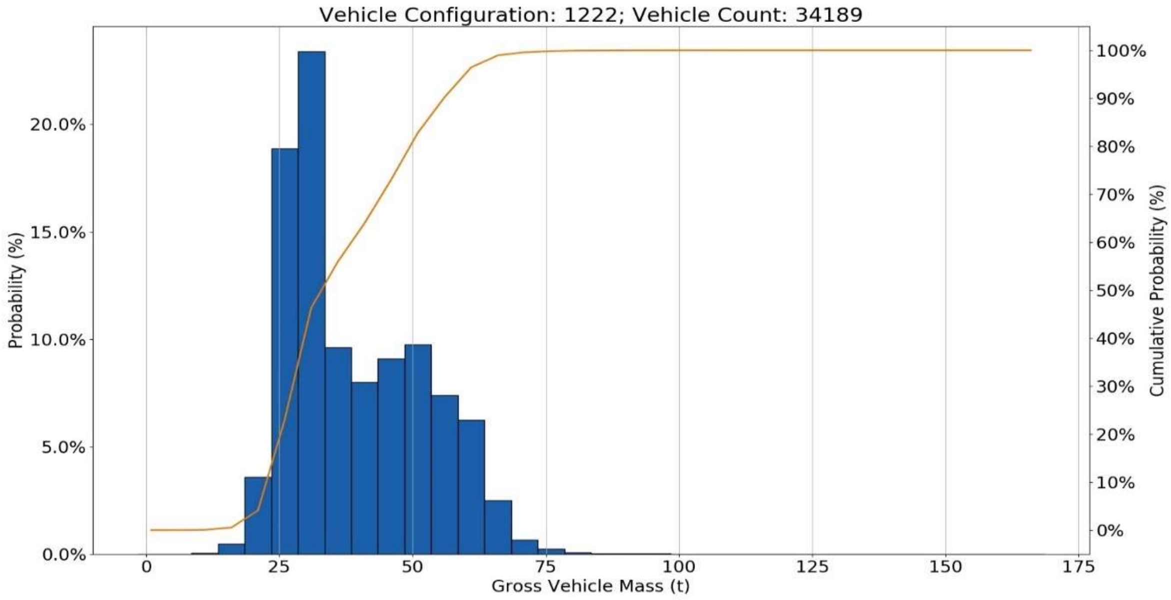


Analysis of the GVMs for individual configurations revealed additional information regarding laden and unladen loads and which types of vehicles carry the heaviest loads. An example of the GVM for a common low loader configuration is presented in Figure 4.12.

Further information on the GVMs for the most common low loader configurations can be found in Appendix G of Eskew et al. (2021). The number of class B confidence records for each configuration is noted at the top of the plots. It should be noted that of the most common configurations, only 12222 configurations (prime mover, tandem dolly and spread quad trailer) have a large percentage of GVMs over 66 t.

Bridge engineers are interested in the likelihood of extreme loads as only one grossly overloaded truck is required to damage a bridge. While GCM is a readily available screening parameter, derived information such as how much the span bends is more important.

Figure 4.12: Confidence B low loader configuration 1222 GVM

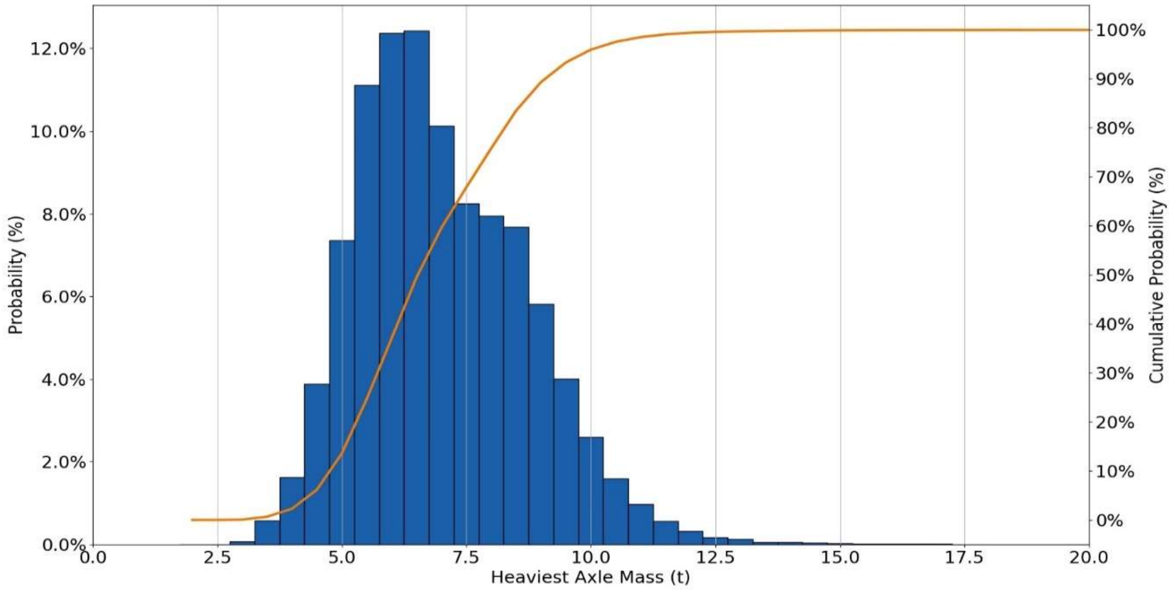


4.3.8 Heaviest Axle Mass

The project aimed to investigate the loads applied by single axles of axle groups on low loaders, using the Class B confidence dataset, by distributing the axle group mass evenly over the number of axles in the group. The heaviest recorded axle mass for each low loader is presented in Figure 4.13.

There is a large peak in heaviest axle masses around 5 to 7 t, likely coinciding with the vehicles unladen self-weight. It should also be noted that over 96% of the heaviest axle masses for low loaders and load platforms fall below 10 t. For the heavier axle masses, additional information on axle ground contact width and the number of wheels per axle would enhance the assessments regarding pavement and structural deterioration.

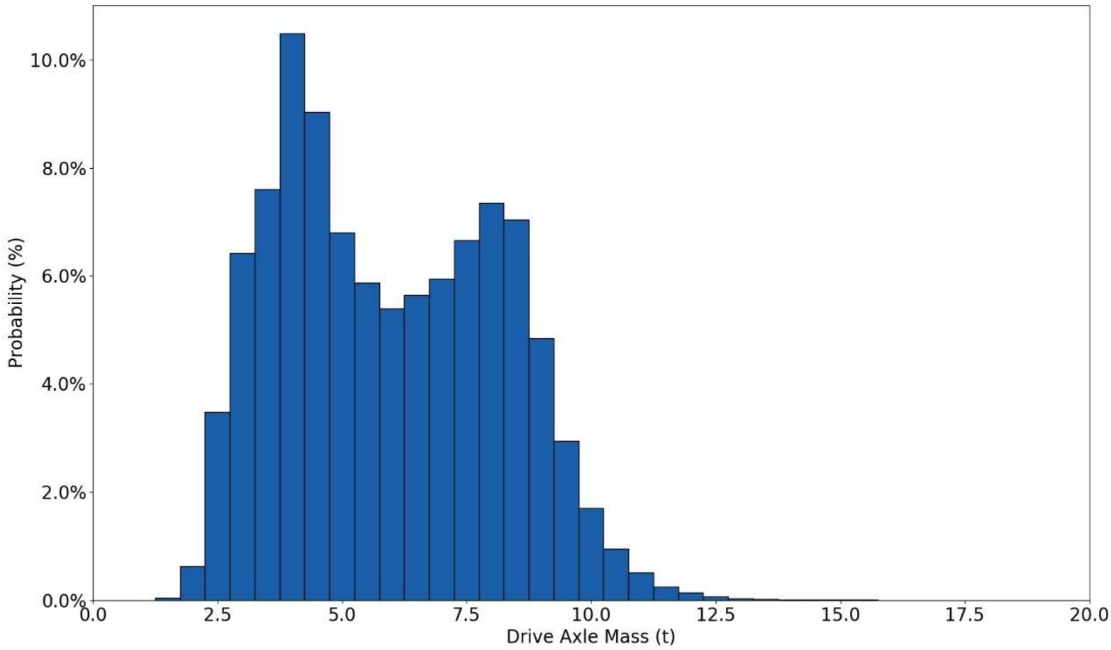
Figure 4.13: Low loader heaviest axle mass distribution – cut off at 20 t



4.3.9 Drive Axle Mass

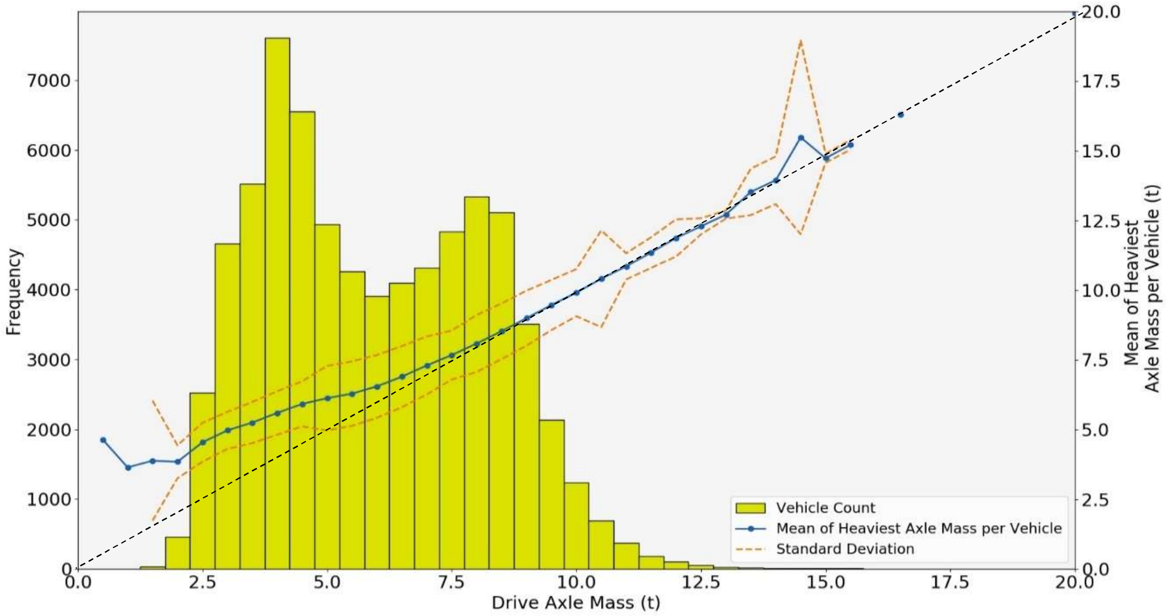
While the steer axle mass is relatively independent of the cargo mass for articulated vehicles, the drive axle mass is impacted by the cargo as the drive axle supports the fifth wheel coupling. The project therefore investigated if the drive axle mass for low loaders were correlated with other key parameters. The axle mass for each drive axle was calculated by distributing the second axle group mass evenly over the number of axles in the group. The drive axle mass distribution is shown in Figure 4.14, which contains the two peaks likely relating to the unladen and laden vehicles.

Figure 4.14: Low loader drive axle mass histogram – cut off at 20 t



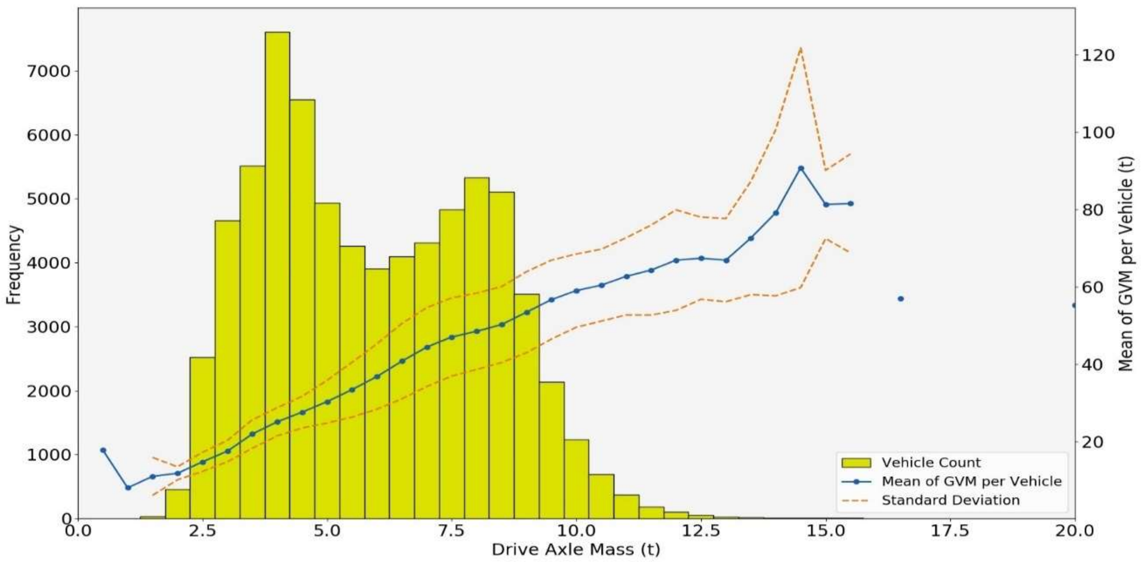
Due to the relationship between the cargo and its drive axle mass, the project analysed the drive axle mass of the Class B confidence low loader dataset compared against its heaviest axle mass, as shown in Figure 4.15. Based upon the linear relationship and low variation of standard deviation, it was determined that the drive axle mass was a good indicator of the heaviest axle mass of the vehicle (see black dotted line in Figure 4.15). This relationship does not hold true between the drive axle mass and GVM, as shown by the wide standard deviations and non-linear mean line in Figure 4.16. However, further analysis of specific configurations may be able to improve the drive axle mass to GVM and heaviest axle mass relationships. This conclusion should be re-visited as the coverage of wide vehicles improves with future enhancements to data collection and processing techniques.

Figure 4.15: Low loader drive axle mass vs heaviest axle mass – cut off at 20 t



The right-hand vertical axis corresponds to the mean (blue line) and standard deviation (dotted orange line) of the heaviest axle masses of the vehicles contained in the counts for vehicles with a drive axle mass in the range represented by each bar (histogram).

Figure 4.16: Low loader drive axle mass vs gross vehicle mass – cut off at 20 t



4.3.10 Discussion

The project analysed the characteristics of the low loaders and came to the following conclusions:

- Most of the low loaders were of the configurations 1222, 1212, 12222, 124, 1221 or 2222.

- There is a slight increase in mean GCM with increasing 'A' distance. There are some low loaders with the 'A' distance < 6 m.
- Low loaders tend to travel at the speed limit, regardless of the cargo they are carrying. Site specific analysis could be performed to confirm this in areas with heavy vehicle speed restrictions (i.e. capacity-reduced bridges).
- Of the most common configurations, only 12222 configurations have a large percentage of GVMs over 66 t.
- Most low loaders have a heaviest axle mass under 10 t. Additional information regarding ground contact width and the number of tyres per axle could be used to assess if vehicles with heavier axle masses are of concern to TMR's assets.
- Drive axle mass shows promise in identifying low loaders with high mass axles. Additional applications to GVM may be gained through configuration specific refinement.
- At present, there is still some concern that the analysed dataset may not contain the heaviest (and widest) low loaders that occupy two lanes or do not have all wheels on the WiM or classifier sensors (see Section 3.2 for more details).

4.4 Load Platforms

Load platforms are combinations including a prime mover and a load platform trailer which consists of at least 5 equally spaced axles in a group at least 1.6 m apart. They may also have a low loader dolly, and there may be more than one prime mover. These vehicles carry the largest indivisible loads across the network and pose the greatest single overload risk to structures.

WiM and classifier data for the load platforms was filtered from the larger dataset. Using the information from all available sites, analyses were performed using the data filters identified in Section 4.2 and summarised in this section.

4.4.1 Configurations

The configuration indicates the type of platform used by the vehicle. Increased number of axles on a platform can be indicative of a capacity to haul larger items, resulting in higher GVMs. Conversely, higher GVMs on a platform with a low number of axles can indicate higher axle masses.

Understanding the configurations on the network can provide valuable information on the heaviest masses being carried. The different configurations classified as load platforms by the project, are displayed in Figure 4.17 and Figure 4.18.

The most common load platform configurations include 127, 126, 128 and 125. There are some large vehicles on the network, with a significant number of 10 axle platforms (120 and 1220), the largest vehicles in the dataset have 12 axles (12B). Further improvements to WiM and classifier data collection will likely reveal larger multi-platform combinations known to access the network but were not observed in the dataset.

Figure 4.17: Load platform configurations

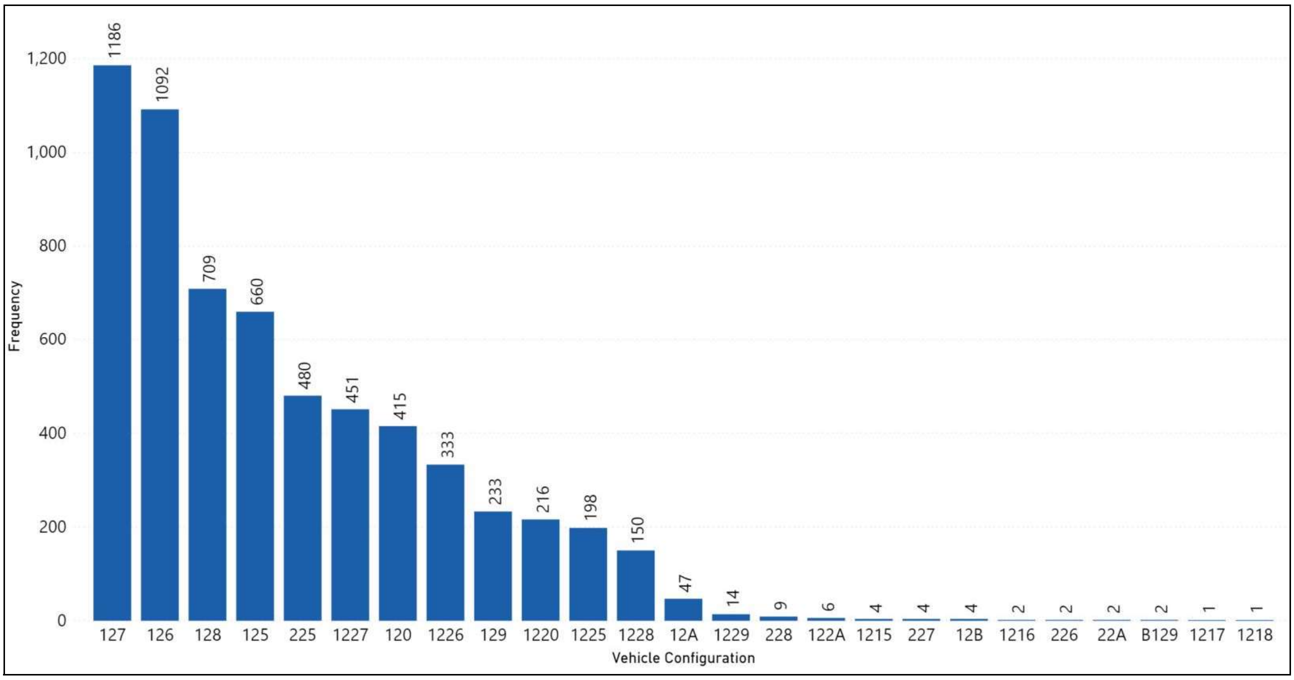
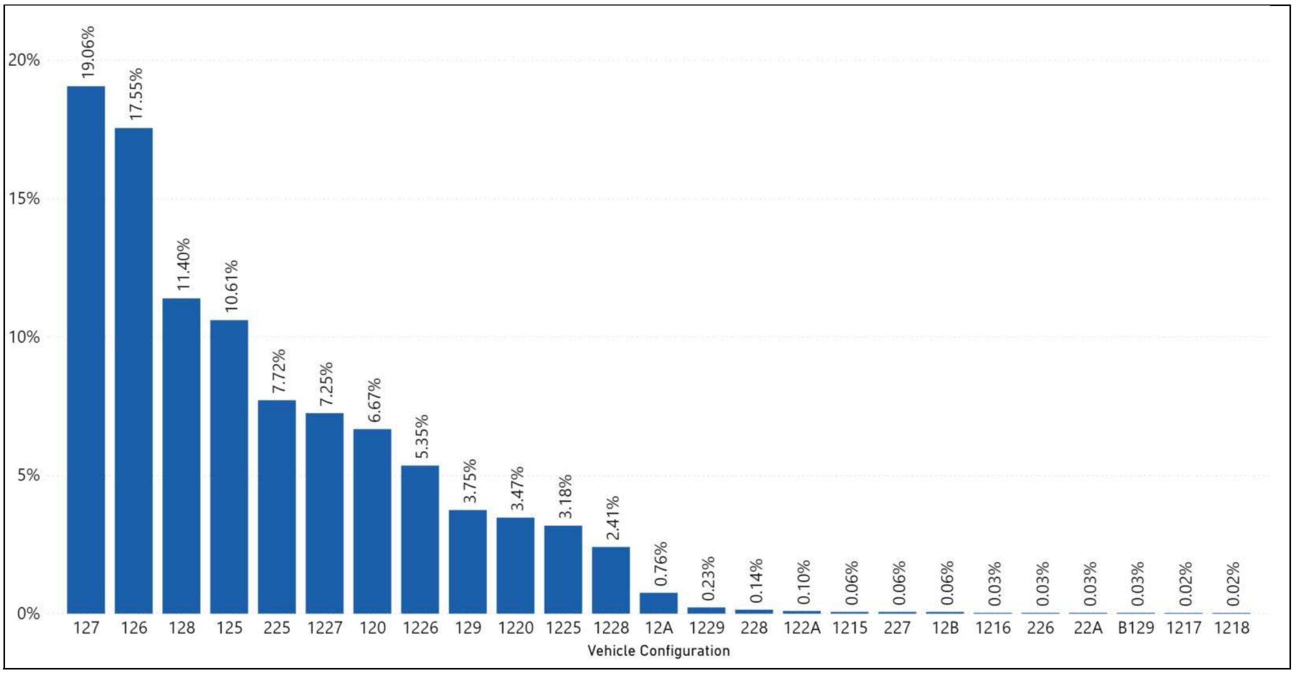


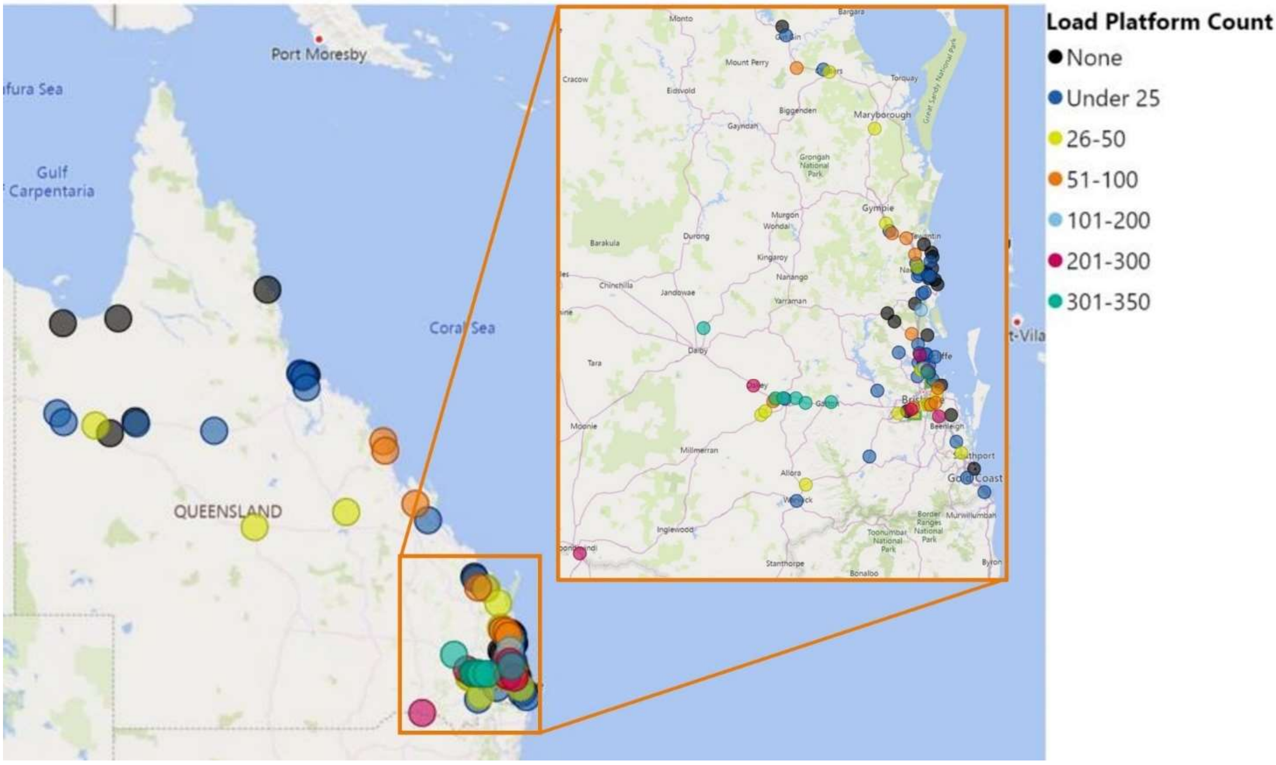
Figure 4.18: Load platform configurations by percentage



4.4.2 Spatial Occurrences

A key question posed to the project regarding the load platforms was '*where are they*?'. The project investigated the locations where the load platforms were recorded. The map in Figure 4.19 shows the locations of the WiM and classifier sites, with the colour of each marker indicating number of low loader records identified between 01/01/2019 and 09/02/2020. The sites with the highest density of low loader records occur in South East Queensland, near Brisbane. Away from Brisbane, there were sites with over 50 records near Mackay and north of Rockhampton. The remaining sites had under 50 load platform records each.

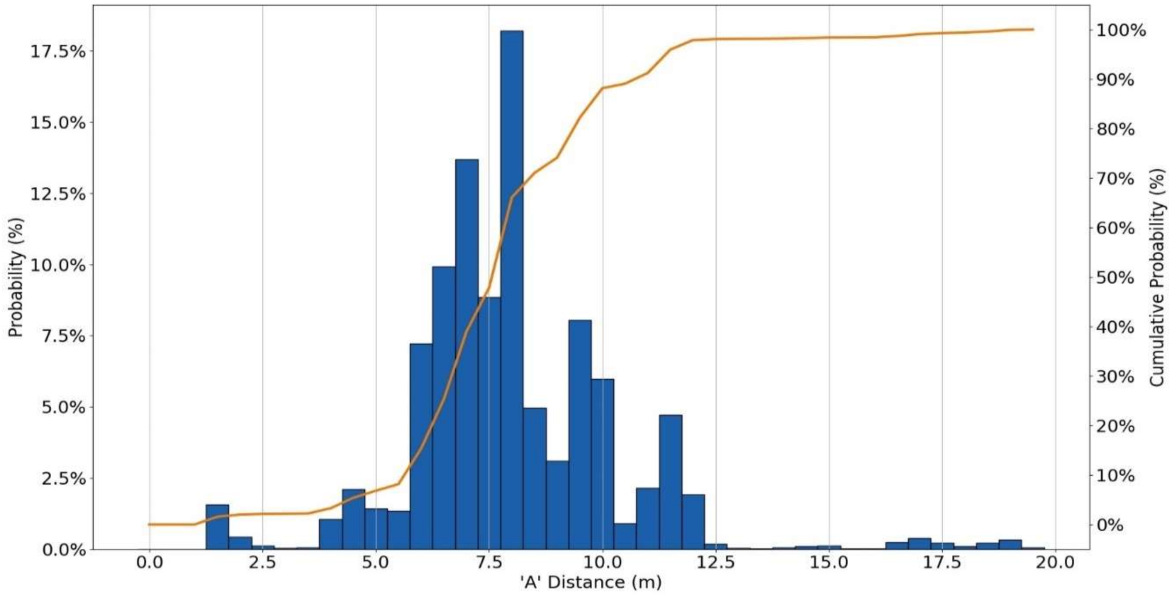
Figure 4.19: Density of load platform records at WiM and classifier sites within dataset



4.4.3 ‘A’ Distance

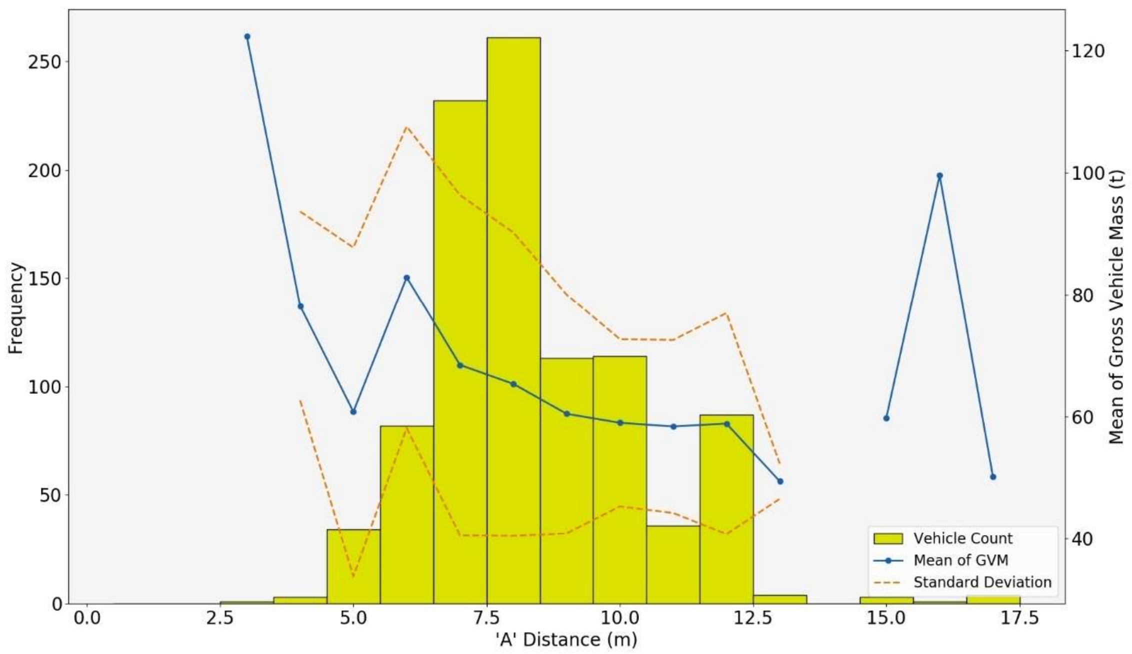
While ‘A’ distance is not a part of the governing regulation for load platforms, the project decided to investigate the relationship between the last prime mover or dolly axle and first load platform axle distance as it is a bridge risk consideration. This relationship between applied loads and distance can have an influence on the shear and bending moments on structures. ‘A’ distance is plotted in Figure 4.20, where the blue bins are the distributions of records (in 0.5 t bins) and the orange line is the cumulative distribution, which shows that approximately 15% of the load platforms had a recorded ‘A’ distance under 6 m and are of concern re impacts on bridges.

Figure 4.20: Load platform ‘A’ distance distribution



The project also investigated if there was a relationship between the load platform ‘A’ distance and the GVM using the class B confidence dataset, shown in Figure 4.21. There does not seem to be a governing correlation between the ‘A’ distance and the GVM, with the GVM mean slightly decreasing with larger ‘A’ distances. These conclusions are likely heavily influenced by the small sample size, as there were only 975 load platform records in the class B confidence dataset.

Figure 4.21: Confidence B load platform ‘A’ distance by GVM



TC-710-4-4-8a

4.4.4 Temporal Traffic

The load platform dataset was analysed for any temporal patterns, by breaking the records down into the day of week (Figure 4.22) and hour of day (Figure 4.23).

While low loaders commonly travelled during the weekday and during work hours (6 am to 6 pm), load platforms were much more likely to travel during the weekend, and in the hours of the day between 12 am to 6 am. Due to their heavy loads and large platforms, load platform vehicles are much more likely to be traveling under permit restrictions, which may be the reason for the variation in temporal patterns.

Figure 4.22: Load platforms by day of the week – percentages

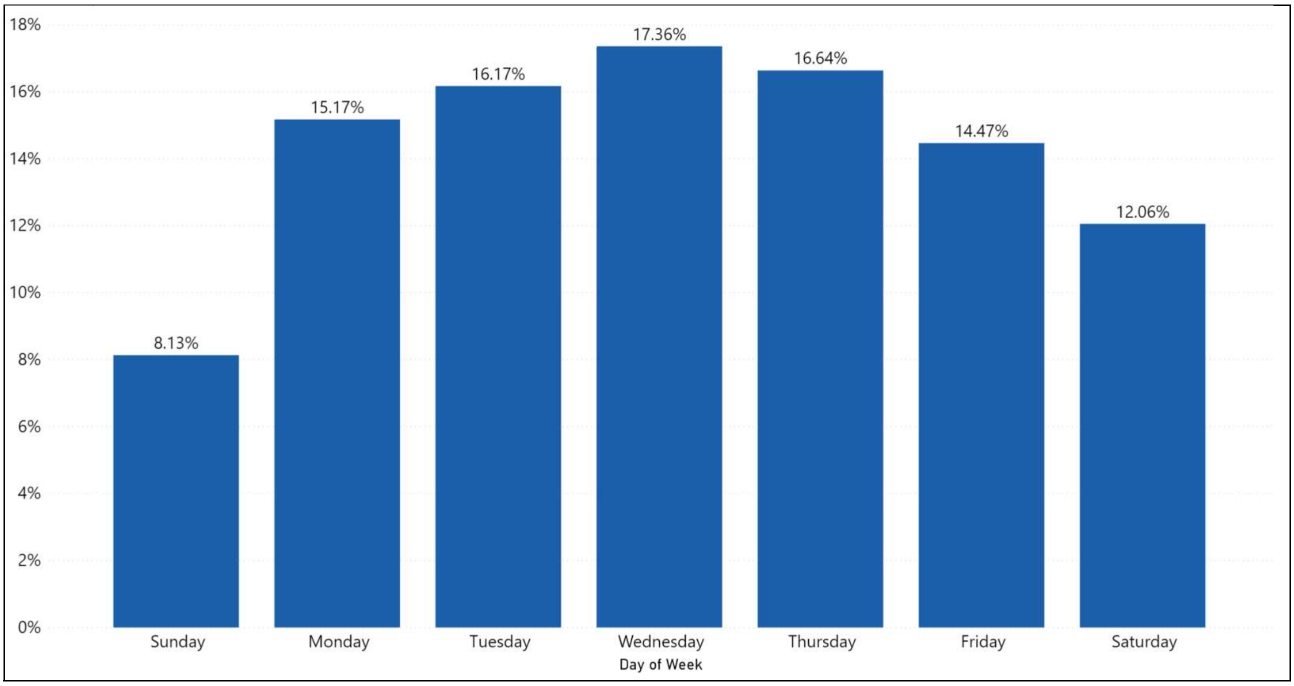
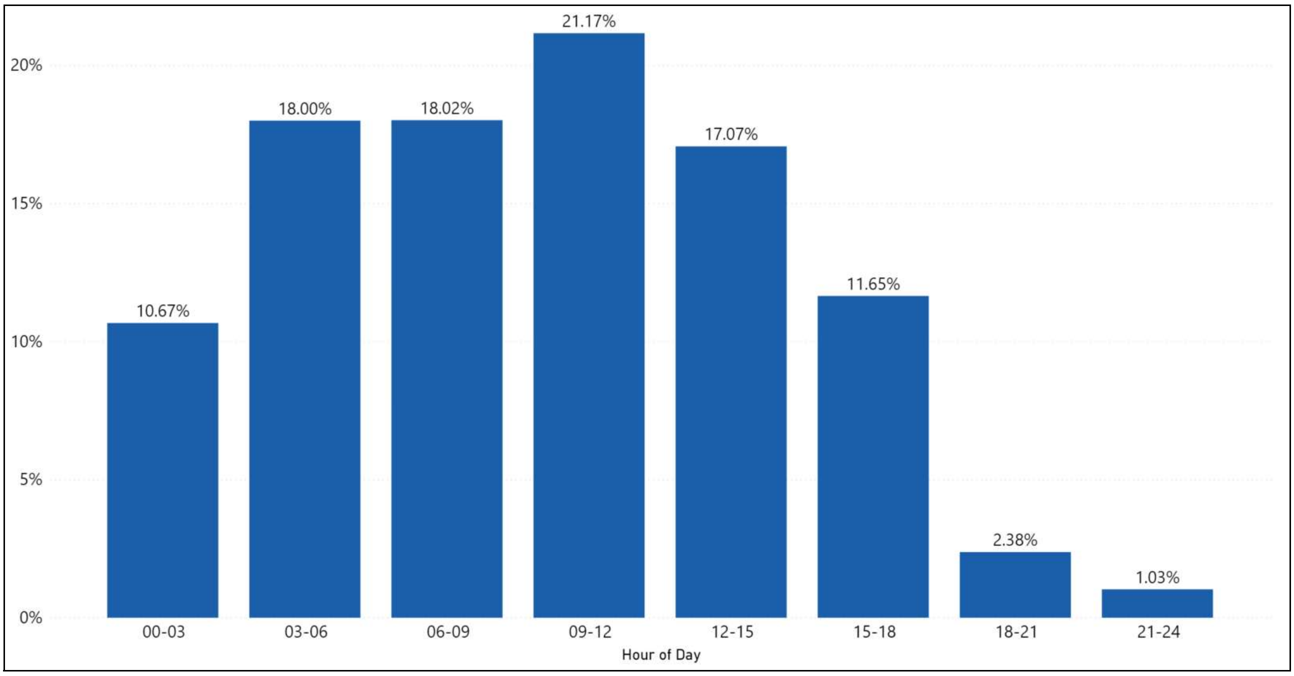


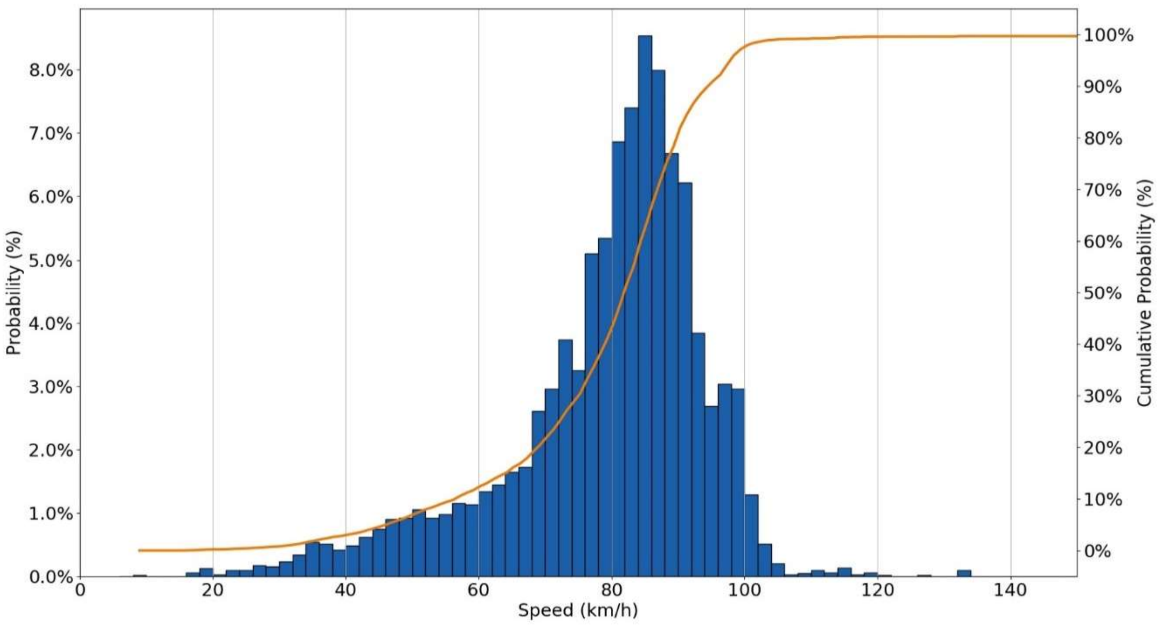
Figure 4.23: Load platforms by hour of the day – percentages



4.4.5 Vehicle Speed

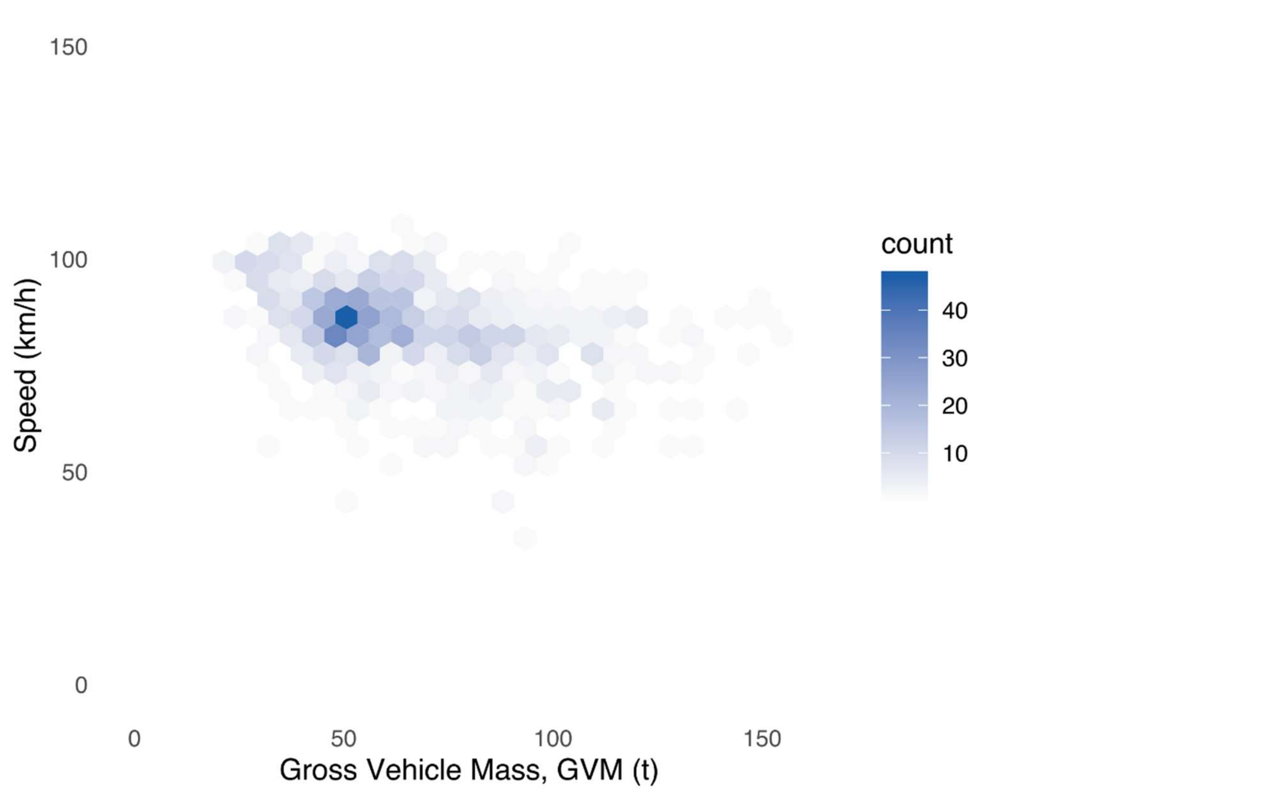
Analysis of the travel speed of the load platforms revealed that approximately 77% recorded speeds between 70 and 110 km/h, with over 99% traveling below 110 km/h. As the speed limits of these roads were typically 80 or 100 km/h, it can be inferred that most load platforms will travel at the speed dictated by traffic. The vehicles noted as traveling slower were likely due to the larger loads they were carrying. A histogram (blue bins) and the cumulative distribution (orange line) of the recorded load platform vehicle speeds are presented in Figure 4.24.

Figure 4.24: Load platform vehicle speed histogram – cut off at 150 km/h



As the dynamic effect a vehicle has on a structure or pavement is influenced by its mass and speed, the project investigated the correlation between these two parameters. The recorded GVM was plotted against the vehicle speed for load platforms from the class B confidence dataset, as shown in Figure 4.25. The highest density of vehicle records tended to exist around the 80 km/h speed reading, regardless of GVM. This indicates that the load platforms will generally travel at the speed limit regardless of the loads they are carrying.

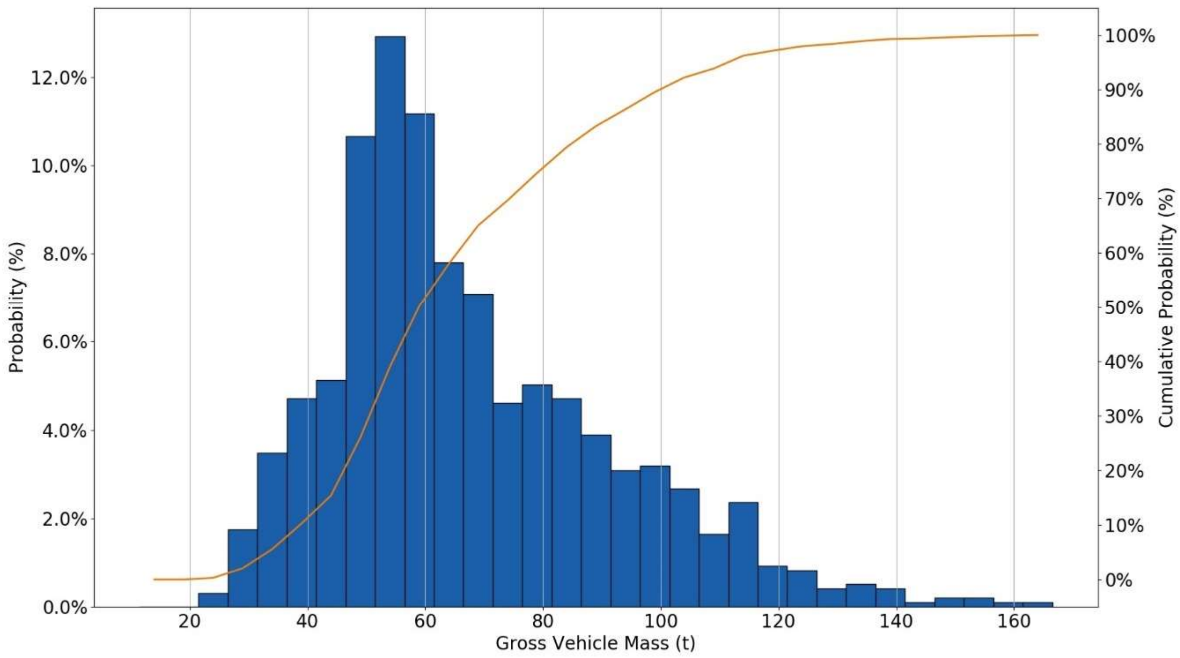
Figure 4.25: Load platform speed by gross vehicle mass (GVM)



4.4.6 Gross Vehicle Mass

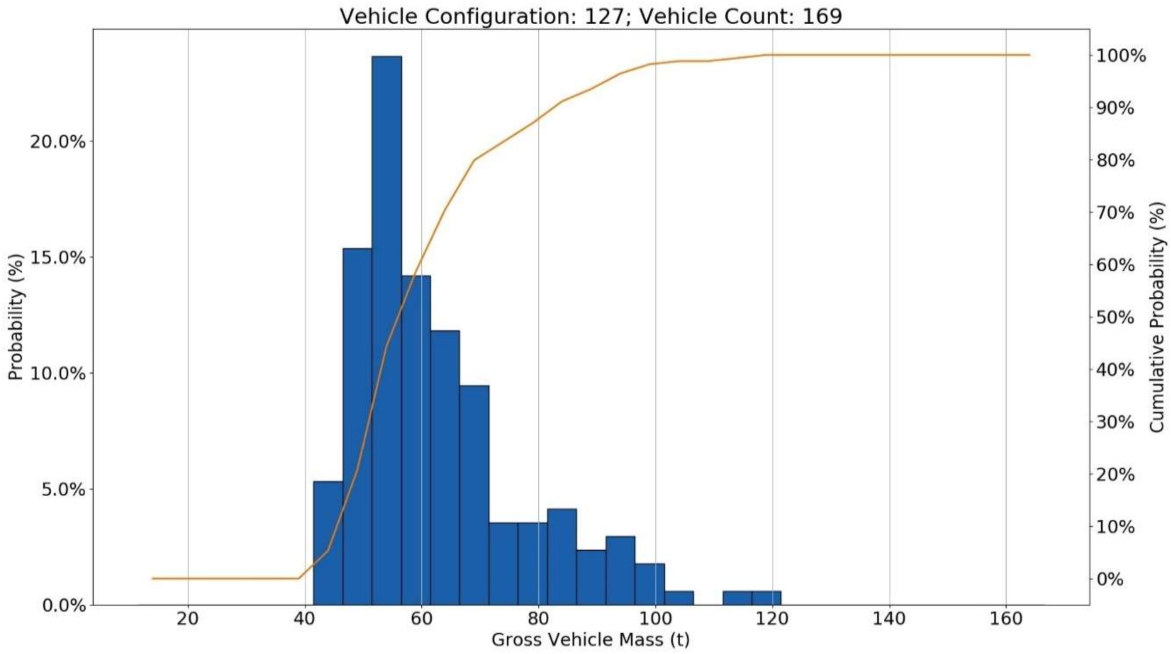
The GVMs of the load platforms were assessed as a percentage of the entire dataset in 5 t bins using the Class B confidence dataset, shown in Figure 4.26 with the orange line representing the cumulative distribution. There is a predominant peak in the data, corresponding to the unladen GVM of the load platforms. The unladen mass has a large spread due to the varying unladen masses of the differing configurations. A local rule of thumb for the unladen mass of load platform trailers is 4 t per platform axle (plus an additional 4 t if it has a gooseneck connection) and an additional 3 or 5 t if the combination includes a low loader dolly. The laden vehicle masses consist of the large right-hand tail, likely due to the varying cargo masses carried by the differing configurations.

Figure 4.26: Confidence B load platform GVM



The project also investigated the GVMs for some of the more common load platform configurations from the class B confidence dataset. An example is shown in Figure 4.27 with the cumulative distribution represented by the orange line. The number of class B confidence records for each configuration is noted at the top of the plots. The unladen peaks can be noted to shift based upon the varying configurations. The specific configurations noted as hauling the heaviest masses can also be identified through analysis of the individual configurations. However, it should be noted that these conclusions are likely heavily influenced by small sample sizes, as there were only 975 total load platform records in the class B confidence dataset.

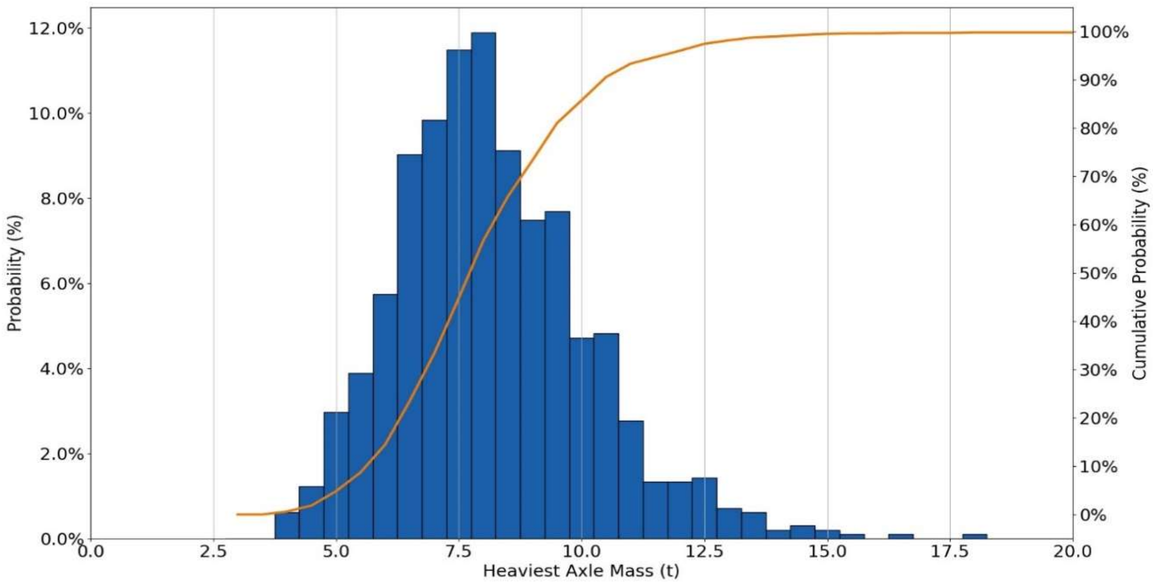
Figure 4.27: Confidence B load platform configuration 127 GVM



4.4.7 Heaviest Axle Mass

The project investigated the loads applied by single axles of axle groups on the load platforms, using the Class B confidence dataset, by distributing the axle group mass evenly over the number of axles in the group. The heaviest recorded axle mass for each load platform is presented in Figure 4.28, with the blue bins representing the distribution of heaviest axle masses and the orange line the cumulative distribution. The load platforms tended to have larger heaviest axle masses than low loaders, with under 86% of load platforms having a heaviest axle mass under 10 t. For the heavier axle masses, gathering additional information on axle ground contact width could allow for assessments regarding pavement and structural deterioration.

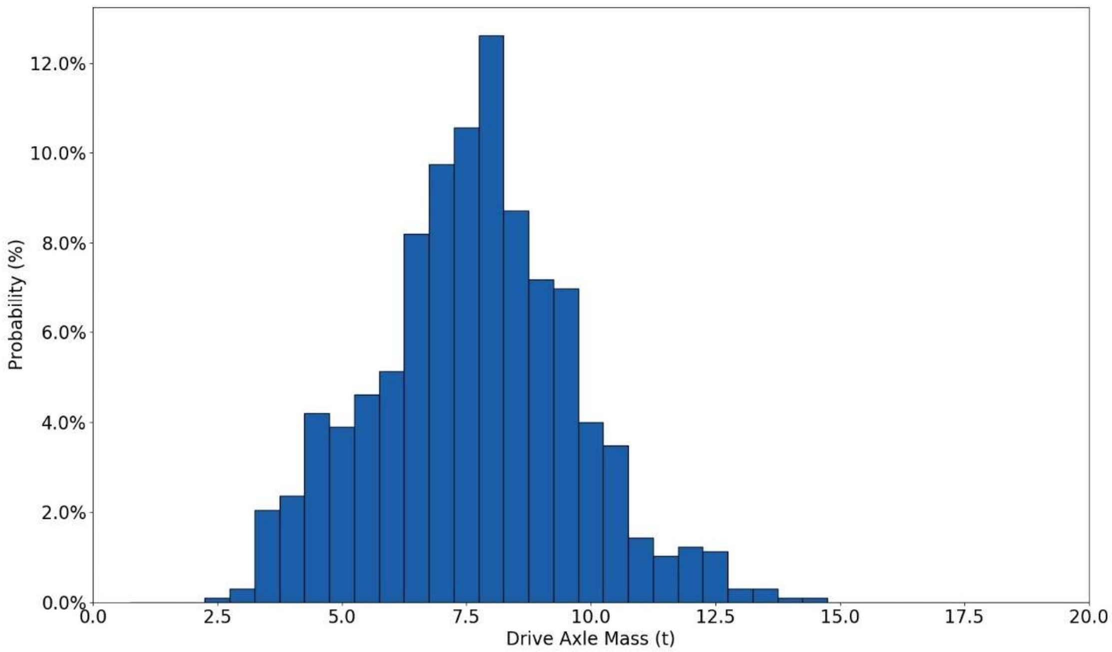
Figure 4.28: Load platform heaviest axle mass distribution – cut off at 20 t



4.4.8 Drive Axle Mass

While the steer axle mass is relatively independent of the cargo mass in articulated vehicles, the drive axle mass is impacted by the cargo due to its proximity to the fifth wheel coupling. The project therefore investigated if the drive axle mass for load platforms were correlated with other key parameters. The axle mass for each drive axle was calculated by distributing the second axle group mass evenly over the number of axles in the group. The drive axle mass is shown in Figure 4.29. Similarities in the distribution of the drive axle mass and GVM can be seen when comparing the figures, shown in Figure 4.29 and Figure 4.14 respectively.

Figure 4.29: Load platform drive axle mass histogram – cut off 20 t



Due to the relationship between the cargo and its drive axle mass, the project analysed the drive axle mass of the Class B confidence load platform dataset compared against its heaviest axle mass, as shown in Figure 4.30. Based upon the linear relationship and low variation of standard deviation, it was determined that the drive axle mass was a good indicator of the heaviest axle mass of the vehicle. This relationship does not hold true between the drive axle mass and GVM, as shown by the wide standard deviations and non-linear mean line in Figure 4.31. Further analysis of specific configurations may be able to improve the understanding of relationships between drive axle mass, GVM and heaviest axle mass.

Figure 4.30: Load platform drive axle mass vs heaviest axle mass – cut off at 20 t

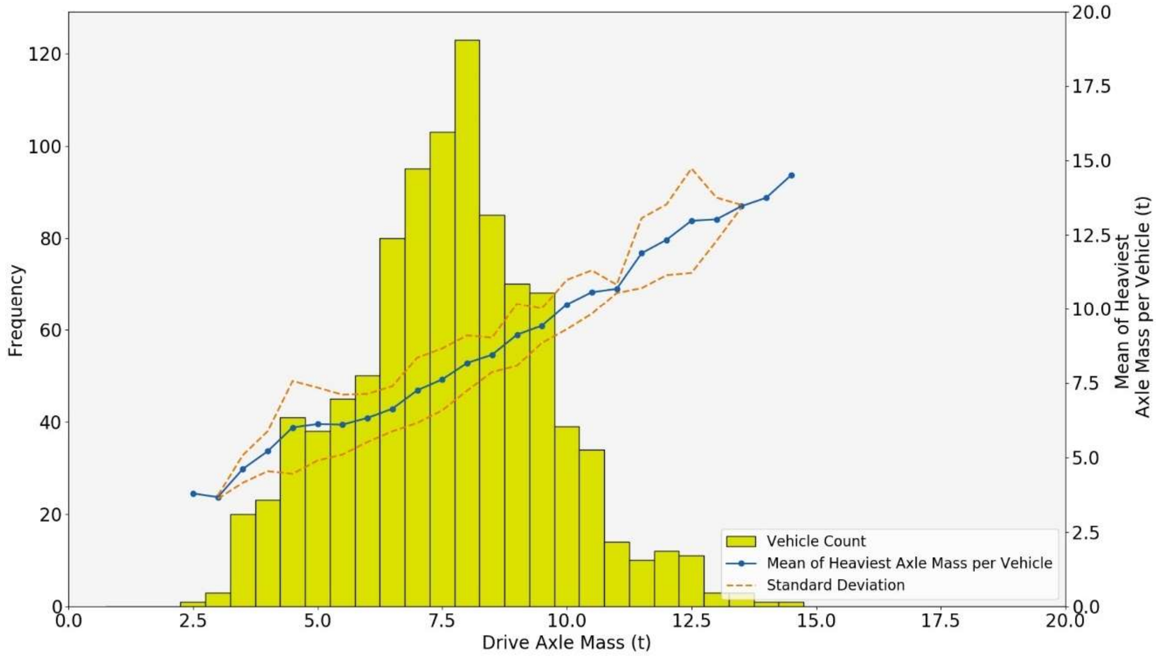
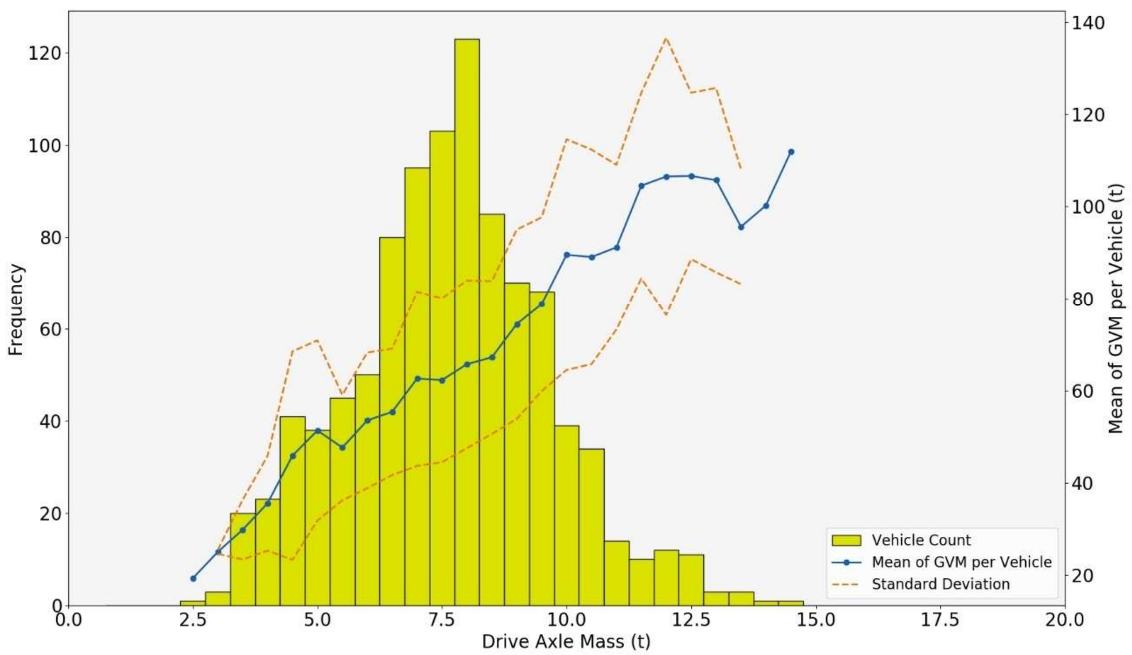


Figure 4.31: Load platform drive axle mass vs gross vehicle mass – cut off at 20 t



4.4.9 Discussion

The project analysed the characteristics of the load platforms and came to the following conclusions:

- The most common load platform configurations include 127, 126, 128 and 125 with significant numbers of 10 axle platforms (120 and 1220). The largest vehicles observed in the dataset have 12 axles (12B).
- The largest configurations may not be included in the dataset as WiM and classifier systems are not established for these vehicles and they may not cross all the sensors.
- As the ‘A’ distance is not a regulatory requirement for the load platforms, it was not correlated with the vehicle masses. About 15% have 'A' distances less than 6 m which is of interest from a bridge risk management perspective.
- The load platforms travelled during non-peak travel times, which is likely due to regulations and permit restrictions. This is in contrast to low loaders that tend to travel during the day on weekdays.
- Load platforms tend to travel at the speed limit, regardless of the cargo they are carrying. Site specific analysis could be performed to confirm this in areas with heavy vehicle speed restrictions (i.e. capacity reduced bridges).
- While not a large part of the network traffic, load platforms had high GVMs and axle masses.
- Around 14% of load platforms had a heaviest axle mass over 10 t. Additional information regarding ground contact width and number of tyres per axle are necessary to assess if vehicles with heavier axle masses are compliant or of concern to TMR’s assets.
- Drive axle mass shows promise in identifying load platforms with high mass axles. Additional applications to GVM may be gained through configuration specific refinement.

4.5 Cranes

Heavy mobile cranes, mostly referred to as all terrain cranes, were also investigated. For the purposes of this report heavy mobile cranes are cranes with 4 or more axles.

Due to their high axle loads, these cranes can induce large, concentrated forces on network assets and thus their access is managed. Additionally, heavy mobile cranes have potential for live calibration or calibration validation of WiM systems. When accessing the road network, cranes nominally run at the same mass and axle loads and their axle spacing signature is constant. In addition, each crane model has a unique ‘axle spacing signature’, potentially enabling individual models of cranes to be identified from the ‘axle spacing signatures’ recorded by vWiM assets.

As an initial analysis, heavy mobile crane data was sorted from the full WiM dataset at 4 sites, Nudgee, Hemmant, Belmont northbound and Belmont southbound. Analyses were performed on the crane records from these heavily trafficked sites using the data filters identified in Section 4.2 and summarised in this section.

4.5.1 Configurations

The IAP crane register consists of 144 crane models. When developing rules to identify these cranes in the dataset, the project determined that some of these cranes had similar configurations. Accounting for models with similar configurations the project identified 83 distinct crane configurations. Based upon the filtering performed using the distinct crane configurations 2,954 cranes were identified in the 13-month dataset (2,292 crane records during class B confidence months). The number of cranes identified at each WiM site shown in Figure 4.32. The number of cranes identified by configuration are shown in Figure 4.33 and Figure 4.34. This data indicates that 80% of the detected cranes were 4 and 5 axle cranes and that these would cross these sites every day or three and thus provide a useful validation of the WiM calibration if they can be reliably detected. Note cranes accessing other sites could be less frequent.

It is worth noting that the same crane may exhibit different configurations. For example, some crane models can travel with or without a trailing boom dolly, as shown in Figure 4.35, which would add another axle group to its configuration. In addition to changing the crane’s configuration, the addition of a trailing boom dolly significantly alters the distribution of mass to the axles, as demonstrated in Table 4.2. Other crane models were noted as having retractable axles, such as shown in Figure 4.35, which gives them the capacity to change their configuration, spacings and loading.

Figure 4.32: Crane records by WiM site

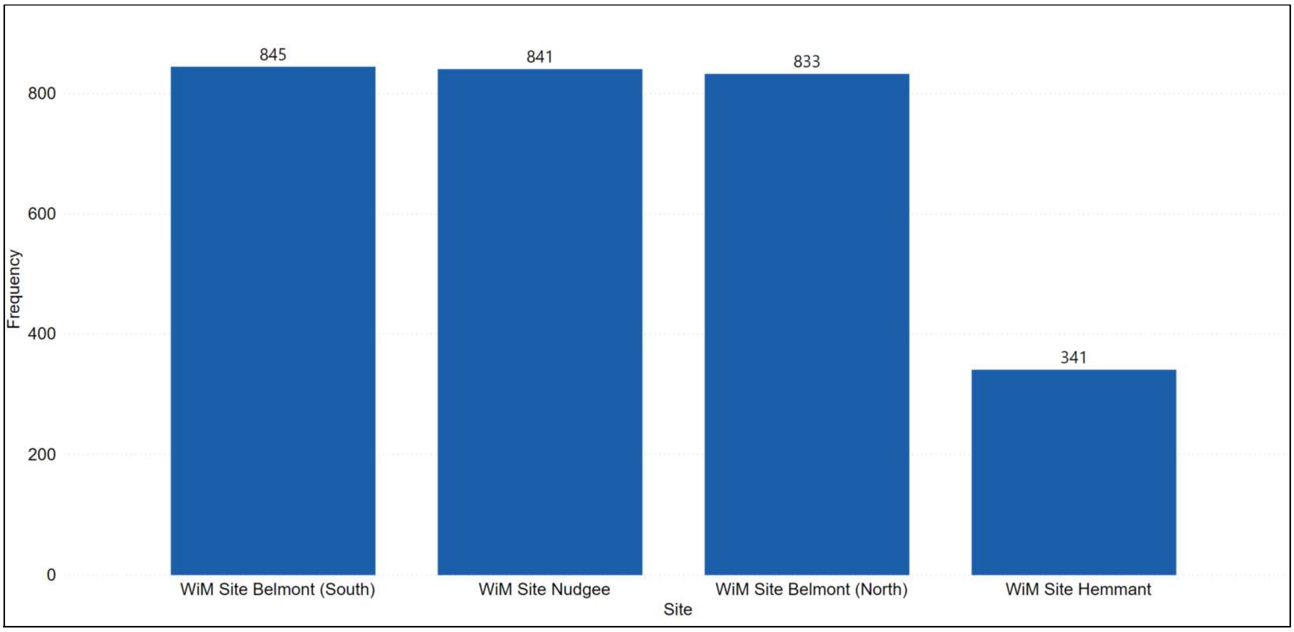


Figure 4.33: Crane records by configuration

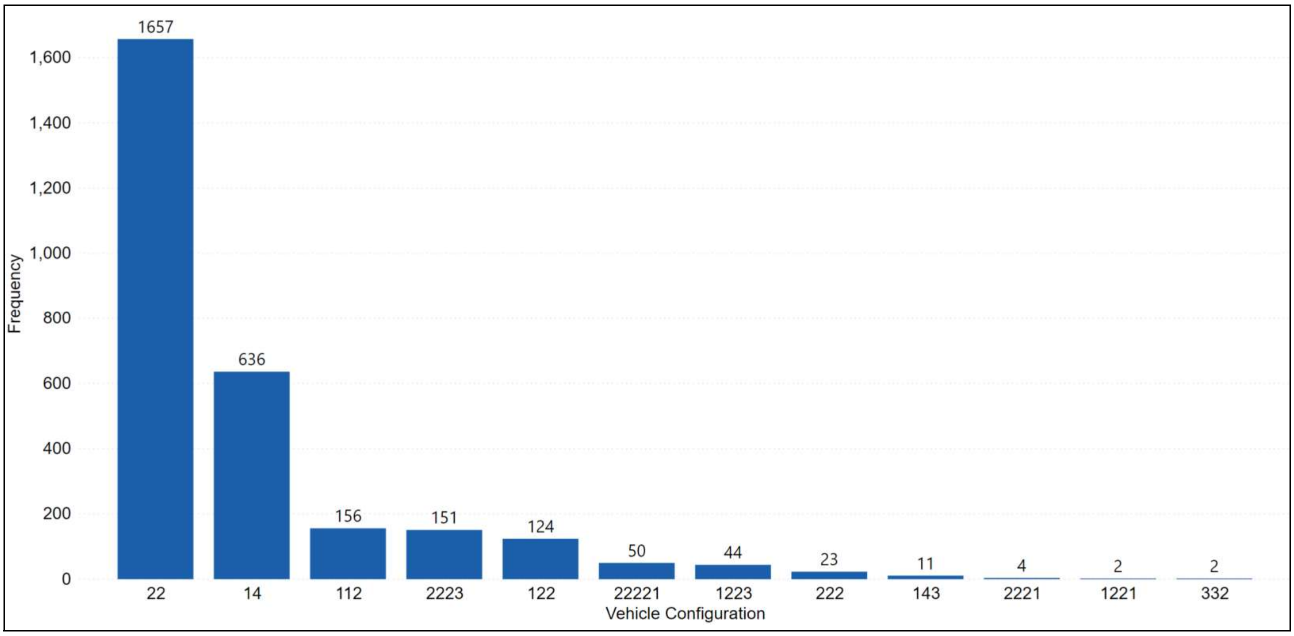


Figure 4.34: Crane records by configuration – percentage

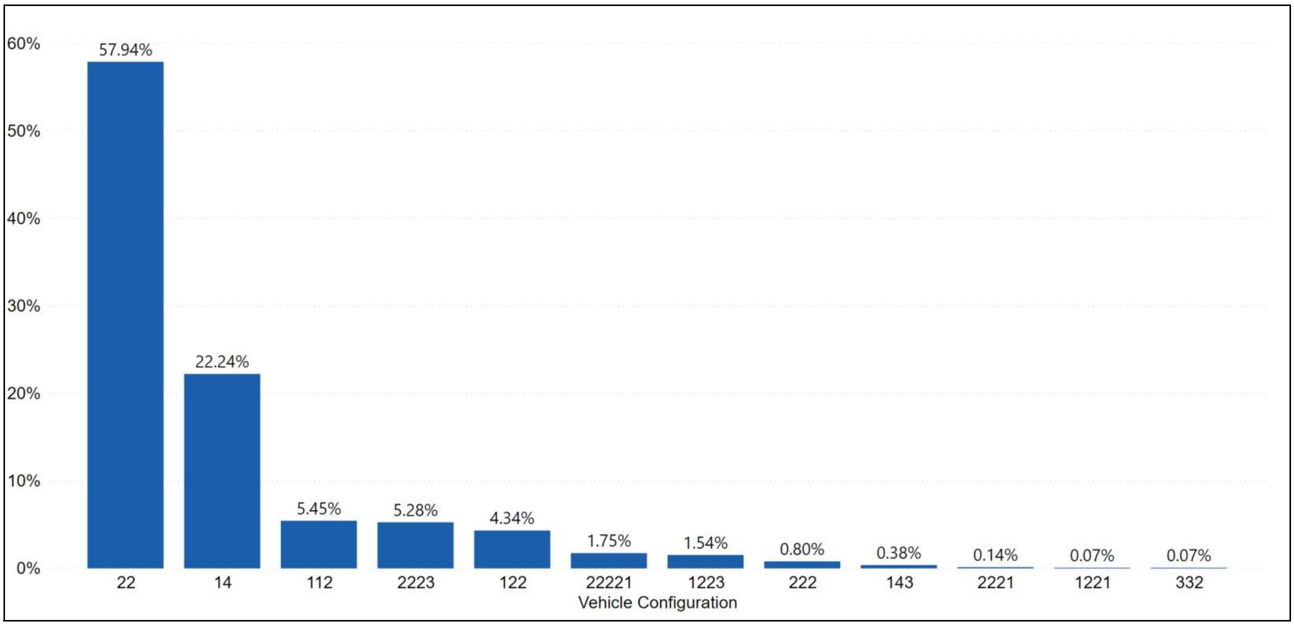
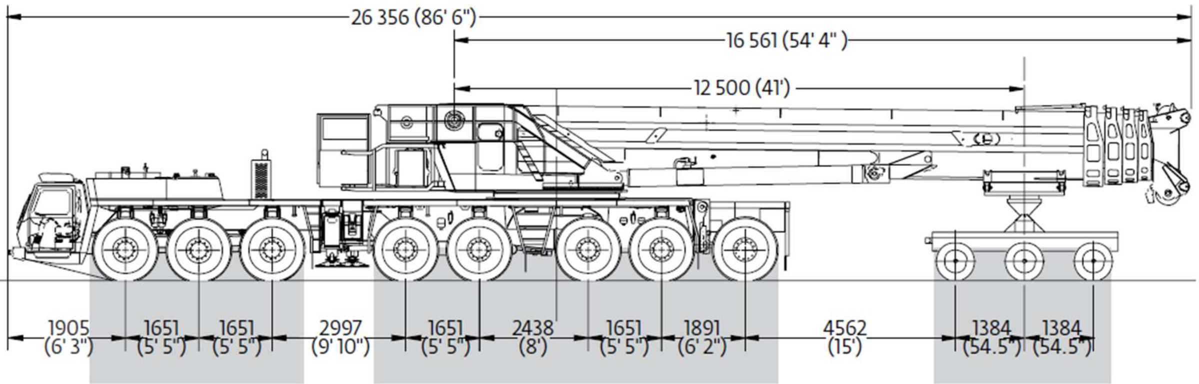
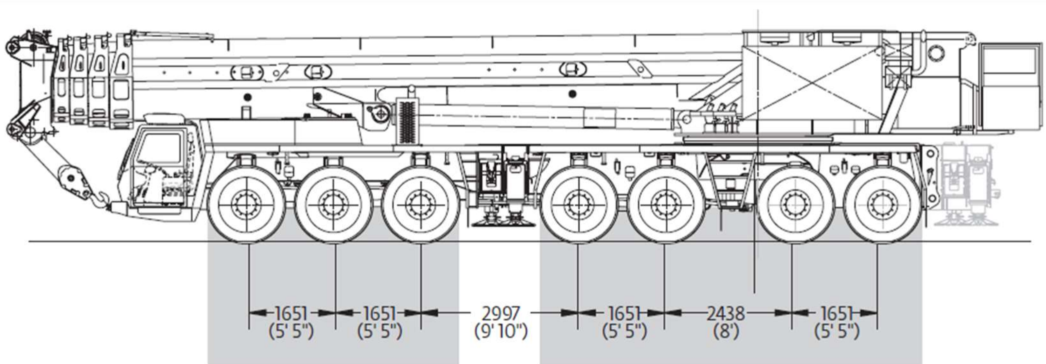


Figure 4.35: Combinations of cranes with boom dolly, boom over front, and retractable axles

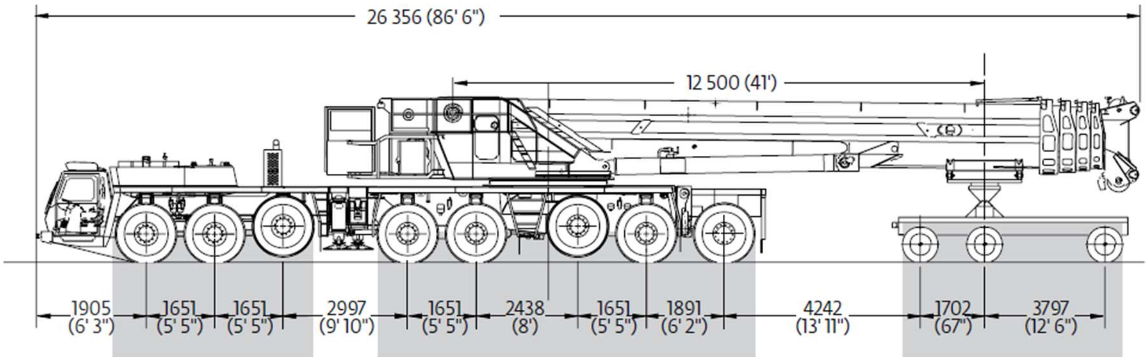
Trailing boom dolly with 8th axle



Boom over front



Trailing boom (spread dolly) with axles 3 and 6 raised



Source: Manitowoc (2020).

Table 4.2: Example of the change in axle mass when travelling with or without boom dolly (for the base crane with no counterweight)

Unit type	Travel mode	Front axle group mass (t)	Rear-axle group mass (t)	Boom dolly axle group mass (t)	GVM (t)
Basic machine with no counterweights	Boom over front	20.631	18.358	-	38.989
	Trailing boom dolly	17.085	14.544	10.202	41.831
Machine with total counterweights of 11.793 t	Boom over front	23.259	27.567	-	50.817
	Trailing boom dolly	18.708	17.937	17.014	53.659

Source: Manitowoc (2015).

4.5.2 Dimensions

While it is generally assumed that all cranes with similar numbers of axles have a consistent axle layout, a review of manufacturer specifications showed that this is not necessarily the case. Varying configurations exist between different crane types and manufacturers, as shown by the varying configurations in Figure 4.36, which displays the axle locations for each crane model in the project as per the manufacturer specifications. Some cranes operate with or without boom dollies, as indicated by trailing axles on some cranes (e.g. GROVE GMK7550). These cranes are still classified in Figure 4.36 as per the number of axles excluding the additional axles supporting the boom.

To further investigate the consistency of crane axle spacings, the cumulative distributions for each axle spacing, per the number of axles on the crane, were plotted. An example for 4 axle cranes is shown in Figure 4.37.

In the cumulative distributions, the axle spacing jumping from 0% to 100% indicates all of the vehicles have similar axle spacings, whereas multiple jumps between 0% and 100% indicates variability in the crane axle spacing data for cranes with the same number of axles.

The comparable axle spacings in the 4 and 5 axle cranes signify that the different crane models use a similar axle layout. They are also the most common (Figure 4.33). The 6–8 axle crane datasets are too small to draw conclusions from, though the spacing between axles 5 and 6 of the 8 axle cranes do exhibit significant variation. Nine axle cranes showed two distinct configurations between axles 8 and 9, and a variety of spacings between axles 6 and 7 which could be due to varying dolly configurations.

Figure 4.36: Crane axle locations per manufacture specifications

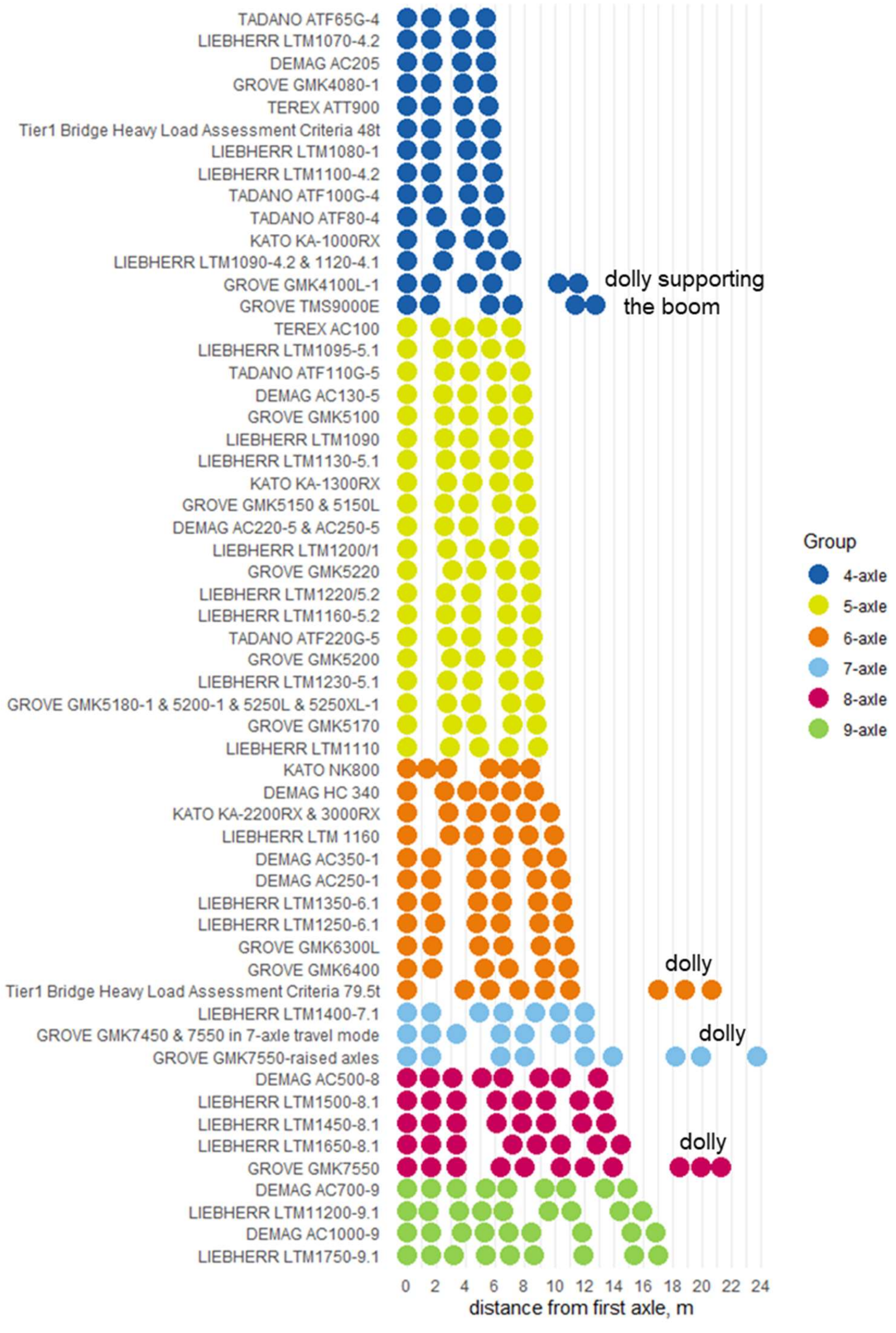
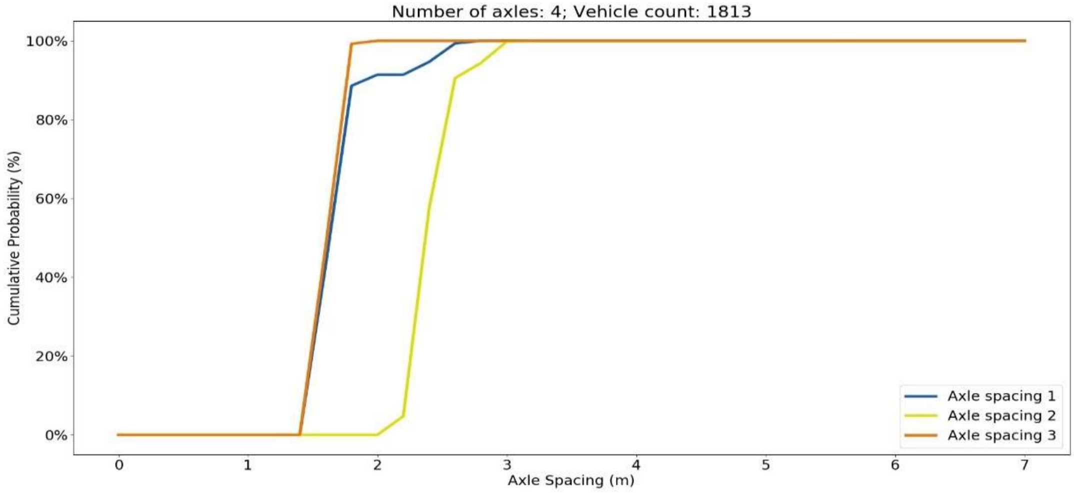


Figure 4.37: 4 axle crane axle spacings



4.5.3 Gross Vehicle Mass

The project investigated the GVM of the cranes.

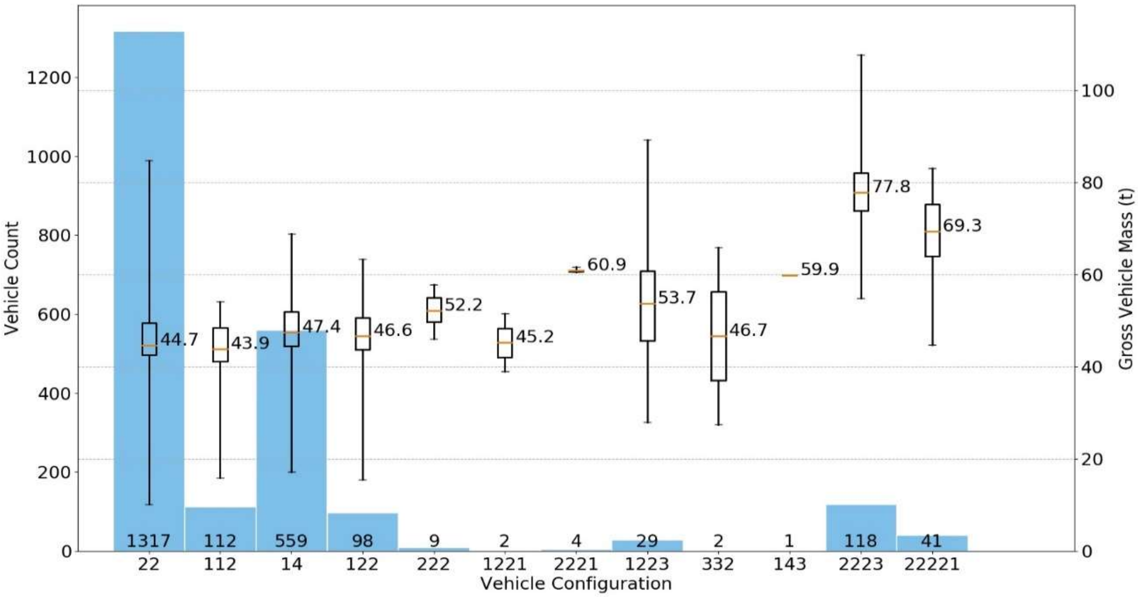
The GVM statistics for each crane configuration, only using records from the months classified as confident according to the class B confidence assessment from Section 3.3.2, are shown in Figure 4.38 as a box and whisker plot. The orange line identifies the mean, the box represents the 25% and 75% quartiles, and the whiskers are the minimum and maximum GVM readings. The mean GVM stays relatively consistent for the 4 to 6 axle configurations, though there is a larger range of values noted in the 22 and 5 axle configurations (the higher masses of the 5 axles in relation to the 6 axles could be from sample size or separate counterweight transport). Higher average masses are generally noted in the 7 to 9 axle configurations.

Comparison of the WiM GVM with nominal GVM from manufacturer’s data indicates the WiM system provides a reasonable estimate for the GVM of cranes around half the time but there are outliers (whiskers) that would benefit from investigation and continual improvement. This is discussed further in Section 3.3.

Positive identification of the make and model of the crane would make these cranes a useful resource in the improvement of WiM data quality. Merging higher precision axle spacing signatures from WiM and classifiers and imagery with manufacturer data would provide the necessary information to help improve the quality and reliability of vWiM data.

The distribution of crane GVMs are presented as the blue bins in Figure 4.39, with the orange line representing cumulative distribution of the crane GVMs.

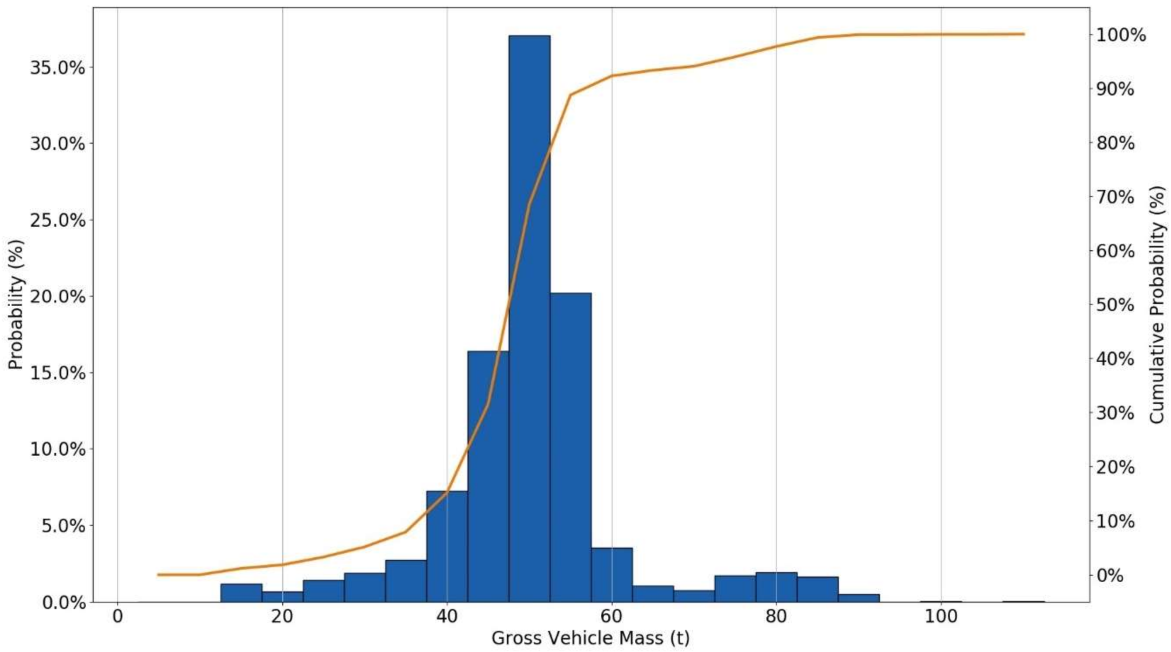
Figure 4.38: Gross vehicle mass distribution of cranes



Notes:

- Some crane configurations may include boom dollies.
- 4 axle cranes typically have a GVM of 40 t (10 t per axle) or 48 t (12 t per axle) per manufacturer specifications.
- 5 axle cranes typically have a GVM of 50 t (10 t per axle) or 60 t (12 t per axle) per manufacturer specifications.
- 6 + axle cranes weigh up to 12 t per axle but often can reduce their axle weight by having their counterweight, boom or other components transported separately.

Figure 4.39: Crane GVM distribution

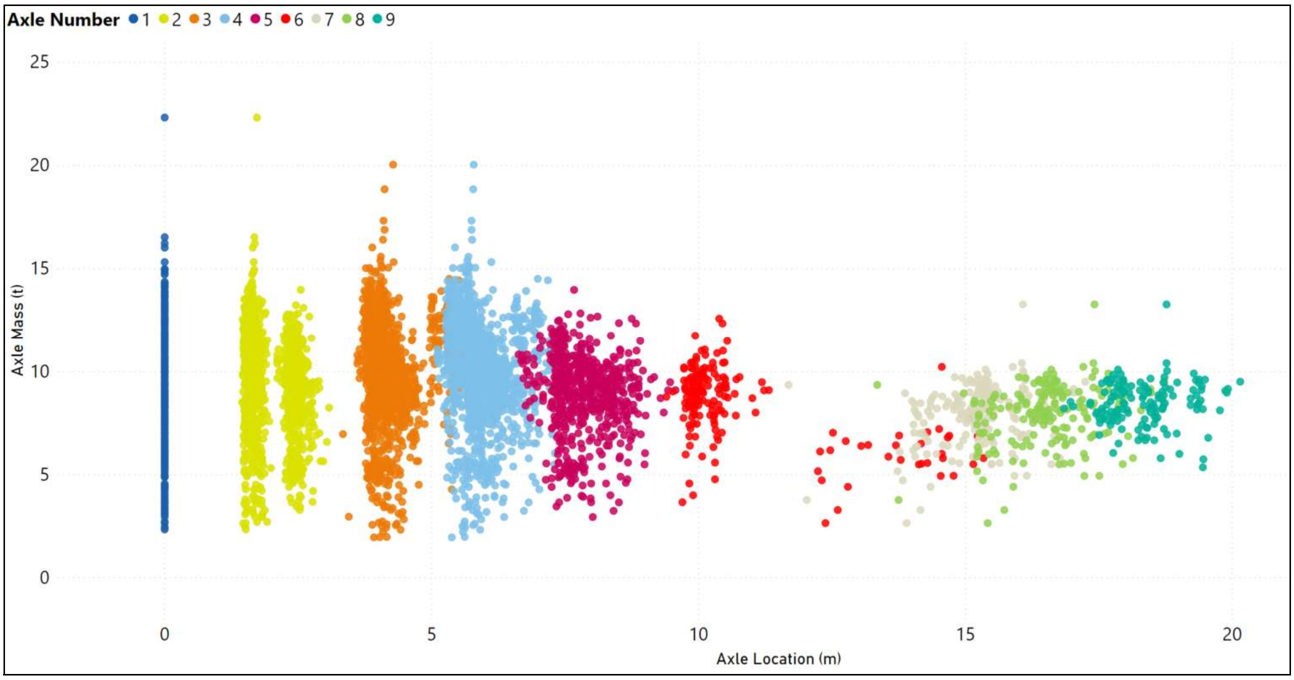


4.5.4 Axle Mass

Due to their high GVMs and low number of axles, cranes can exhibit large, concentrated axle masses. To assess the individual axle masses of cranes the axle group masses were distributed evenly to all axles in the group (i.e. if a group of 2 axles had a group mass of 30 t, each axle was assessed as having an individual mass of 15 t). The axle location (distance from the front axle of the crane) and the axle masses for each recorded crane, are shown in Figure 4.40[10]. In general, the larger axle masses are associated with the first 5 crane axles, likely from the cranes with 4 and 5 total axles.

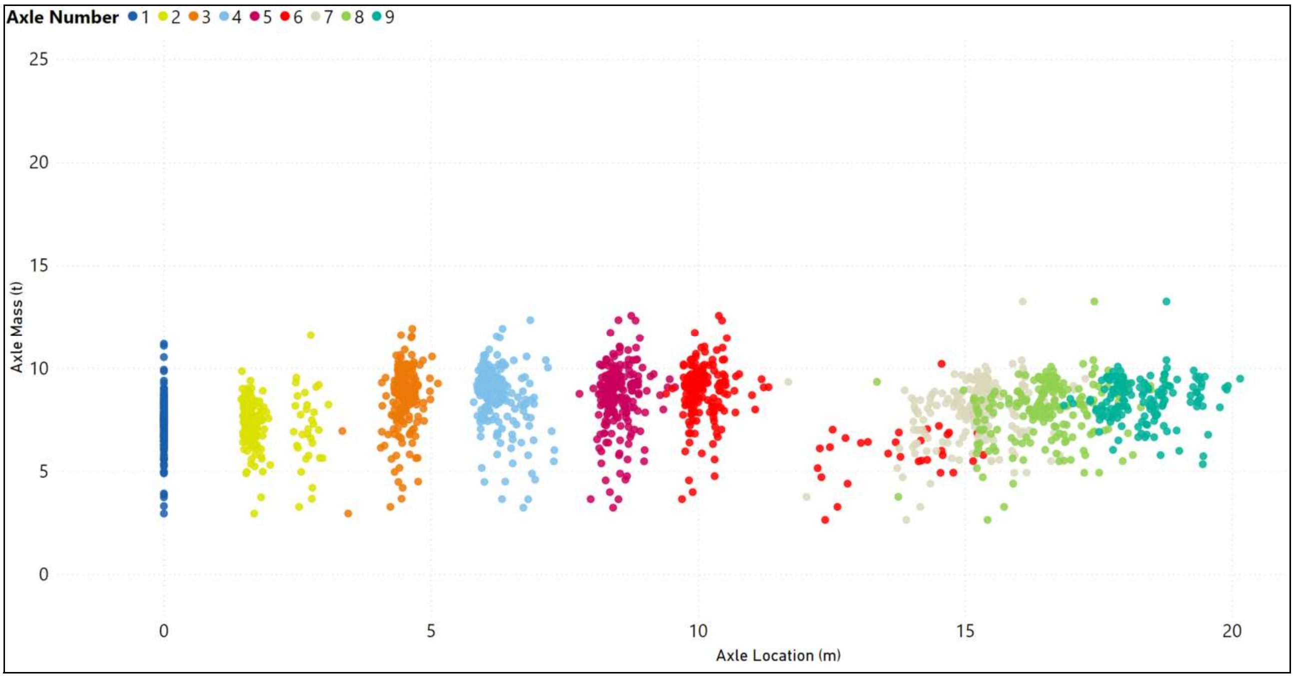
[10] Using records from months classified as confident according to the class B confidence assessment from Section 3.3.2.

Figure 4.40: Axle masses – all cranes



While cranes with over 6 axles tended to have higher GVMs, their masses were also spread over a greater number of axles reducing the mass per axle, as shown by the reduced distributed axle masses for configurations with 6 or more axles (287 records total) in Figure 4.41. Most of the higher axle loads evident in Figure 4.40 but not in Figure 4.41 are therefore related to 4 and 5 axle cranes or similar. Understanding the variability in the axle mass for 4 and 5 axle cranes would be useful given the peak estimated axle loads are possibly twice the nominal mass and thus significant for the management of both road and bridge assets, should the loads be real. It is noted that some of these shorter cranes can generate pitch modes that would accentuate the axle loads at the beginning and end of short cranes.

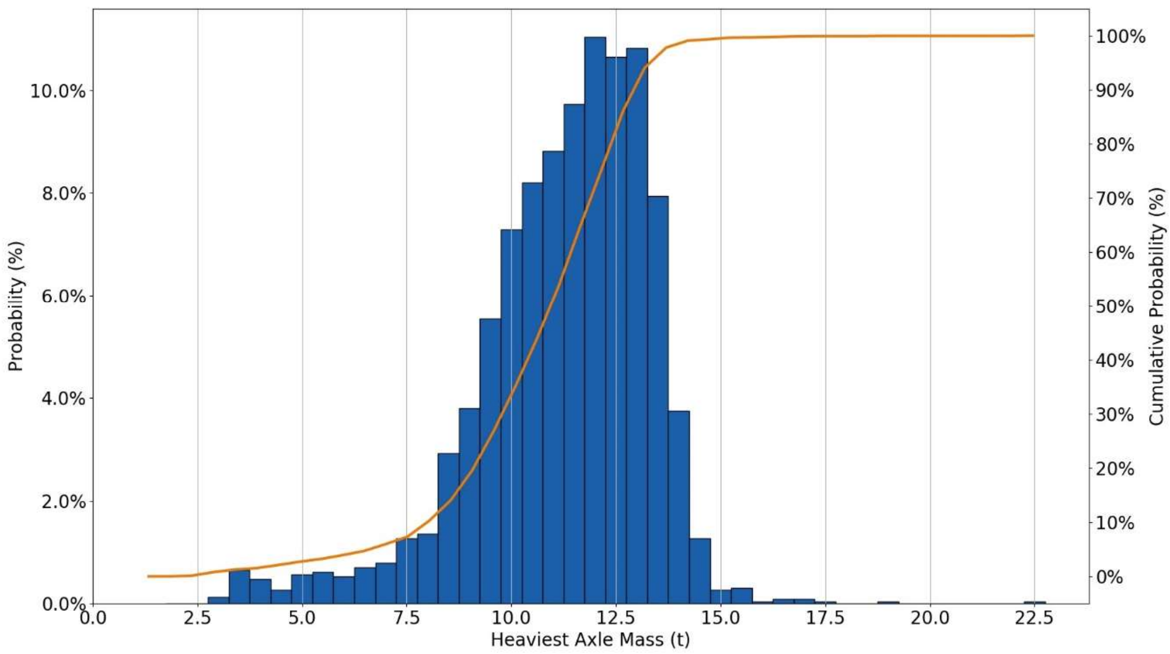
Figure 4.41: Axle masses – configuration with 6 or more axles



4.5.5 Heaviest Axle Mass

Assessments of the distributed axle mass led the project to investigate the heaviest distributed axle mass per crane, to evaluate the highest concentrated axle loads per record. The distribution of heaviest axle mass per crane, only using records from months classified as confident according to the class B confidence assessment from Section 3.3.2, are presented in Figure 4.42. Over 55% of the crane records were noted as exhibiting heaviest axle masses over 11 t, and approximately 25% of the cranes had a heaviest axle mass over 12.5 t, with very few over 15 t. The lower axle masses (less than approximately 8 t) suggest some vehicles with similar 'axle spacing signatures' are included within the crane dataset. Investigating the low and high outliers provides an opportunity for continual improvement.

Figure 4.42: Crane heaviest axle mass distribution



4.5.6 Vehicle Speed

Vehicle speed can impact the force applied by a vehicle to a pavement or structure while traveling on the roadway. To better understand the speed of the recorded cranes the distribution of their speeds is plotted in Figure 4.43. Most of the cranes travel between 80 to 90 km/h at WiM sites in the dataset. The speed limit at each recorded WiM site is 100 km/h, apart from Hemmant (80 km/h). The distribution of vehicle speed in relation to the site speed limit is shown in Figure 4.44. Most cranes are noted as tending to travel at approximately 80% to 90% of the speed limit.

Figure 4.43: Crane vehicle speed

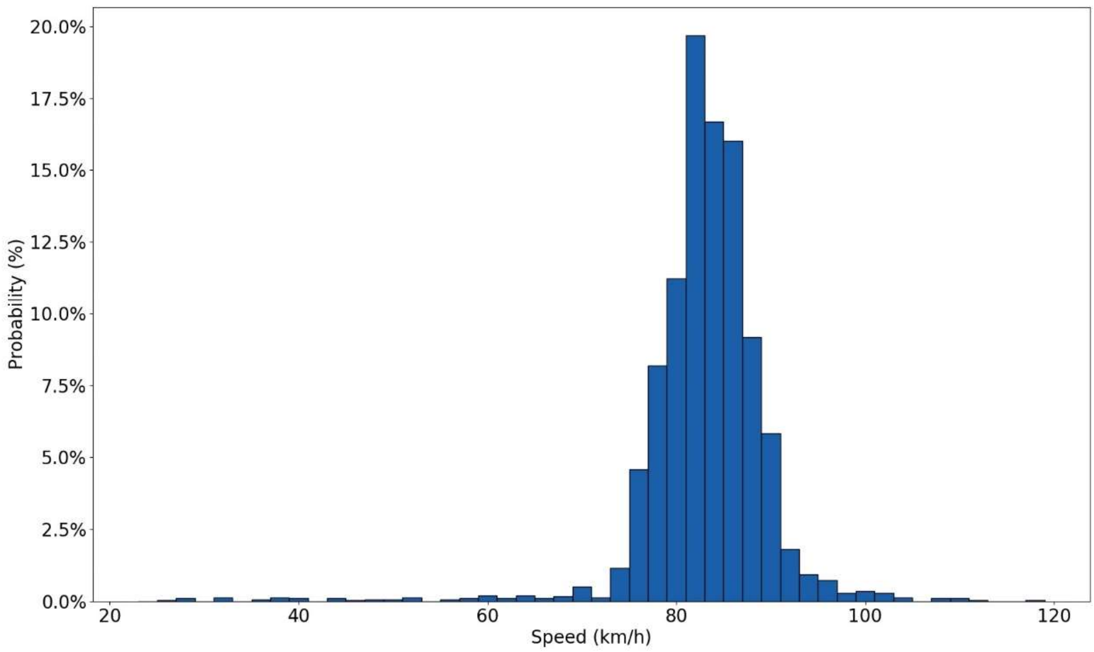
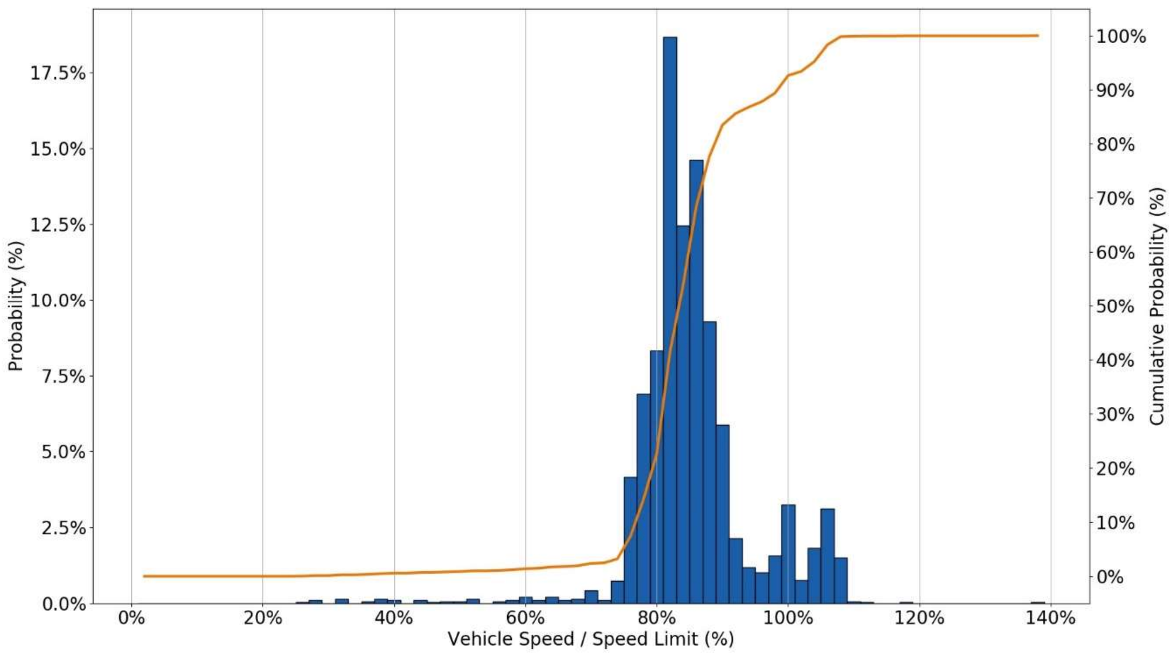
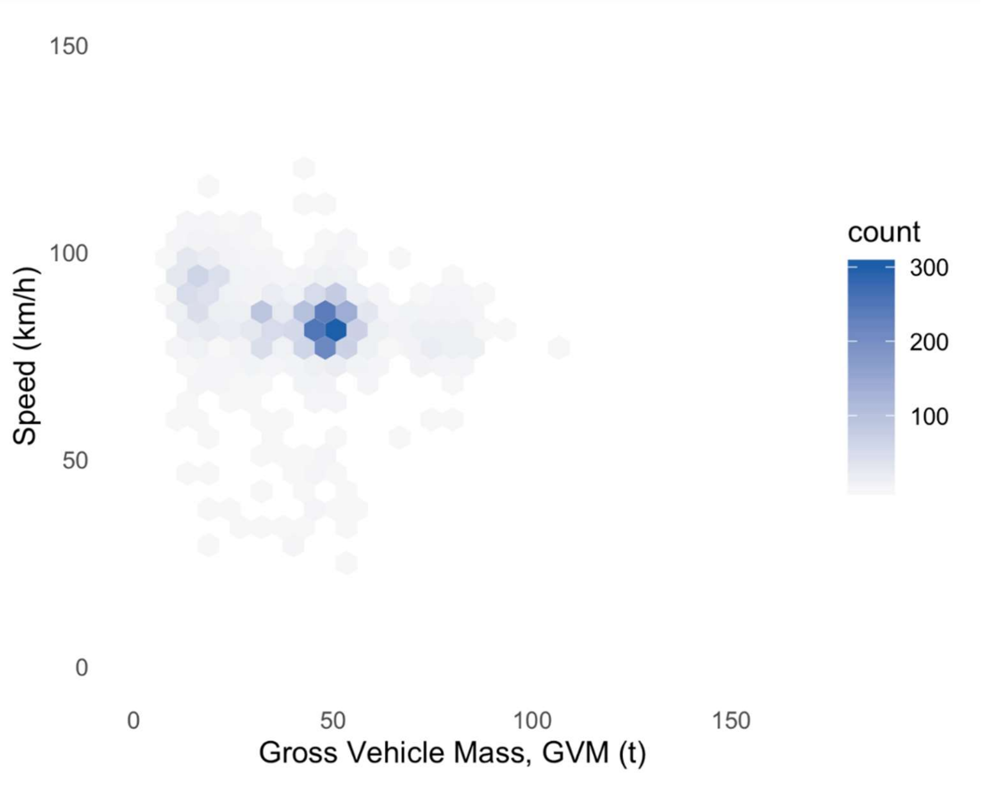


Figure 4.44: Crane vehicle speed in relation to site speed limit distribution



As the dynamic effect a vehicle has on a structure or pavement is influenced by its mass and speed, the project investigated the correlation between these two parameters. The recorded GVM was plotted against the vehicle speed for cranes, as shown in Figure 4.45. Cranes are often limited to 80 km/h according to manufacturers' specifications, so the high density of vehicle records at this speed indicates they travel near their maximum speed. A cluster of significantly lighter vehicles (less than approximately 30 t) can be seen travelling closer to the speed limit, which is 100 km/h at most WiM sites, are likely to be rigid trucks with unusual axle spacing geometry incorrectly identified as cranes.

Figure 4.45: Crane speed by Gross Vehicle Mass (GVM)



Note: Typical image from TMR bridge load model report

4.5.7 Discussion

Cranes are noteworthy as their high concentrated axle masses can be of concern for pavements and structures. Due to these factors the project investigated their presence at 4 WiM sites. The project analysed the crane dataset in regard to their configuration, mass and speed. Some conclusions from the analysis include:

- Over 60% of cranes have a GVM between 40 and 60 t.
- Cranes with 4 to 6 axles tend to have higher concentrated axle masses than cranes with more axles, despite cranes with more axles having heavier GVMs.
- Over 55% of cranes have a heaviest axle mass of over 11 t.
- Cranes tend to travel below the speed limit (around 80 km/h consistent with maximum speeds noted by manufacturers).
- Cranes can be largely detected in the data stream via their axle signatures, although there is some dilution from other vehicles with similar axle signatures.
- The crane data, particularly the most common 4 and 5 axle cranes, provides an opportunity for
  - continual improvement of WiM and classifier data
  - understanding the appropriate bridge assessment criteria for cranes.

4.6 Summary

Recent improvements to the WiM and classifier processing algorithms to better detect heavy vehicles occupying two lanes made a dataset available for low loaders, load platforms and heavy mobile cranes throughout Queensland for the first time.

The project analysed this new data both to better understand the vehicles of interest to Queensland and to provide insight into the capabilities of the data. Analyses were performed to better understand:

- load platforms throughout Queensland
- low loaders throughout Queensland
- cranes at 4 south-east Queensland locations
- the opportunity to utilise crane data for continual improvement of WiM and classifier data
- the loads applied to bridges by low loaders, load platforms and cranes.

The insights generated, together with the improved understanding of data quality, provide the basis for more informed, credible decisions regarding access and asset management across the network.

The results of these analyses are presented in the following section.

5. Applications of Virtual WiM

This section discusses the application of the learnings to Virtual WiM which are summarised into three areas:

1. data quality and integration
2. WiM to classifier extrapolation
3. prototype tracking tool for vehicles of interest.

Additional data sources were investigated as part of this project and are outlined with the consideration of integration to expand the value and functionality of WiM or to improve the quality of the WiM data.

5.1 Data Integration and Quality

A series of case studies in the following sub-sections explore the integration of (or possible integration of) WiM data with other datasets enriching the understanding of heavy vehicle traffic and improving the quality of, and confidence inspired by the data. The case studies and related findings are summarised in Table 5.1.

Table 5.1: Case studies – exploring data integration and data quality

Case study	Section	Sources of data	Key outcomes and opportunities
Integrating bridge monitoring data	Section 5.1.1	Bridge sensors (Gateway Arterial Flyover) CCTV camera ANPR-capable camera Classifier data (0.8 km from bridge) WiM data (12 km from bridge) Manufacturer data (payloads) Vehicle registered mass data	Integrating the bridge monitoring system with WiM data revealed that the vehicles posing the greatest risk to the bridge (load platforms) were not visible in the WiM and classifier data due to their unusual configurations. The combination of data provides powerful opportunities to independently verify and validate outlier events and to inform bridge risk and the continual improvement of both data collection and the asset management decisions.
Integrating crane WiM and ATO data	Section 5.1.2	WiM data for cranes (based on axle footprints identified in Section 4.5.2) ATO permitted mass data for cranes IAP telematics (GPS location data)	Confirmed potential to validate and calibrate (live) WiM and classifier systems using ATO data. Integrating WiM and ATO data with ANPR or video detection would benefit this use case especially on busy multi-lane highways where matching is more challenging.
Integrating WiM and OBM data	Section 5.1.3	WiM data OBM data IAP telematics (GPS location data)	Similar to crane ATO data, there is an opportunity to use integrated OBM data for the live calibration of WiM and classifier data. Additionally, it may be possible to use WiM sites to calibrate OBM sensors or identify vehicles where on-board sensors have drifted out of calibration. Only a small proportion of the heavy vehicle fleet is instrumented with OBM sensors and there is room-for-improvement in the quality of this data.
Integrating WiM and ANPR data	Section 5.1.4	WiM data ANPR data	Matching vehicle permit data and registration data with WiM data to improve understanding of rare vehicle combinations. Further enhance live calibration of WiM sites in combination with ATO, OBM and/or permit data. Currently the ANPR and WiM data is not automatically integrated. Rear number plates (of load platform trailers for example) may be required for certain applications.
Assessing data quality using steer axle mass	Section 5.1.5	WiM data (only)	The steer axle mass of '123' configuration semi-trailers provides a reliable way of assessing quality and there is potential to further enhance this capability.

5.1.1 Integrating Bridge Monitoring Data

It was identified during the monitoring of the Gateway Arterial Flyover (GAF) during an upgrade project strengthening deficient components of the bridge structure that there is value in combining datasets. To better understand the response of the GAF to heavy vehicle traffic and inform the access, risk management and due diligence for the structure, the monitoring team combined data from:

1. nearby WiM and classifier sites
2. two overhead CCTV cameras (one with ANPR capability)
3. publicly available manufacturer data and registered tare mass data (ATO data)
4. strain gauges on the bridge.

The project's stakeholder engagement (Heldt et al. 2019) highlighted the increased value achieved by integrating multiple data sources, including: data from WiM, classifiers, bridge monitoring data, cameras, ATO, permits, IAP and OBM data and other data sources such as bridge maintenance expenditure and bridge assessment data to make better evidence-based decisions for bridges, pavements, and planning.

Integration with ATO data, IAP and OBM data, and ANPR were investigated and reported in this section. Each data source provided valuable information.

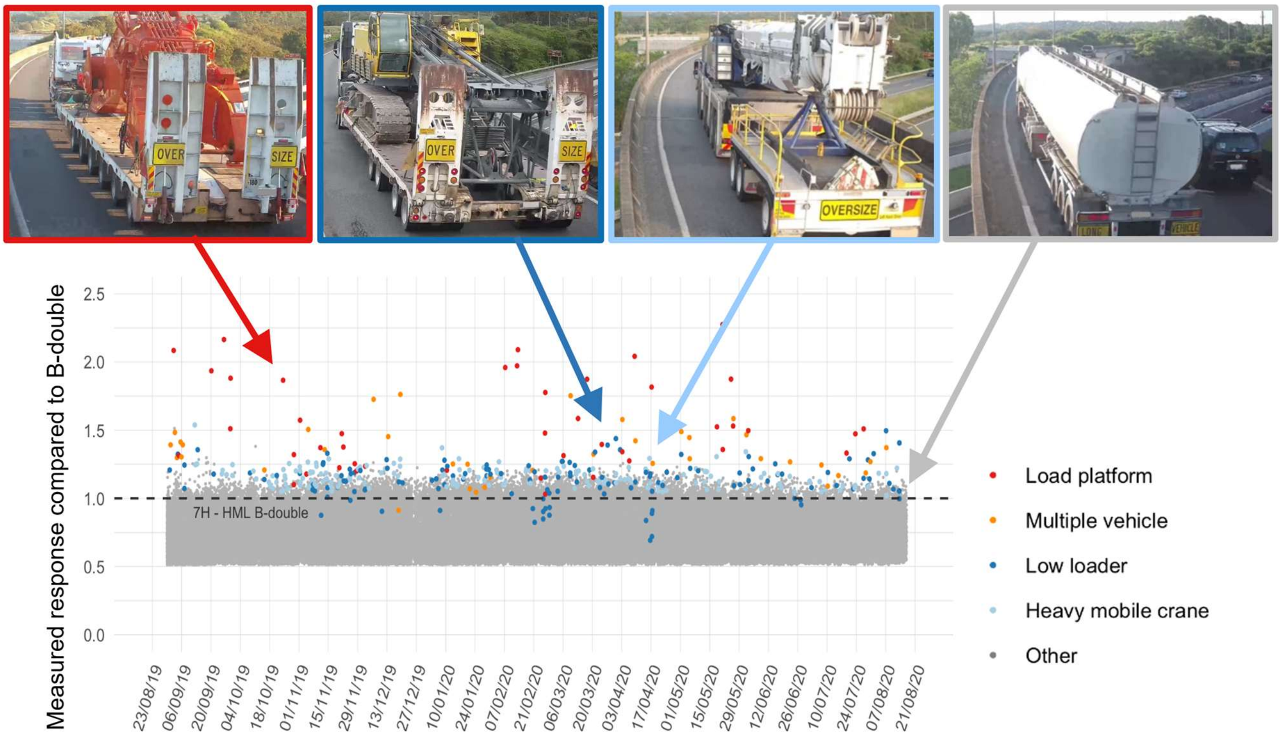
At GAF, the bridge monitoring system was on the same route as nearby WiM and classifier sites, which provided axle spacings and mass records for the vehicles. Strain gauges measured the response of the bridge to traffic loads and the overhead camera provided video and still images of the vehicles causing the largest strains in the structure. Manufacturer data provided estimates of the tare mass of vehicles and in some cases, the loads they were carrying. When the three datasets were combined it was possible to:

- calibrate the sensors using multiple crossings of vehicles identified within the traffic stream (i.e. without a specific calibration vehicle or vehicles)
- estimate the mass and dynamic component of load for individual vehicles travelling across the GAF
- understand the largest observed events in detail
- provide evidence to encourage compliance with the access restrictions that were in place on the bridge during strengthening works.

The combination of the three data sources also led to valuable discoveries including that:

- The largest strains on the bridge were caused by load platforms, followed by low loaders, heavy mobile cranes and freight vehicles (Figure 5.1).
- Low loaders and load platforms were not being detected by the WiM and classifier stations.
- The low loaders and load platforms were occupying two lanes but the fragments of data from each lane could be merged to provide the total for the two lanes and greater visibility in the dataset to these vehicles.
- It was likely some wide low loaders and platforms were running with wheels in the shoulders (therefore outside of the WiM sensors resulting in lower measured mass) and were thus underestimating the mass.
- With the combined data it was possible to provide granular feedback regarding the effectiveness of access management decisions and risk controls and to inform the ongoing management of the structure.

Figure 5.1: Load platforms pose the greatest risk to the Gateway Arterial Flyover followed by low loaders, heavy mobile cranes and freight vehicles



5.1.2 Integrating Crane WiM and ATO Data

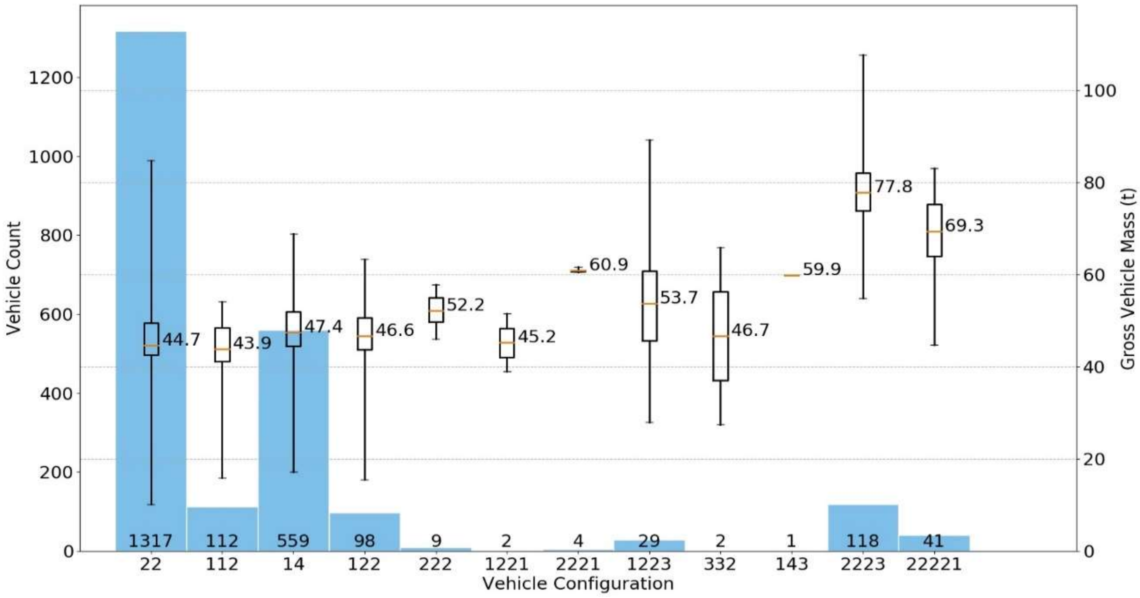
The objective was to explore the possibility of using crane ATO data matched to WiM data to validate and improve the quality of WiM data, as identified by Eskew et al. (2021).

Eskew et al. (2021) analysed the GVM of crane records identified using axle spacing footprints in the project dataset (see Figure 5.2).

Given the relatively fixed mass of cranes (subject primarily to different configurations and boom, dolly and counterweight arrangements), these vehicles present an opportunity to inform the live calibration of WiM systems. However, larger than expected spread in the range of recorded GVM was found for the different crane configurations, prompting further investigation.

The ATO mass records for each of the crane configurations were compared with the WiM records using IAP data to match known ATO cranes to WiM results at the approximate time the cranes (fitted with IAP) passed through a WiM station.

Figure 5.2: Gross vehicle mass distribution of cranes identified using axle spacing footprint in the WiM data



Notes:

- Some crane configurations may include boom dollies
- 4 axle cranes typically have a GVM of 40 t (10 t per axle) or 48 t (12 t per axle) per manufacturer specifications.
- 5 axle cranes typically have a GVM of 50 t (10 t per axle) or 60 t (12 t per axle) per manufacturer specifications.
- 6 + axle cranes weigh up to 12 t per axle but often can reduce their axle weight by having their counterweight, boom or other components transported separately.

Background

To operate on the Queensland road network, Class 1 cranes and special purpose vehicles are required to obtain Authority To Operate (ATO) certificates. These certificates are issued and valid only for a specific configuration and operating weight. The vehicle dimensions and individual axle masses are measured and recorded on the certificate at the time of issue.

In the ATO database, the following information is recorded for each vehicle:

- vehicle ID (de-identified for this project)
- make (and model in some cases)
- vehicle dimensions (length, width, height, axle spacing and ground contact width)
- vehicle mass details (individual axle mass, tare mass and gross vehicle mass or gross combination mass)
- the number of tyres per axle.

Most cranes are also required to enrol in the Intelligent Access Program (IAP) which provides live telematics data every 30 seconds. IAP data includes the following information:

- vehicle ID (de-identified for this project)
- date and time stamp
- latitude and longitude
- speed
- make (and model in some cases)
- vehicle type.

Method

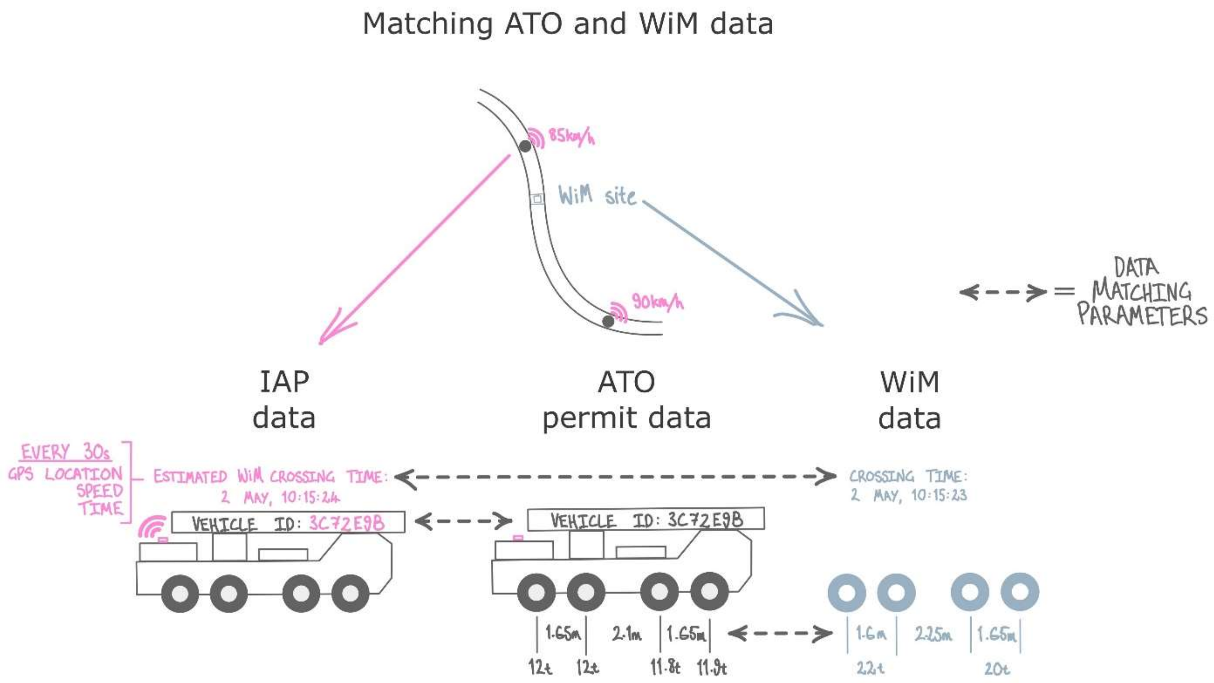
To facilitate a comparison between ATO data and WiM measurements, WiM, ATO and IAP data was extracted for cranes (or suspected cranes in the WiM data) passing the Nudgee WiM site between 1 May and 30 June 2020.

IAP and ATO data was combined into a single dataset using the de-identified vehicle IDs (which although de-identified, were consistent between the two datasets).

The combined IAP+ATO data was then related with the WiM data where possible using the IAP telematics data. Successful matches were those where both WiM records and IAP+ATO records existed with 'matching' (within a tolerance) axle footprints and crossing times. Crossing times were recorded directly at Nudgee WiM station and estimated from IAP records (using a process of dead reckoning).

Vehicle mass was used as a tiebreaker when multiple 'matching' WiM records were identified for a single crossing in the IAP records. A summary of the method used to find matching records is shown in Figure 5.3.

Figure 5.3 Method used to match ATO and WiM data (using IAP telematics data reported at 30-second intervals



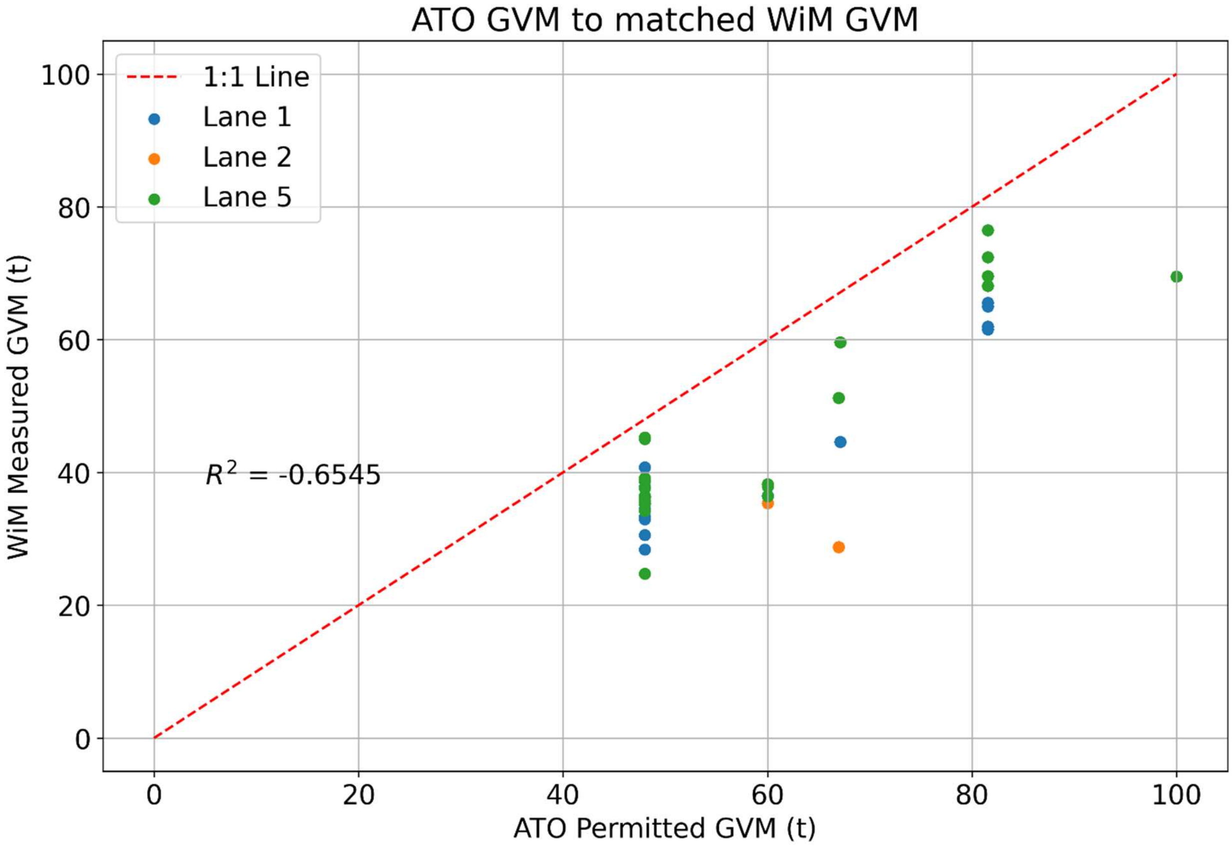
Note: *Where two WiM records existed around the same time as the estimated crossing time with matching configuration, a comparison between the ATO mass and WiM mass was used to break ties (with the 'match' being taken as the WiM record with mass closest to the mass in the ATO data).*

Results and discussion

The above method did not identify suitable matches for all vehicles. This may be due to several reasons, including the frequency of the IAP records, not able to determine the lane the vehicle is travelling as well as the exact time which the vehicle goes over the WiM site. It is noted that filtering based on mass match may introduce bias as it assumes that the WiM data is accurate. A similar approach to matching was used for On-board Mass Measurement (OBM) data from the same period.

Figure 5.4 shows the comparison of the ATO permitted GVM versus the WiM measured GVM per lane. The most important finding was that all the WiM results were below the ATO permitted GVM. This finding is at odds with the results of Eskew et al. (2021) presented earlier in Figure 5.2, which suggests both under and over-estimates.

Figure 5.4: ATO vs WiM – GVM



Continuing with the comparison of IAP/ATO and WiM comparison, Figure 5.5 shows the comparison of the ATO permitted tare mass versus the WiM measured GVM per lane. A review of the ATO data for cranes identified that the tare mass can be similar to the GVM, but it can also be vastly different, ranging from no change to 22 t.

Figure 5.5: ATO vs WiM – Tare Mass

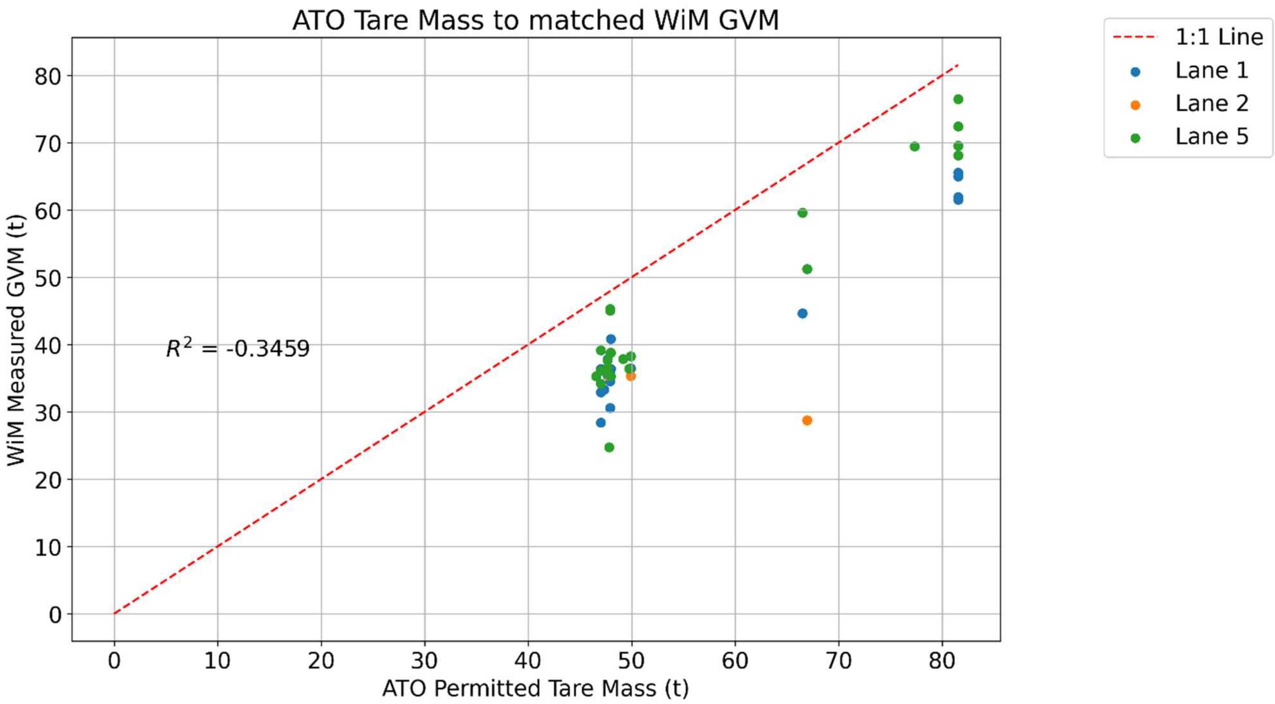


Figure 5.6 shows (for the same vehicles) a comparison between the ATO permitted group mass and the WiM measured individual group mass coloured by lane.

Figure 5.6: ATO vs WiM – Group Mass per Lane

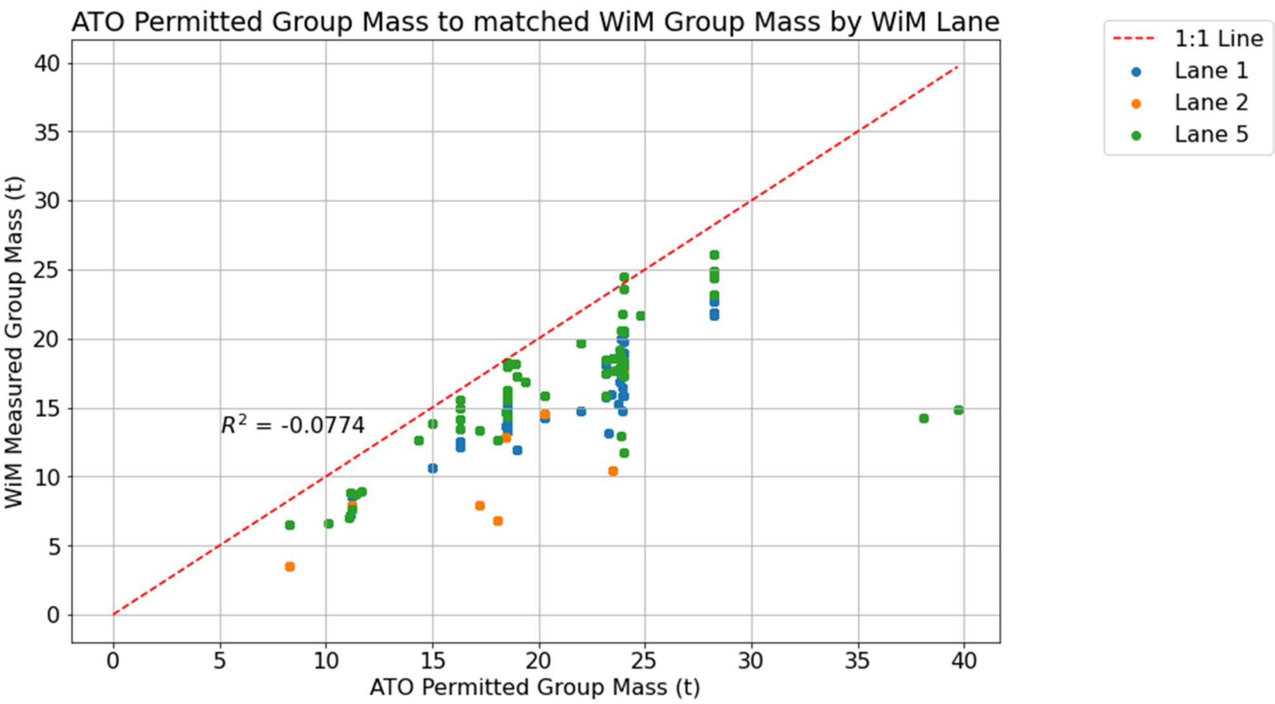


Figure 5.7 shows the same comparison of the ATO permitted group mass versus the WiM measured group mass but coloured by axle group (numbered in order from the front axle group).

Figure 5.7: ATO vs WiM – Group mass per group

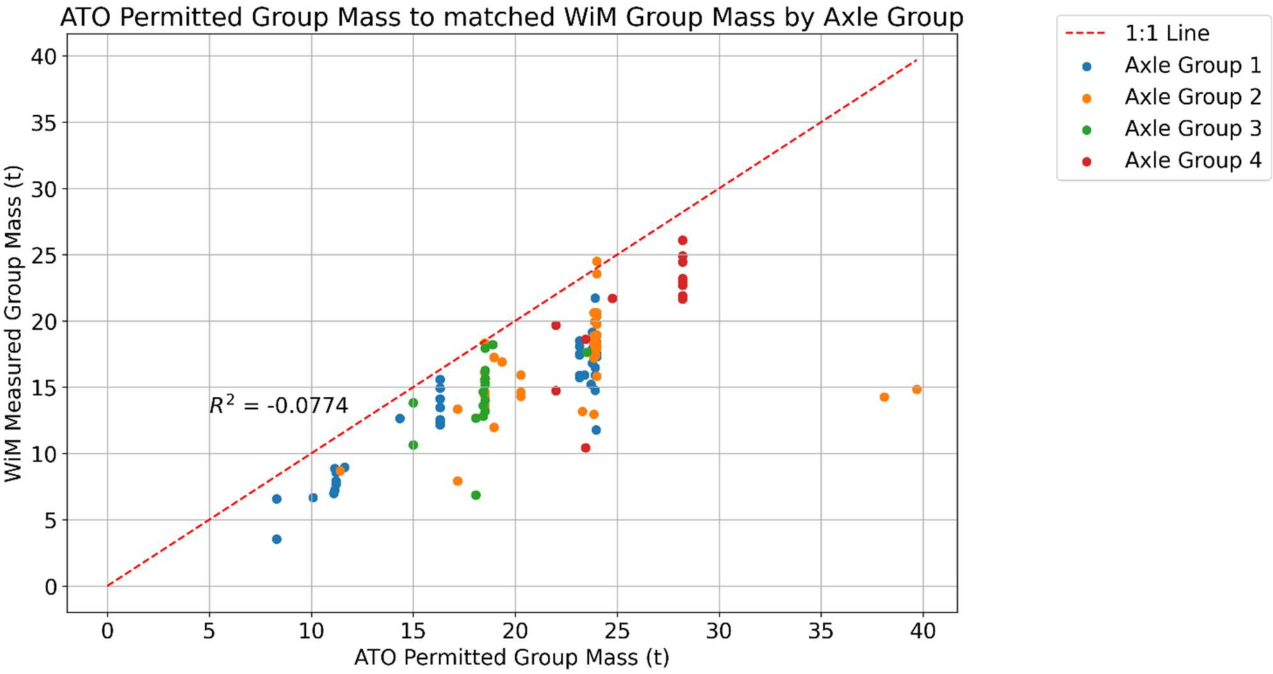
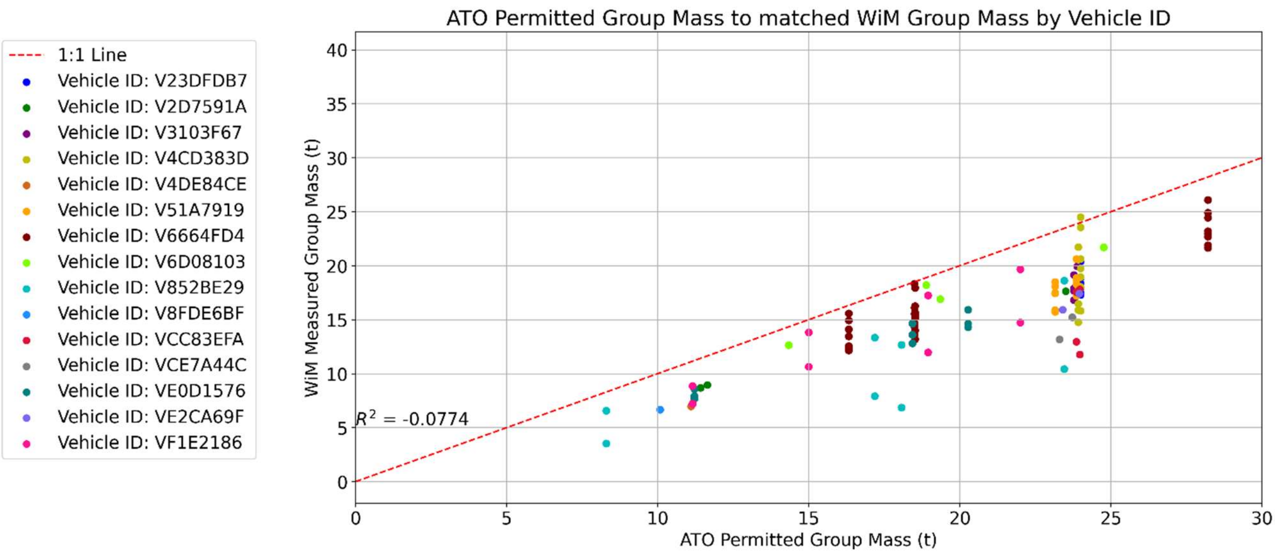


Figure 5.8 shows the same comparison of the ATO permitted group mass versus the WiM measured group mass coloured by the vehicle ID. Presenting the data in this way shows clusters of repeated crossings for each axle group of each vehicle. The clusters reveal the variability of the group masses in WiM, while the ATO permitted mass is static (constant, and does not account for the variability associated with fuel tank level for example).

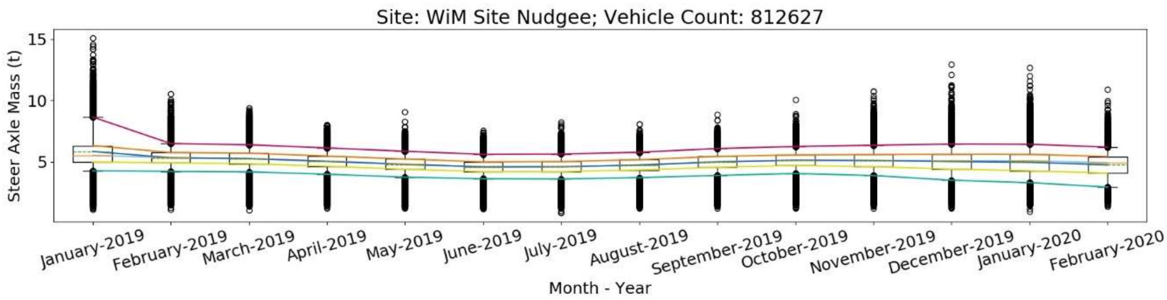
Figure 5.8: ATO vs WiM – Group mass per vehicle



As noted earlier, the above figures show that the data from ATO is generally higher than the measured mass from WiM.

It is noted that Eskew et al. (2021) identified that during the time-period analysed (May to July), the Nudgee WiM values were lower than other months in 2019 due to seasonality, which will influence the results (Figure 5.9. The mean steer axle mass during this period was 4.6 t to 4.8 t, which is around 20% less than a nominal 6 t steel axle and 15% less than the average steer axle mass of semi-trailers of 5.5 t from the project WiM data (Table 3.5 and Table 4.1). This suggests the WiM data at this time was underestimating mass by a similar amount as compared to the ATO data in Figure 5.4 to Figure 5.8.

Figure 5.9: Nudgee WiM site monthly 123 steer axle statistics



	Mean	Median	25% Quartile	75% Quartile	2σ below mean	2σ above mean
January-2019	5.85	5.52	4.99	6.32	4.27	8.65
February-2019	5.33	5.33	4.91	5.76	4.22	6.49
March-2019	5.26	5.27	4.85	5.70	4.18	6.39
April-2019	5.04	5.05	4.64	5.47	3.99	6.13
May-2019	4.79	4.81	4.39	5.23	3.75	5.86
June-2019	4.59	4.59	4.20	4.99	3.62	5.61
July-2019	4.60	4.60	4.20	5.02	3.60	5.63
August-2019	4.73	4.74	4.33	5.17	3.71	5.78
September-2019	4.99	5.01	4.56	5.44	3.89	6.08
October-2019	5.12	5.13	4.70	5.56	4.05	6.25
November-2019	5.10	5.11	4.61	5.59	3.88	6.35
December-2019	5.02	5.09	4.40	5.62	3.50	6.45
January-2020	4.96	5.08	4.27	5.61	3.30	6.43
February-2020	4.75	4.92	4.08	5.43	2.94	6.20

Manual matching was undertaken to confirm why there was a large difference between the permitted mass from ATO and the recorded mass from WiM for some vehicles. It was found through manual matching of the data from the two datasets, using the configuration, mass and time was possible. However, it was noted that there is not a perfect match. For a larger crane with a dolly, it was noted that the crane appeared to be over two records in the same lane, with the mass and axle group displayed such that it was distributed over multiple axle groups (VE8E40B4_20200617_055405_999901). This may be due to the size of the wheels being larger than the standard truck tyre, such that the sensor thinks there are multiple axles.[11]

Another record was found with what appears to be a crane over multiple lanes, based on the weight and timing, but the configuration was displayed slightly differently (V852BE29_20200605_021928_999901).[12]

Another finding was that several cranes were found to have recorded at a much lower weight than the permissible GVM, in the order of 15 tonnes difference for a 48-tonne crane, which exceeds the 10% threshold. A review of the vehicle type showed that this vehicle can change its weight dependent on the boom/jib which is on the vehicle (Figure 5.10 and Figure 5.11. This highlights that the mass of cranes is not as static as originally thought.

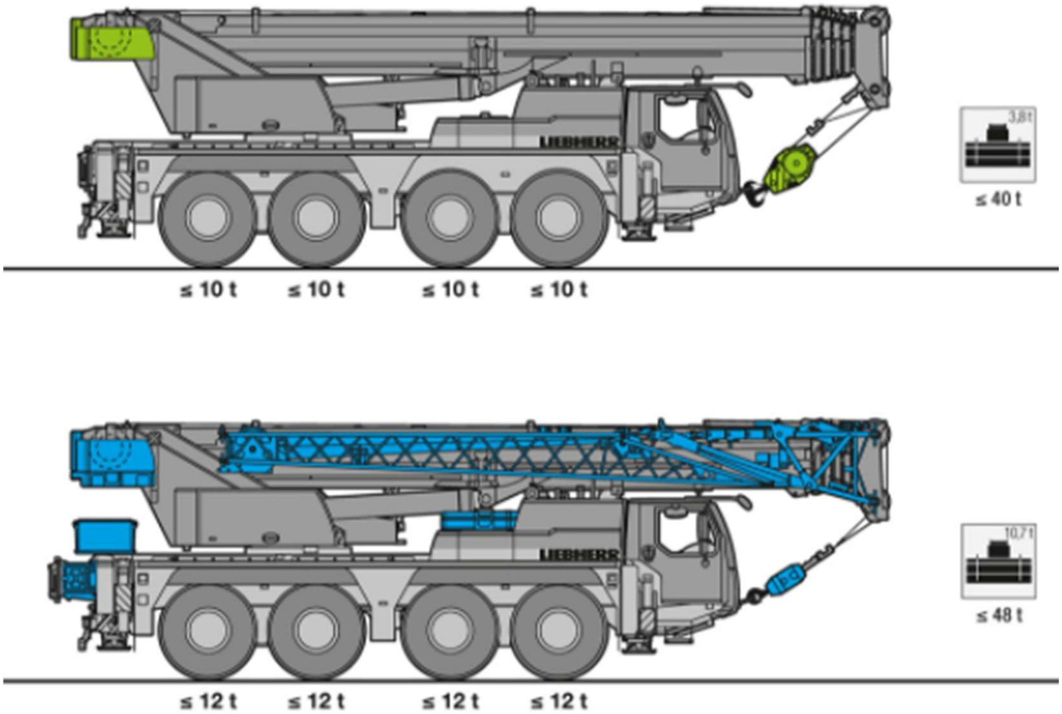
While the manual matching improved the understanding of why the ATO and WiM values do not always match up, it also identified time periods when cranes passed the WiM site based on the IAP but no WiM records identifiable as the crane were observable (VA23859C_20200615_121216_999901). This hypothesis should be confirmed via video footage.

[11] This may be due to a vehicle closely following, this could be confirmed with ANPR. The weight discrepancy may be due to the vehicle being on the edge of the detector, example provided in Figure 5.14.

[12] This may be due to a vehicle in the adjacent lane, this could be confirmed with ANPR. The weight discrepancy may be due to the vehicle being on the edge of the detector, example provided in Figure 5.14.

These findings highlight why the mass from the WiM may differ from the ATO such that there is in excess of the 10% threshold and accentuates that the ATO will only provide the maximum mass of the vehicle, which limits its use. It is noted that for some of the vehicles it could not be explained as to why their mass was lower than expected (VCC83EFA_20200523_102228_999902).[13]

Figure 5.10: LIEBHERR LTM 1070-4.2 – driving configurations



Source: Liebherr (n.d.).

[13] The weight discrepancy may be due to the vehicle being on the edge of the detector, an example is provided in Figure 5.14.

Figure 5.11: LIEBHERR LTM 1070-4.2 – boom/jib combinations

Source: Liebherr (n.d.).

Another difference identified when comparing the data is the configuration, for example the configuration of a crane in the ATO data was recorded differently in the WiM site as a dolly had been attached. This highlights that in addition to the errors noted based on mass, filtering by configuration can also provide error, refer to Figure 5.12 for a crane and Figure 5.13 for a crane with dolly.

Figure 5.12: LIEBHERR 1220-5.2 five axle

Source: https://www.liebherr.com/en/ind/latest-news/news-press-releases/detail/liebherr-presents-the-ltm-1220-5.2-five-axle-mobile-crane-at-bc-india-2014.html.

Figure 5.13: LIEBHERR 1220-5.2 five axle with dolly

Source: http://redskymedia.com.au/design1/listings/used-cranes/all-terrain-cranes/2007-liebherr-ltm-1220-5-2-all-terrain-crane/.

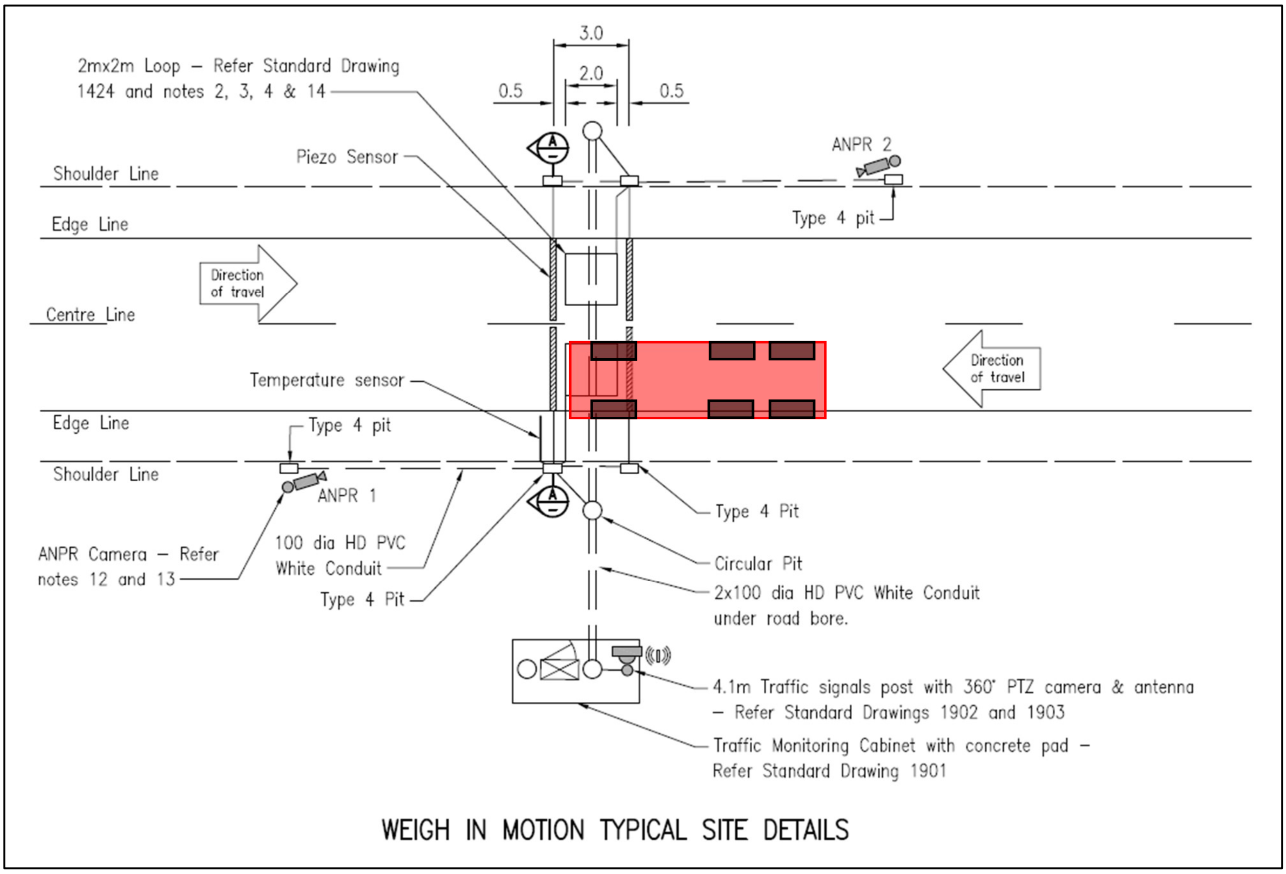
A further look at the configurations of the suggested fragments of cranes highlight that they are more likely to be part of a tandem or tri-axle group and less likely to be part of a crane. Some of the vehicle types which are more common than cranes but have configurations similar to those noted as being fragments are shown in Table 5.2. The mass discrepancy may be due to the detectors not picking up the full mass of the vehicle due to the vehicle driving over multiple lanes or in the shoulder, as shown in Figure 5.14. ANPR should be used to confirm whether these are fragments of crane data or are the more common vehicles.

Table 5.2: Common vehicle configurations

Configuration	Common vehicle
o oo oo ooo (1223)	Prime mover towing 5-axle '23' dog trailer
o oo o oo (1212)	Prime mover towing 5-axle '12' dog trailer
o oo ooo (123)	Semi-trailer
oo oo (22)	Rigid twin-steer truck (gravel truck or rubbish truck)

Note: Configuration is using typical axle spacings 1.2 m to 1.4 m between axles in the '2' (tandem) and '3' (tri-axle) axle groups.

Figure 5.14: Example of vehicle driving on shoulder



Source: Based on TMR (2020c) SD 1906.

In summary, the ATO data for cranes provides an opportunity for live calibration of WiM systems provided care is taken with the selection of the ATO vehicles and that they are identified reliably through accurate axle spacing detection and preferably confirmed with camera technologies.

5.1.3 Integrating WiM and OBM (On-Board Mass) Data

The objective was to investigate the relationship between OBM data and WiM data and explore opportunities to calibrate WiM data using OBM data.

Discussion

On-board mass systems, which are type approved by Transport Certification Australia (TCA), monitor the mass of the axle groups on the vehicle, linking it back to IAP. The OBM is in addition to IAP, where vehicles enrolled as part of the IAP program elect to have OBM installed, and in some cases are required.

As part of the analysis, data in May and June 2020 from OBM and WiM located at Nudgee, with the IAP data filtered by the proximity to WiM was used. The IAP data was then flagged based on the best match for time and weight relative to the WiM station.

As the IAP records the location every 30 seconds the vehicle required dead reckoning to determine the approximate time it passed the Nudgee WiM site, using the direction of travel, location relative to WiM site, distance to WiM site and speed. The matching process then compared the WiM and IAP records within the time period, using a time range of 30 seconds. The filtered records were then compared based on the configuration of the vehicle and the mass of the vehicle.

It is noted that the above method did not manage to find a suitable match for all the vehicles. This may be due to several reasons, including the frequency of the IAP records, lack of ability to confidently determine the lane the vehicle was travelling in as well as the exact time which the vehicle went over the WiM site. It is noted that filtering based on mass match may bias the graphs below as this assumes that the WiM provides an accurate representation of the mass. This analysis is trying to show the correlation.

It is noted that lane 6 was not utilised for the analysis due to providing poor quality WiM outputs, with the mean of the steer axle mass being half of the expected value as indicated in Table 5.3.

Table 5.3: Mean steer axle mass recorded in each lane at Nudgee WiM site between May and July 2020

Nudgee May – July 2020		
	Steer axle mass mean	**Count**
Total	4.15	136,322
Lane 1	4.38	16,939
Lane 2	4.71	29,480
Lane 3	4.55	8,429
Lane 5	4.95	31,552
Lane 6	2.7	38,760
Lane 7	4.72	11,162

Note: the low mean mass in Lane 6 indicates a likely issue with sensors in this lane.

A review of the raw OBM data found that there were inconsistencies in the way that data was recorded from vehicle to vehicle. Some vehicles recorded the steer and drive under the first axle, others recorded just the drive axles. Similarly, the location of the mass for the axle groups differed, some had all the groups filled, some had no data for some then an axle group mass filled out after having no mass filled for the previous groups. This is likely due to not having OBM installed on the axle groups, caused by swapping trailers or dollies. Improving the governance of the axle load collected would increase the value of this dataset.

Figure 5.15 provides a comparison of the GVM based on the OBM and WiM masses, showing the correlation of all the GVM records as well as the lanes in which each vehicle was travelling. This shows that the GVM for the OBM and WiM correlate well. This correlation may be due to a bias caused by the matching process, this identified the best match based on proximity, time and weight. The data clearly shows clusters, the first is in the 10 to 30 tonne range, with the second in the 65 to 75 tonne range.

Figure 5.15: OBM vs WiM – GVM

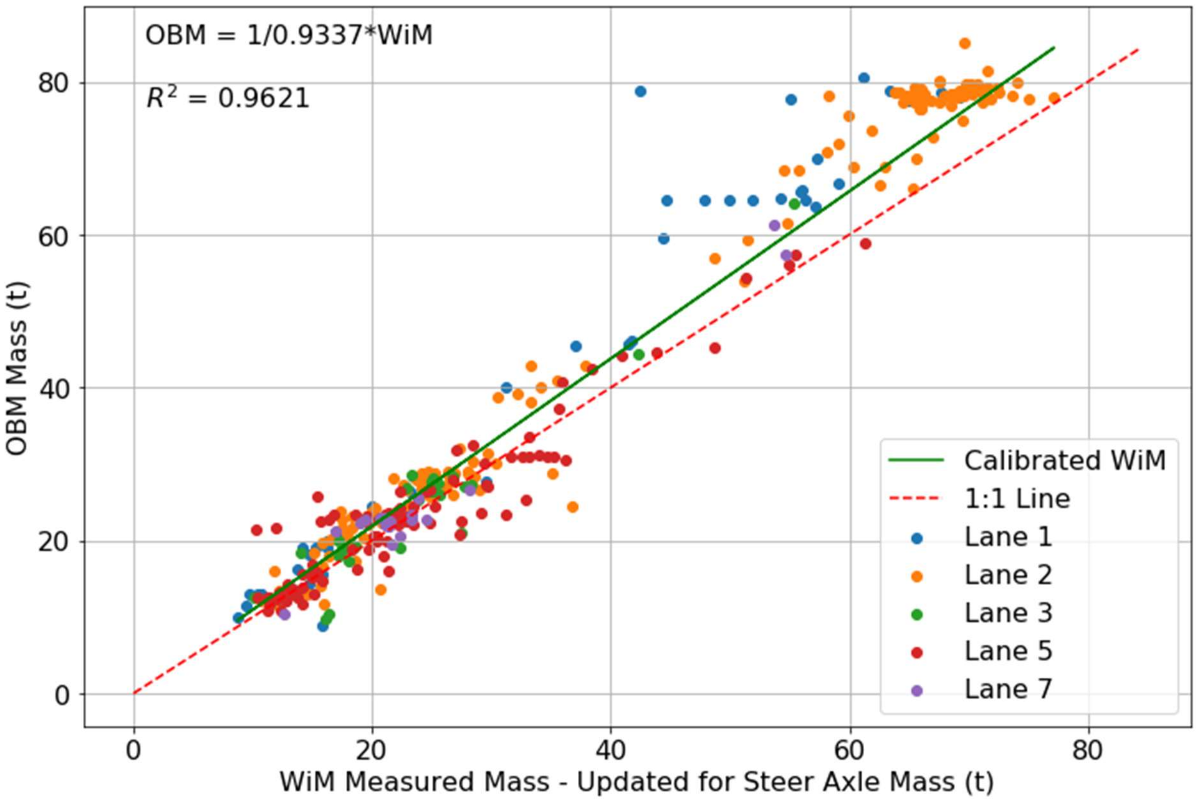


Figure 5.16 provides a comparison of the GVM based on the OBM and WiM masses, showing the correlation of the GVM records per lane. The lane level GVM analysis shows a good correlation between WiM and OBM.

Figure 5.16: OBM vs WiM – GVM per lane

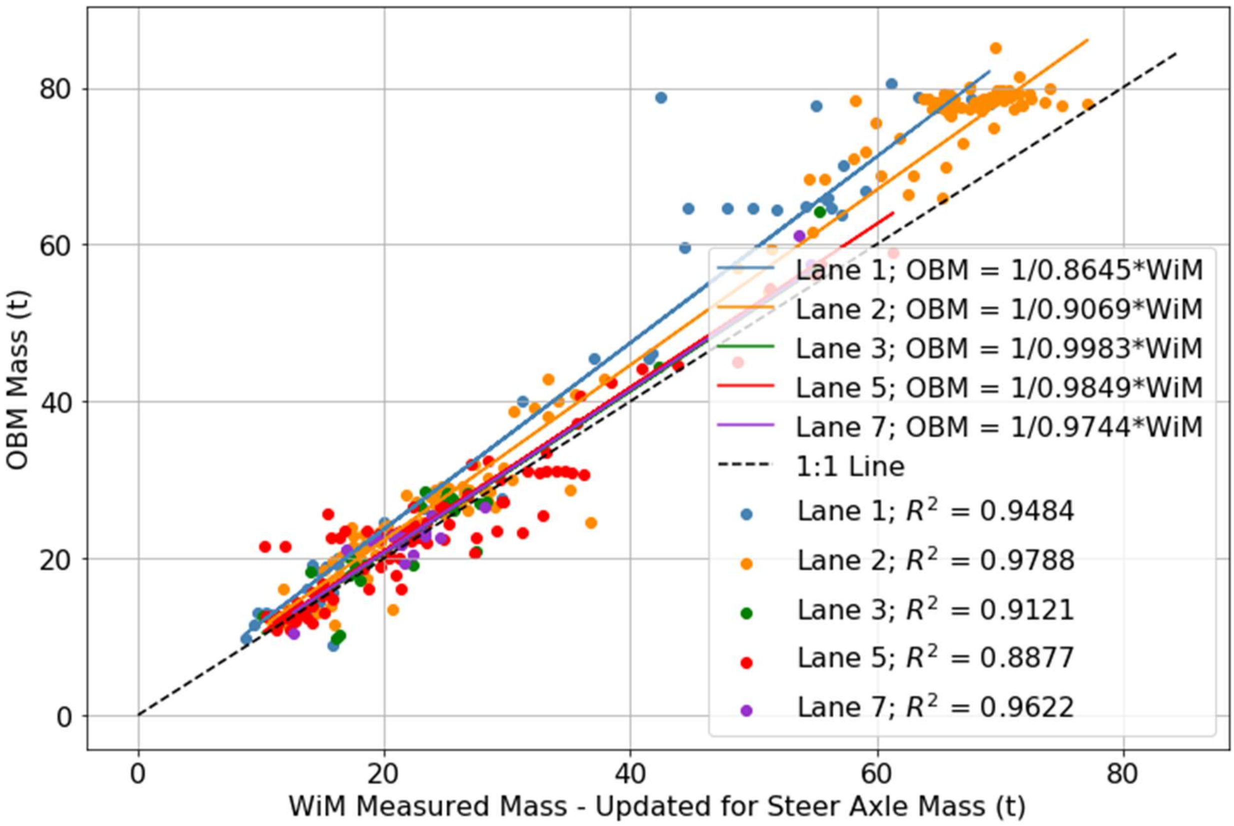


Figure 5.17 provides a comparison of the axle groups based on the OBM and WiM masses, showing the correlation of the axle group masses using all the axle groups and the lane of travel.

Figure 5.17: OBM vs WiM – Axle groups per lane – relationship using all axles

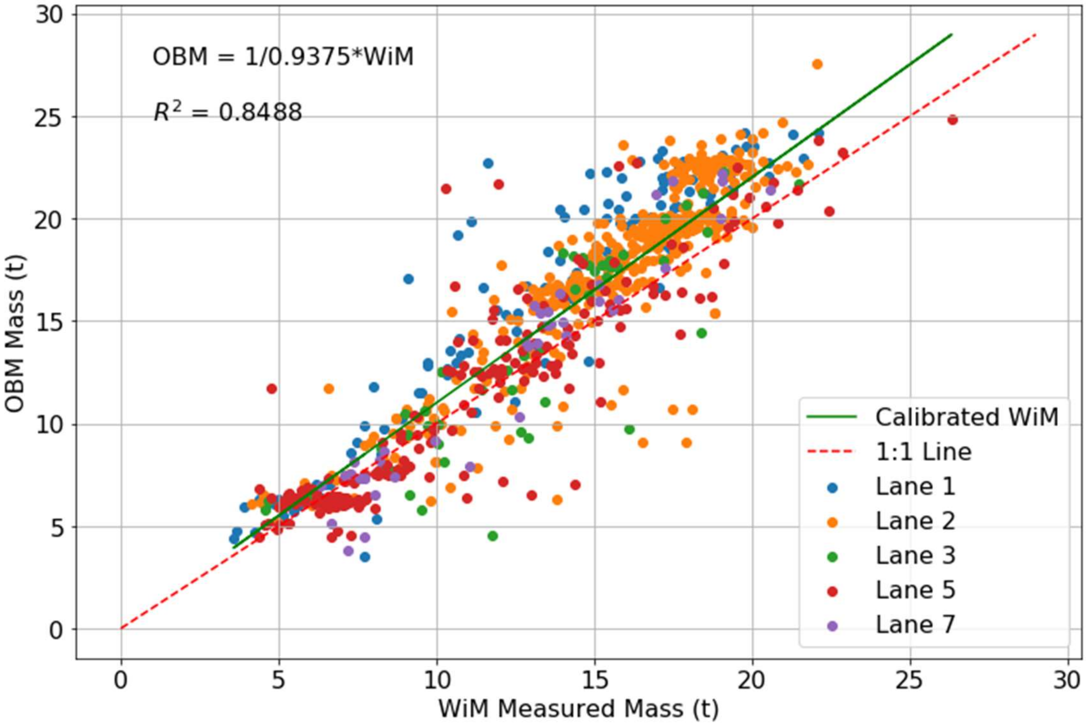
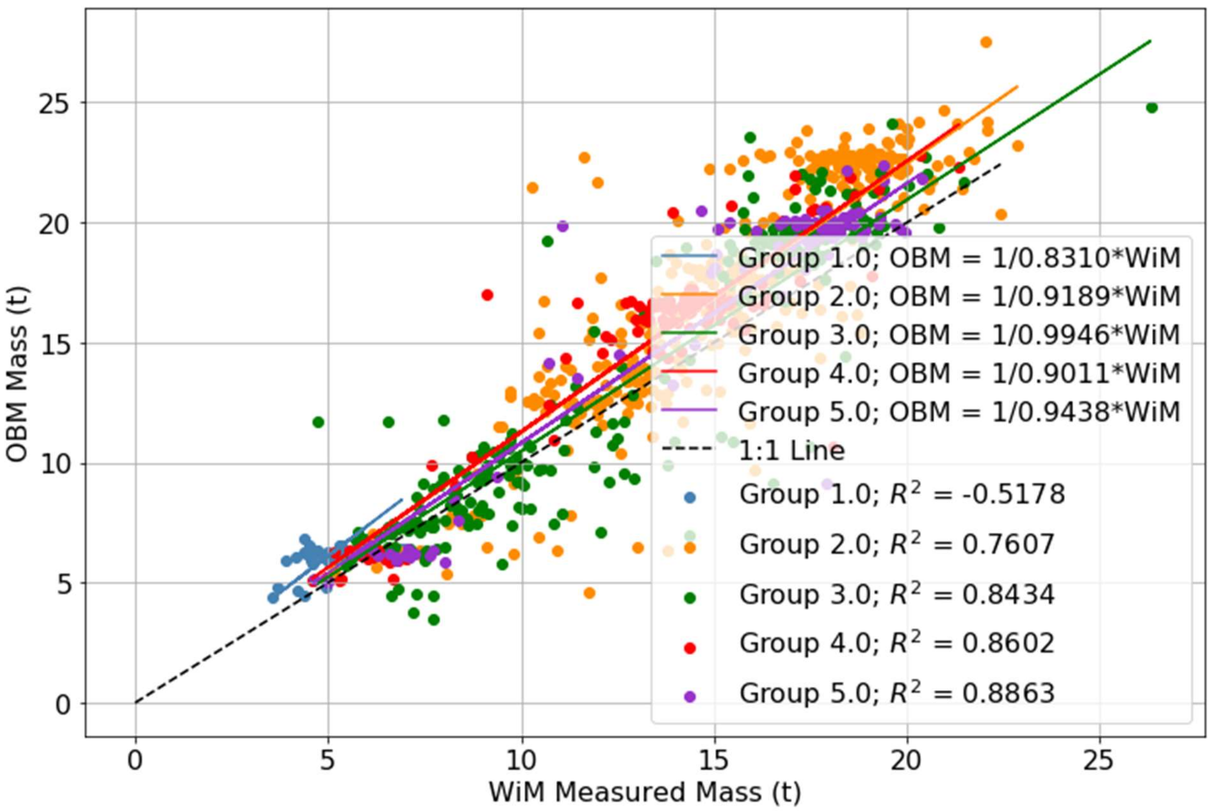


Figure 5.18 provides a comparison of the axle groups based on the OBM and WiM masses, showing the correlation of the axle group masses using each axle group. It is noted that to improve the correlation of the axle groups, the steer and drive masses were merged, based on trial and error.

Figure 5.18: OBM vs WiM – Axle groups – relationship using each axle



It was found that the GVM analysis had a better correlation than the axle group masses. As identified above, this may be due to the matching method which matches based on GVM.

The estimated WiM mass at Nudgee was less than the mass estimates from both the OBM and IAP data extracted from vehicles passing the site. This suggested the Nudgee WiM data was consistently underestimating mass during this time and highlights the value of integrating WiM, OBM and IAP crane data to improve confidence of mass data from both OBM and WiM data.

Another possibility is based on the way that the OBM data is managed. A review of the raw data shows:

1. There is no standardisation in how the OBM data is input and stored. As an example, (i) group 1 can sometimes have extremely high values likely to be the total mass but has no other mass recordings, (ii) it can also have the steer mass values or (iii) it may not have any mass recorded. When group 1 has no mass value recorded, the steer mass may be included in the group 2 mass, or it is not provided.
2. Other issues include skipped axle groups, with some having multiple axle groups skipped. The reason for skipping the axle groups is unclear. This may be due to the trailers or dollies utilised which do not have OBM sensors, alternatively the OBM identifies or is instructed that there are no axle groups in-between the locations where mass has been indicated. If all the masses are not recorded this would mean that the total mass identified in the raw data is not the same as the GVM, which has been assumed in this analysis.

It was generally found that the masses from OBM were larger than from WiM.

The current alignment is largely based on matching on mass between the two datasets. Other factors to consider in the difference between the data are:

1. The relationship between WiM and seasonal effects – as presented in Figure 5.9 found seasonal variation in WiM data at Nudgee, with a lower range in winter months. If the confidence in the OBM data can be improved this may enable improved calibration to account for seasonal variations at WiM sites. This may also allow for an improved understanding of seasonal calibration factors.
2. Adjacent ‘ghost’ vehicle – as identified in the Section 5.1.2 on crane WiM and ATO data, the manual matching of vehicles identified that there could be vehicle records which are likely to belong to another record, both before/after the record vehicle or beside the recorded vehicle. This will result in a vehicle’s record underreporting vehicle mass.

OBM can be useful to calibrate WiM. The following improvements to OBM data will improve its value:

- standardisation of installation location reporting
- standardisation of reporting, such that a review of the data does not have uncertainty on the location of the sensors
- increased frequency of reporting location.

By providing improved specification and governance, this would allow for improved alignment and may enable improved understanding if integrated with WiM data and other data sources. This may include the integration with ANPR, which may enable the confirmation of the lane and time in which the vehicle of interest goes over the WiM site. The use of improved OBM may also be useful to infer vehicle mass on trips based on classifier data, as discussed in Section 5.2.

Using OBM would allow for an improved inference between the WiM and classifier sites based on where the vehicles of interest are known to have been. With enough heavy vehicles on the network with OBM, this could allow for a real-time understanding of the loads that are occurring on the road infrastructure.

The OBM dataset remains small and highlights the value in maintaining WiM data collection and integrating these datasets with the IAP crane data to improve the quality of both datasets.

Multi-lane WiM sites make the confident matching of OBM with the WiM record difficult. This would be much more straightforward for WiM data collected on two-lane two-way highways.

In summary, there is value in its integration with WiM to improve the ongoing calibration of both datasets, even though the OBM dataset is small. Targeted enhancements in the way the OBM is installed, as well as how the data is reported, would improve the one-to-one correlation between WiM records and OBM vehicles.

5.1.4 Integrating WiM and ANPR Data

The objective was to establish the extent to which ANPR data can augment other data sources to improve WiM data quality.

In Queensland, ANPR cameras are installed at 18 WiM sites while an additional 6 camera points are planned. An ANPR system typically consists of several video cameras to recognise the image of a heavy vehicle and identify the number plate using image processing techniques. ANPR systems are mainly deployed for monitoring and enforcement activities.

At present, WiM measurements and ANPR detections are not automatically integrated. There is an opportunity to augment existing TMR WiM activities with the integration of ANPR data to provide more definition and quantification of the vehicle categories of interest to this project to better understand the causes of extreme effects and the associated risk. Greater integration would also facilitate superior event traceability and value extraction from data, for example:

- Is a vehicle identified with an event or effect in compliance with its licence conditions? Timely WiM data can provide more focused enforcement, which in turn can inform WiM calibration.
- The combination of WiM data and ANPR data could improve the understanding of the relationship between WiM data and vehicles with unusual configurations.
- The combination of (vehicle) on-board weighing, ANPR and WiM data may provide the opportunity for auto-calibration of WiM stations.
- Better data integration could assist with quantification of levels of service and the application of fee structures that better reflect value and usage.

A limitation of WiM systems is their inability to distinguish between overloaded vehicles and vehicles operating at higher mass limits under permit. Being able to identify vehicles operating under different mass concessions should be addressed to ensure that WiM data has an increased value beyond being used simply as a guide to industry behaviour. Thus, linking WiM with systems such as ANPR could allow the user to remotely authenticate permits for operation at higher mass.

Several integrated WiM/ANPR systems are already in operation, both internationally and nationally. Examples of the integration of ANPR data with WiM in Victoria, New Zealand and NSW are detailed in this section and further details on integrated WiM technologies can be found in Appendix B of Karl et al. (2021).

WiMs and vehicles of interest to this project

WiM systems situated at locations frequented by oversize and performance-based standards (PBS) scheme vehicles could support growing industry adoption of OBM systems for regulatory applications by providing a verification option for mass management purposes under the National Heavy Vehicle Accreditation Scheme (NHVAS) or a calibration option for OBM systems. At present, it is difficult for transport operators working in remote regions to meet the frequency of calibration required for regulatory applications which WiM systems could help resolve.

WiM data can be integrated with other data sources including traffic volumes, traffic composition (i.e. classified counts) and turning movement counts, pavement condition rating, traffic management data, road crash data and asset management data such as the location of bridges and tunnels, which may be able to further inform the decision-making process for infrastructure expenditure.

WiM systems can be incorporated with road safety systems, such as steep-descent and rollover warning systems, where recording vehicle mass is a critical measurement to ensure that accurate information is provided (Austroads 2016). By incorporating variable message signs (VMS), personalised warnings can be provided directly to at-risk vehicles.

WiM systems can also be used with VMS at locations with infrastructure such as bridges that could be affected by vehicles with heavy axle loads or overall vehicle mass. By using the WiM system as a screening tool, messages can be provided to these vehicles advising them to seek alternative routes.

5.1.5 Assessing Data Quality Using Steer Axle Mass

Before any dataset can be used for any analysis, it must be cleaned of known inaccurate and erroneous data as well as filtered to focus on the areas of interest. This allows for increased confidence in the dataset and ensures there will not be an impact on the analysis.

A process of benchmarking the steer axle mass of 123 vehicle configurations to identify the level of confidence in the dataset was created (Section 3.3.2). This process also identified where a WiM site may be out of calibration. This is important as the WiM data provides insight into the heaviest vehicles on the network and informs the risk management and due diligence of the bridges on the network. The additional tasks undertaken to improve the understanding of the data, thus the quality, included:

- identifying the accuracy of WiM and classifier axle spacing measurements
- the impact of measurement accuracy in determining configuration
- the impact of measurement accuracy in identifying vehicles of interest.

The characteristics of the WiM and classifier data as well as the resulting quality measures and filters are discussed further in Section 3.

5.2 WiM to Classifier Extrapolation

5.2.1 Introduction

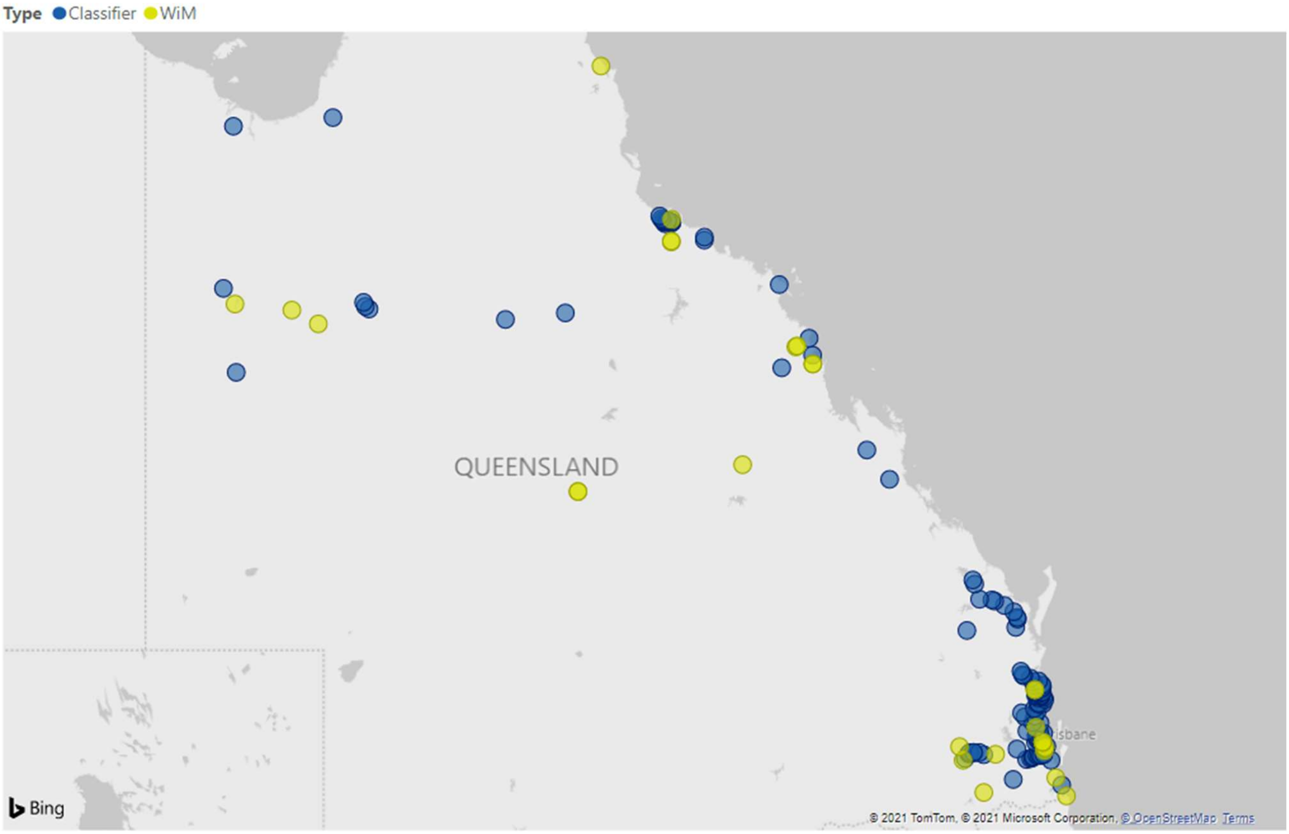
Over the next few years, 1,000 classifiers across Queensland are expected to come online as temporary classifier installations become mobile network connected and begin to transfer data to TMR servers daily, as shown in Figure 5.19 as blue points. Classifiers are also cheaper to install and maintain than WiM sites. As noted in Appendix B, these sites provide information on the vehicle types and counts traveling over a site. However, **they do not provide vehicle mass data and therefore cannot replace WiM data**.

During the study 23 WiM sites located on important road segments such as major highways and near vulnerable infrastructure were active, as shown in Figure 5.19 as green points.

This presents the opportunity to leverage the existing WiM infrastructure to increase the value of the growing classifier network. The project explored the capability of using existing WiM sites to augment classifier data, by extrapolating mass records from a WiM site with similar traffic onto the classifier records.

The extrapolated WiM would allow for the assessment of the expected vehicle mass for the vehicles of interest across Queensland, while maintaining the benefit of the reduced costs associated with the classifier sites.

Figure 5.19: Location of WiMs and classifiers used in the project



Note: WiM sites are shown in yellow and Classifiers in blue.

5.2.2 Objectives

This section has three objectives:

1. evaluate the similarity of heavy vehicle traffic at WiM sites and classifier sites
2. predict mass at classifier sites from WiM sites with similar vehicle distributions
3. identify how extrapolating mass can increase the coverage and understanding of the axle loads on the Queensland road network.

These objectives cover the when, how and how-many questions of WiM to classifier extrapolation. The second objective is dependent on the first, a similarity statistic must be defined which provides information regarding the quality of an extrapolation. It is trivial to take data recorded at a WiM site and apply it to a classifier location, however it is not clear if this data is representative of the local traffic and movements and the target location. Therefore, a similarity statistic (objective 1) is required which can evaluate how similar a source WiM site is to a target classifier location before extrapolating WiM data (objective 2). The final objective considers how the process of extrapolation is dependent on the similarity between WiM and classifier sites, and if there is enough similarity between them to perform extrapolation for a sufficient number of sites.

5.2.3 Evaluating WiM Similarity

To understand if the WiM data measured at one site is likely to be representative of the WiM data at a classifier site, a method was developed which assessed the similarity between sites comparing the data types available at both sites.

The method relies on an assumed correlation between the distributions of axle spacing and configuration to the GVM. This correlation is taken advantage of using the site similarity objective function, detailed in Equation 1 and Appendix M of Eskew et al. (2021). The degree of similarity between the sites was compared using axle spacings, distributions of configurations and GVM. This was undertaken first at the WiM sites only, to allow for validation of the similarity. This assessed:

- similarity between vehicle configuration probability distributions indicating similar general traffic
- similarity between the axle spacing probability distributions for similar configurations indicating that the specific vehicles in traffic are similar
- similarity of the axle group mass probability distributions for similar configurations (where available) indicating that the vehicles are transporting similar loads.

The site similarity statistic is determined through a weighted ratio of the difference in axle spacing θ_{AS} and configuration θ_{VC} between sites. These weights were balanced ($W_{VC} = W_{VC} = 1$).

$$\theta_{1,2} = \frac{W_{VC}\theta_{VC,1,2} + W_{AS}\theta_{AS,1,2}}{W_{VC} + W_{AS}} \qquad (1)$$

where

$\theta_{1,2}$	=	multi-objective assessment between the reference and comparison datasets
1	=	the reference dataset
2	=	the comparison dataset
W_{VC}	=	the vehicle configuration objective function weight
$\theta_{VC,1,2}$	=	the objective value for vehicle configuration distribution between the reference and comparison datasets
W_{AS}	=	the axle spacing objective function weight
$\theta_{AS,1,2}$	=	the objective value for axle spacing between the reference and comparison datasets.

Using this statistic, the similarity of WiM or classifier sites can be calculated using axle spacing and configuration frequencies. As the primary purpose of this statistic is to establish how similar a WiM and classifier site is, GVM data cannot be used to calculate the similarity statistic but can be used to validate the methodology by comparing WiM sites. To evaluate the viability of this statistic in choosing WiM data which may be extrapolated to classifier sites, the difference in GVM profiles between these sites must correlate with the similarity objective function. This can be evaluated using the D-statistic of the two sample Kolmogorov-Smirnov test, where a high site similarity objective function value should yield a low D-statistic value[14]. To test this hypothesis, WiMs of confidence class B or greater from January 2019 to February 2020 at 20 sites was used to calculate the GVM, vehicle configuration and axle spacing distributions on a per site basis.

[14] The D-statistic measures the maximum vertical difference between the cumulative distribution functions of the two samples. A high D-statistic implies that two distributions are dissimilar.

5.2.4 Site Similarity Statistic Correlates with GVM Similarity

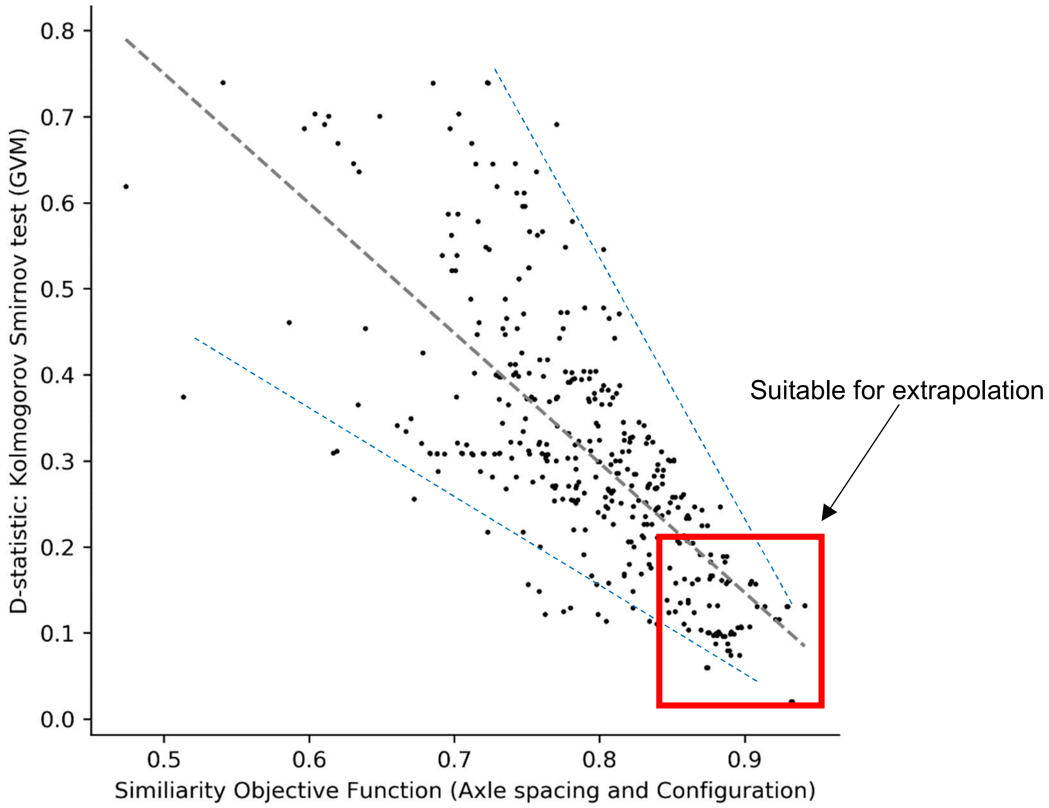
The similarity statistic, as explained in Section 5.2.3, combines discrete distributions of vehicle configuration with the continuous distribution of axle spacing grouped by configuration. Using this statistic, WiM sites with a high degree of similarity were identified and the relationship between the similarity statistic and the difference in GVM distributions was considered (via the Kolmogorov-Smirnov two sample test). This process acts as **ground truth** or benchmark for the predicted similarity score that can be calculated between WiM and classifiers. The regression statistics of this relationship are shown in Table 5.4, with a reasonably high R^2 value of 0.75. Site pairs with high similarity correlate well with the D-statistic, however medium scores for site similarity were found to be less well correlated. This population may indicate that the site similarity statistic can be further optimised. In its current form, the site similarity statistic is unable to be used as a continuous predictor of how representative a WiM site is of a classifier. Instead, a threshold value is proposed where as long as the similarity statistic is above some value, the sites are considered similar.

The population of interest shown in the red box in Figure 5.20 has high site similarity and low D-statistic, indicating that the site pairs within this area may have the data extrapolated. This is due to the much higher degree of correlation (closeness to the 45-degree line) and the very low difference in GVM distributions between the sites (low values in the y-axis or D-statistic) This population can be numerically defined as site pairs with a similarity statistic greater than 0.85. Alternatively, this population can also be defined as those pairs with a D-statistic of less than 0.2, however this definition is not useful when comparing WiM to classifier sites, as the D-statistic between GVM distributions cannot be calculated.

Table 5.4: Regression statistics for D-statistic against objective function

Regression statistic	Value
R square	0.748
Standard error	0.011
Observations	380
Intercept	1.51
Slope	−1.50

Figure 5.20: Site similarity statistic against KS statistic two sample test



Note: The blue dashed lines show how correlation increases as site similarity increases. The higher the correlation the more likely the objective function is a strong indicator of site extrapolation viability. The closer the points are to the 45-degree line the better correlated the GVM KS D-statistc is to site similarity.

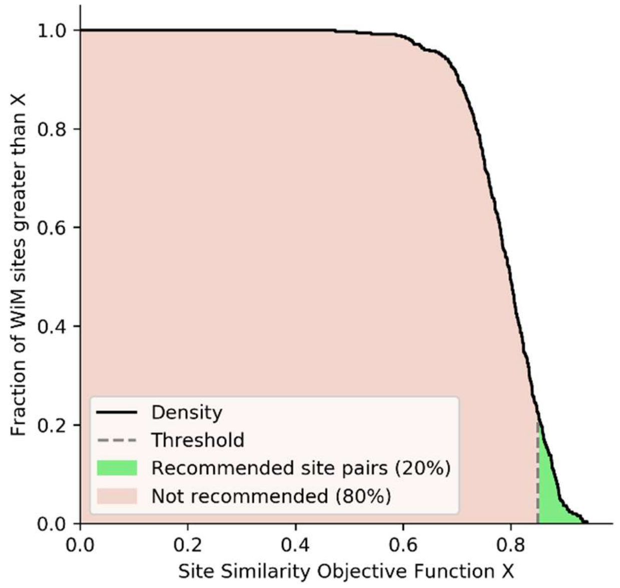
Based on the correlation between GVM similarity and the site similarity objective function (R^2 = 0.75), **approximating GVM profiles to classifier sites was concluded to be viable. This statistic can predict how similar a site's GVM profile is without GVM data**.

Extrapolating GVM profiles requires high site similarity

Extrapolating dissimilar WiM data to classifier sites will result in unrepresentative GVM profiling. Crucially, the objective function similarity statistic, as discussed above, can identify appropriate instances to extrapolate (the higher the similarity the better). The minimum similarity index can was set at a lower bound of 0.85 based on a reduced correlation to the D-statistic below this threshold. When similarity values below 0.85 are observed, the correlation between D-statistic and similarity score diminishes, and the predictor is no longer describing how similar the two sites are. Secondly, when the similarity score is higher than 0.85, the observed low D-statistic values show that the GVM distributions between the sites are similar, which is a key criterion for extrapolation, as the source of data should match the targeted or missing data's GVM distribution.

Approximately 20% of WiM site pairs have a similarity objective function value greater than 0.85 as seen in Figure 5.21. Based on these results alone it is believed that at least 20% of WiM to classifier site pairs could benefit from extrapolated WiM data. A systematic analysis of the relationship between the acceptable level of error in the extrapolated GVM and the true GVM could result in an updated lower bound which may increase the volume of classifier sites for which mass can be extrapolated without introducing substantial error.

Figure 5.21: Volume of WiM site pairs with an acceptable level of site similarity



Note: The green population is the same as that in the red box shown in Figure 5.20.

The site similarity statistic suggests that care is required in selecting sites to extrapolate between and WiM sites distributed across the highway network at locations representing the various access regimes and freight tasks/demands will provide the best opportunity for extrapolating data to all areas of the state.

5.2.5 Extrapolating WiM Data

WiM data inspiring an appropriate level of confidence (use case dependent) can be used to generate measured distributions of parameters of interest by vehicle configuration.

The measured distributions can then be extrapolated based on vehicle counts (by configuration) at a classifier site with similar traffic. In other words, distributions of vehicle characteristics from an origin site are scaled by the ratio of the number of vehicles at the origin site to the number of vehicles with the same configuration at the target site.

This gives an estimate of the expected mass at the classifier site without additional capital expenditure. While the objective is to extrapolate WiM data to classifier data, the accuracy of this procedure cannot be directly assessed as the GVM profile is unknown at the classifier site. In contrast, WiM data can be extrapolated from one site to another WiM site and the error in the predicted GVM profile can be calculated. The effectiveness of the extrapolation from WiM to classifier can therefore be inferred from the results of extrapolation from WiM to WiM.

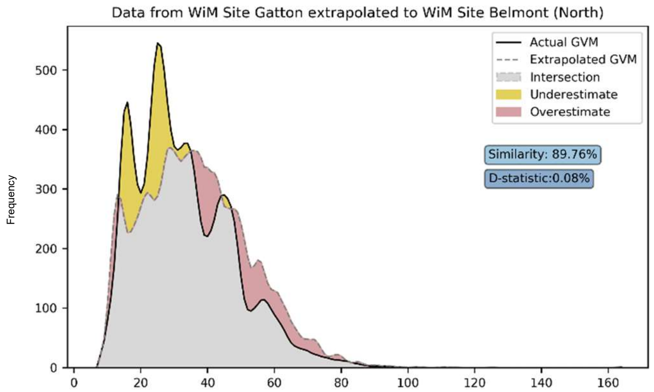
An example of this procedure, carried out between two WiM sites, is shown in Figure 5.22(a) and Figure 5.23(a) where the solid line is the actual GVM distribution and the dashed line is the extrapolated distribution. Overestimations of the GVM are shaded red and underestimations shaded yellow. The larger errors in Figure 5.23(a) are associated with a poor similarity whereas the smaller errors evident in Figure 5.22(a) are associated with a much higher similarity. The cumulative extrapolated distributions are shown in Figure 5.22(b) and Figure 5.23(b) where the actual GVM cumulative distribution is shown in light blue, and the extrapolated GVM in dark blue. The solid red lines in Figure 5.22(b) and Figure 5.23(b) show the error in the extrapolation. The figures show that the site similarity statistic is accurately predicting the quality of the extrapolation, with the Gatton extrapolation having a high similarity and low error while the Cloncurry extrapolation has low similarity and much higher error. **This consistency in the site similarity**

value is emphasised because it is the only available indicator of the quality of an extrapolation between a WiM site and a classifier site.

Figure 5.24 shows the extrapolation of the multi-objective function for five sites based on the similarity of WiM sites. The columns show mass distribution for the target site, while the rows show the site which was used to extrapolate the data from. For example, the top right figure shows the target site of Belmont (north) WiM - Barcaldine WiM was used to extrapolate for Belmont (north). Similarly, the bottom left figure shows the target site of Barcaldine WiM, for which the mass from the Belmont (North) WiM was used to extrapolate for Barcaldine. The distribution matrix shows how similar the extrapolated (dashed line) and true (solid line) GVM distributions are. Over-estimates are shaded red, and underestimates yellow. The higher the similarity between the sites, as shown in the top right of each chart, the less shaded area is expected.

Figure 5.22: Extrapolation of GVM from a WiM site to a classifier – validation example using the class B confidence records from Gatton WiM to the Belmont (north) WiM

(a) Extrapolation



(b) Absolute error of extrapolated GVM and cumulative distribution

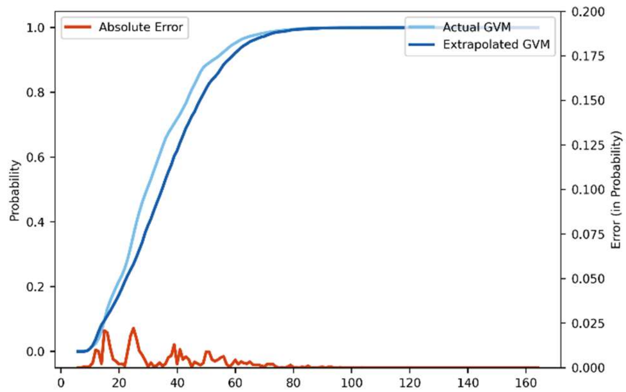
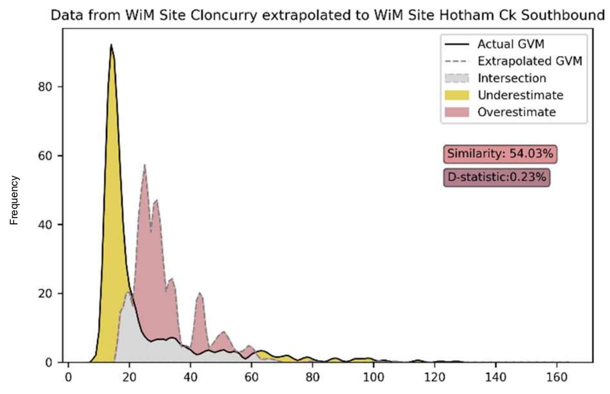


Figure 5.23: Extrapolation of GVM from a WiM site to a classifier – validation example using the class B confidence records from Cloncurry WiM to the Hotham WiM

(a) Extrapolation



(b) Absolute error of extrapolated GVM and cumulative distribution

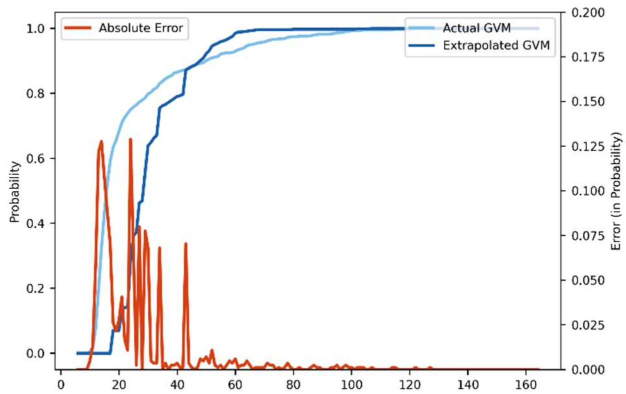
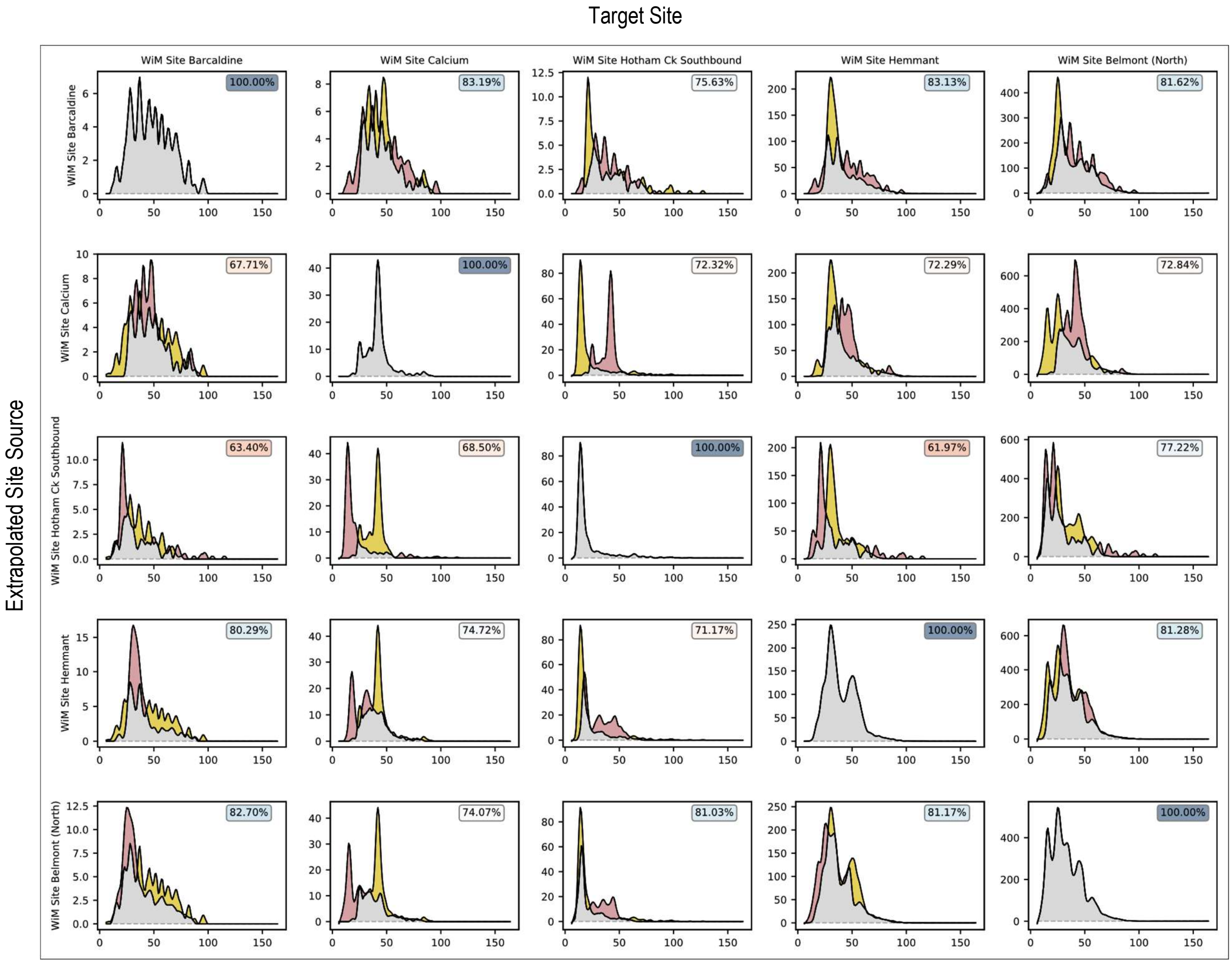


Figure 5.24: Extrapolation of GVM from a WiM site to a classifier



Note: X-axis provides the GVM of the vehicle in tonnes.

5.2.6 Classifier Coverage

Section 5.2.5 shows the method of extrapolating WiM data and when the extrapolation will be representative of the site of interest. These methods satisfy objective 1 and objective 2 of Section 5.2.2, however they may be impractical if there are insufficient WiM sites which are representative of classifier sites. To investigate this, the closest WiM site which could be used to extrapolate data to a classifier was calculated using the method shown in the pseudo code in Figure 5.25. As per the pseudo code, the similarity score was calculated for each WiM to classifier pair in the dataset. The closest classifier and WiM pair with a similarity score greater than 0.85 is plotted in Figure 5.26.

These WiM and classifier pairs show a general tendency to cluster, as expected based on the classification criteria. In the zoomed image, the southernmost WiM site is identified as the best candidate to extrapolate data to several classifiers along a continuous highway, which the WiM site is also on. In this case, the WiM site chosen as the most likely to represent the classifier sites is consistent with the flow of traffic. In other cases, the cause of the similarity is less clear. For example, the northernmost WiM site in the left image of Figure 5.26 is considered more representative for classifiers in Townsville than the WiM site just south of the city. The similarity score only factors in the frequency of vehicle configurations and distribution of axle spacings when determining similarity. It is possible that while some sites may be closer, this northern WiM site is more representative due to the similarity in vehicle activity in the local area, this could be confirmed by conferring with local experts familiar with vehicle activity and industrial activity in these regions. In absence of an expert familiar with the types of vehicles and loads travelling through classifier sites, **this algorithm**

shown in Figure 5.25 can automatically identify potential WiM sites which can be used to extrapolate data to classifiers.

Figure 5.25: Pseudo code for finding the closest WiM site which data can be extrapolated from

```
FOR each classifier site C_i
    FOR each WiM site W_j
        Similarity: S = L1(C_i,W_j)   [See Figure 5.20]
        Distance D  = Geodetic_distance (C_i,W_j)
        IF S > 0.85 :
            Set Covered_by_WiM[C_i] = TRUE
        IF D < Minimum_distance_to_WiM[C_i]
            Set Minimum_distance_to_WiM[C_i]= Distance(C_i,W_j)
            Set Best_WiM_site[C_i] = W_j
FOR each classifier site C_i
    If Covered_by_WiM[C_i] is TRUE
        Plot classifier site C_i
        Plot best_WiM_Site[C_i]
        Plot line between site C_i and Best_WiM_site[C_i]
```

In Figure 5.26, classifier sites which did not have a similarity score greater than 0.85 for any WiM site are not plotted. To see how many WiM to classifier pairs were viable (similarity > 0.85), 95 classifiers were compared against 20 WiM stations to generate Figure 5.26. 93 classifier sites had a similarity score of greater than 0.85 for at least one of these WiM sites. **This indicates 97% of classifier sites have enough similarity to WiM sites to allow for extrapolation from at least one site**. Previously, the likelihood of one WiM matching with another classifier was inferred to be ~20%, but because there are multiple WiM sites across the network the likelihood that at least one has a similarity score greater than 0.85 for any given classifier is much greater than 20%.

Figure 5.26: Closest WiM site (blue) which could be extrapolated to a classifier site (red) – black lines are drawn between the WiM and classifier pairs

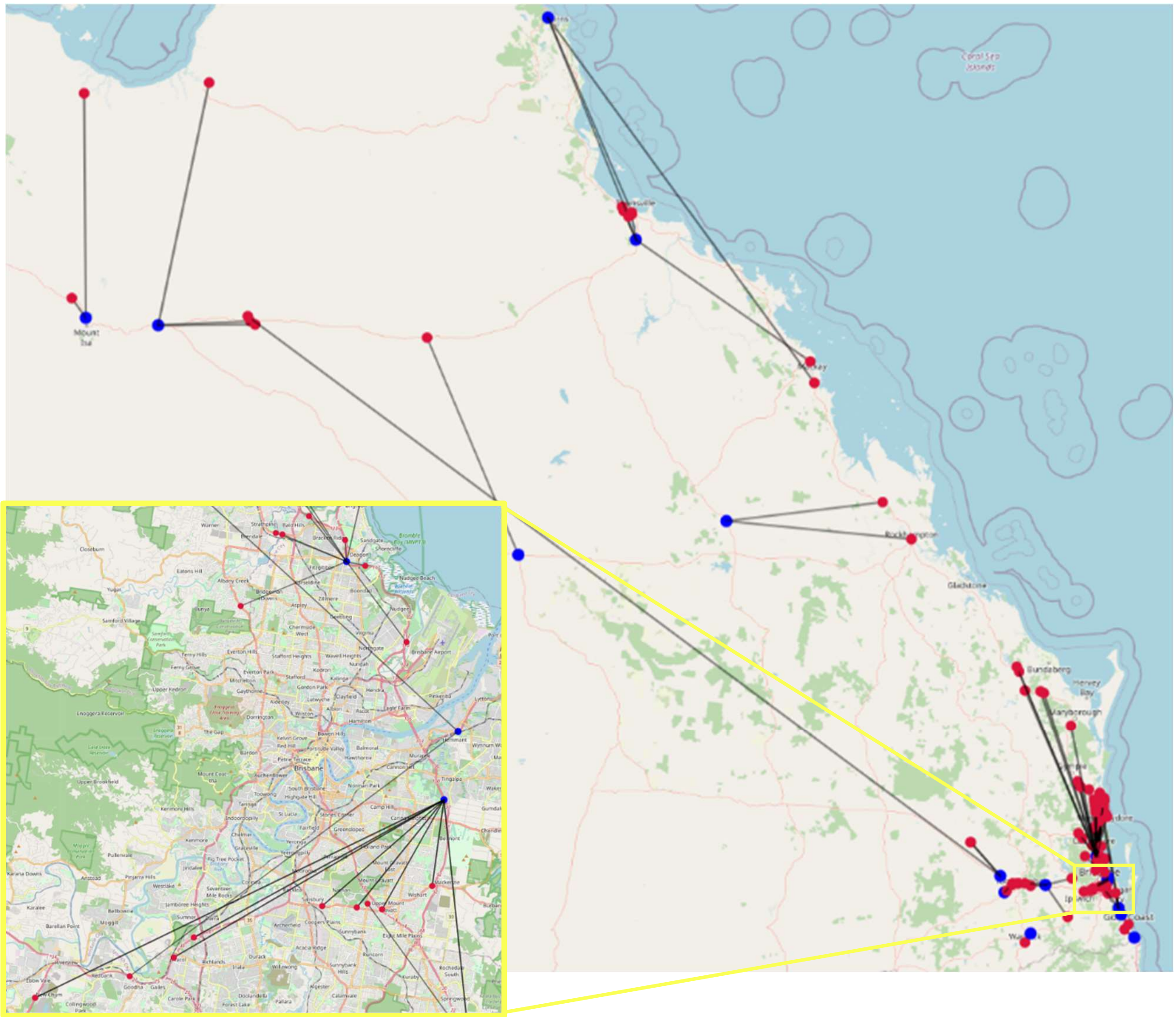
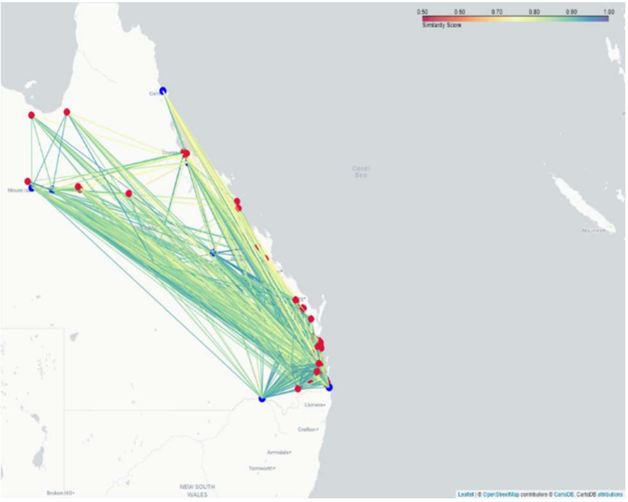


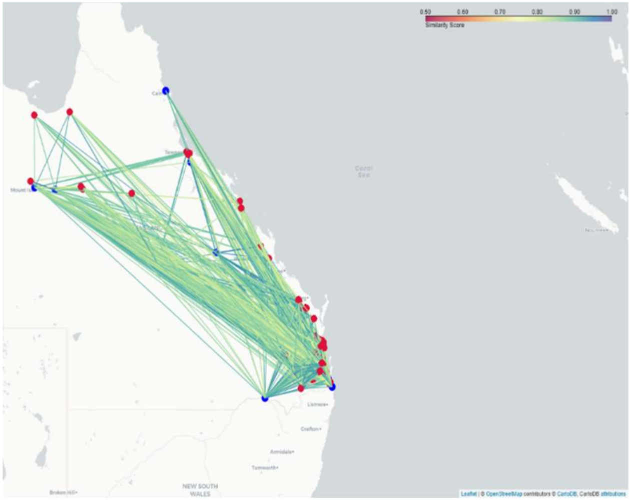
Figure 5.27 shows the sensitivity of the coverage to changing the threshold similarity score where the higher the threshold similarity score the lower the number of WiM sites which can be extrapolated to classifier sites.

Figure 5.27: Closest WiM site (blue) which could be extrapolated to a classifier site (red) based on similarity

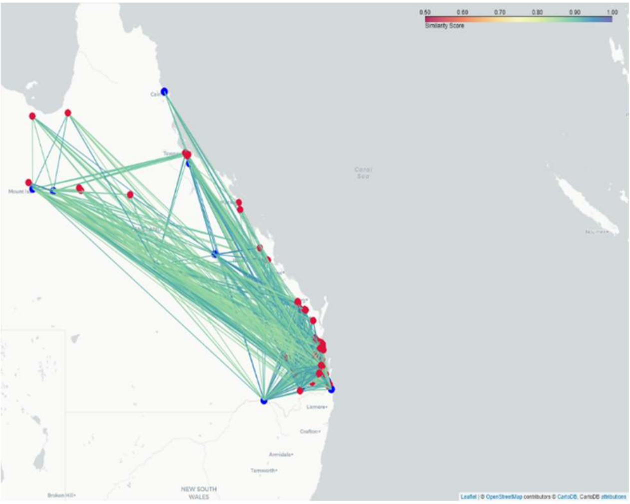
(a) Similarity threshold of 0.70



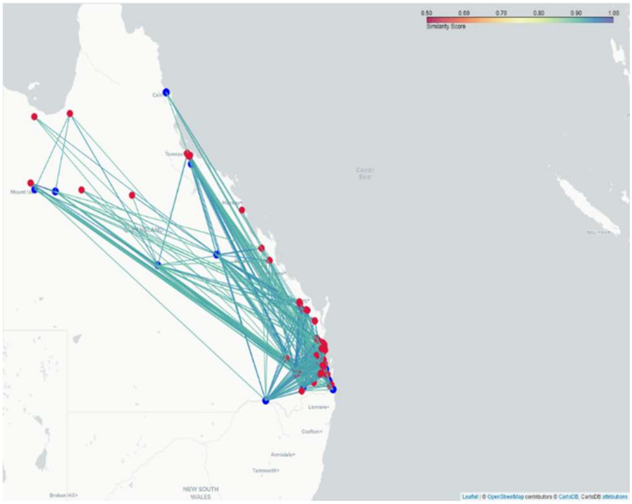
(b) Similarity threshold of 0.80



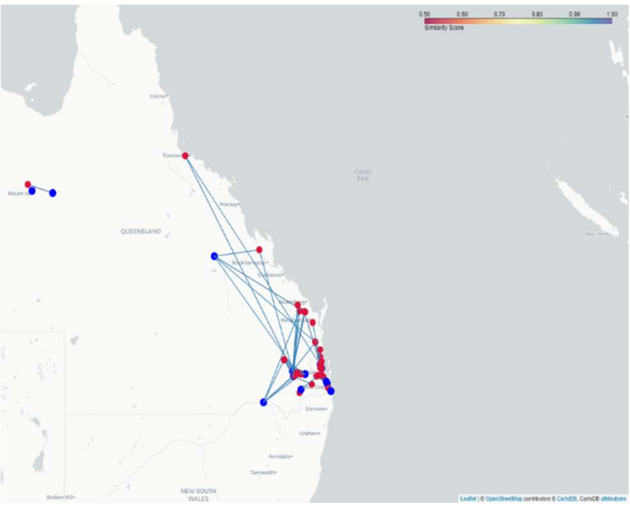
(c) Similarity threshold of 0.85



(d) Similarity threshold of 0.90



(e) Similarity threshold of 0.95



(f) Similarity score legend

5.2.7 Discussion

The site similarity statistic is used to identify candidates for pairing WiM and classifier sites, where an extrapolation of WiM GVM data would be representative. While strong correlation was seen at values greater than 0.85 to the D-statistic, the value of the similarity score diminished greatly below 0.7. This is a non-issue when performing a single one-site to one-site extrapolation, however future efforts may consider how WiM data from multiple sites can be combined to increase the quality of the extrapolated data. Optimisation of the similarity score formula could greatly improve the accuracy of this proposed multi-site extrapolation by better distinguishing between different sites with similar similarity scores.

This optimisation task is designed to tune to the weighted effects of axle spacing and configuration differences which serve as inputs to the objective function shown in Equation 1. Through minimising the difference in similarity score and the D-statistic by adjustment of the weights, deviation from the linear correlation line in Figure 5.20 is reduced and the predictive value of the similarity score is improved.

Furthermore, it may be possible to extrapolate WiM data to locations where neither a WiM site, nor a classifier is present through integrating several classifiers and WiM sites. Song et al. (2019) proposes a geospatial extrapolation methodology to predict traffic volumes of heavy vehicles across a road network based on point data sources. This methodology interpolates traffic count data between points in the network through using a regression model known as kriging (Song et al. 2019). One primary advantage of kriging methods over WiM to classifier site extrapolation is that the GVM distribution of any road segment in Queensland could be predicted. Previous attempts to perform kriging with the existing WiM network were significantly limited by the rate of coverage of WiM across the network (Hore-Lacey et al. 2020). While not impossible to perform kriging interpolation when network coverage is low, confidence intervals over resultant predictions are so wide they offer little value relative to guess work.

Strong correlations between axle spacing and GVM distribution that became evident as part of this investigation can contribute to future extrapolation and interpolation investigations. While the methodology focused chiefly on extrapolating WiM data to classifiers, if traffic data is available, this methodology can be easily extended to other datasets, such as ANPR, segmented IAP and even telematics data. The site similarity and extrapolation procedures required aggregated data on vehicle type and axle spacing. Where this data is available the methodology can be repurposed. Combining the point-to-point based methods documented here with kriging interpolation could greatly improve the geospatial coverage of GVM profiling.

5.2.8 Recommendations and Conclusions

These methods aim to replace missing data in the case of failing or unreliable WiM sites or to generate GVM profiles where WiM records do not exist. The investigation has generated the following recommendations for proper extrapolation of WiM data to classifier data:

- Extrapolation of WiM data to other sites is possible with care.
- The similarity score provides a method for rating the appropriateness of the extrapolation.
- WiM data should only be extrapolated if the site similarity statistic is greater than 0.85.
- It is not clear if a site with a higher site similarity statistic will result in a better extrapolation than another if both are greater than 0.85.
- In the analysed dataset (98 classifiers and 20 WiM sites) 97% of classifier sites had a similarity score greater than 0.85 with at least one WiM site.
- Extrapolation of WiM data via other technologies such as ANPR may also be effective.
- The trial has demonstrated the viability of the extrapolation process for GVM. It may be possible to extend this extrapolation of other parameters such as axle group mass, pavement and bridge loading statistics.

5.3 Prototype Tracking Tool

5.3.1 Introduction

Tracking oversized overmass vehicles across the Queensland network enhances the value of WiM data by allowing the investigator to know where a vehicle of interest has been before. Not only can multiple records be attributed to the same vehicle, but the trip and destination of the vehicle can also be inferred. The data can be used in real-time predictive and monitoring applications as well as retrospective analysis.

In contrast to an isolated WiM record, a vehicle trip can be used to confirm all infrastructure crossings even if these assets are far from any WiM or classifier sites. Knowing the source of a WiM record at different sites can also be used to improve confidence in the axle spacing and mass data for the vehicle, for retrospective mass calibration at the site, particularly when the vehicle is known to have a consistent weight, as in the case of cranes and load platforms transporting indivisible loads. Given the numerous potential values of tracking vehicles in combination with measuring mass, this section explores the practicality of tracking vehicles using WiM and classifier data.

WiM and classifier records[15] do not contain a unique vehicle identifier. This limits applications of WiM for tracking vehicles to vehicles where the ‘axle spacing footprint' is uncommon during the travel window. This is the case for the specific vehicles of interest to this project, such as low loaders, load platforms and cranes.

This section focuses on methods which can identify WiM records originating from the same vehicle on the same trip, with an emphasis on vehicle tracking.

A key principle of vWiM is achieving additional value through the combination of complementary datasets, allowing the data within each to offset the limitations of the other(s). An example of this is vehicle tracking. Because the numbers of load platforms and low loaders on the network are low (< 1% of daily traffic), it is possible in many instances to identify records from a specific vehicle as it travels across Queensland based on its configuration and axle 'footprint'.

5.3.2 Objective

The objective of this section is to understand the feasibility of tracking special vehicles of interest and future requirements needed to extend this function to routine activity.

5.3.3 Methodology

By merging WiM and classifier data, the density of sites collecting data is effectively increased, improving the odds of identifying the trips taken by vehicles of interest. If, for example, a vehicle tracked across multiple classifier sites also crosses a WiM site, the data from the WiM site becomes ‘virtually’ known at the other sites. It is possible that a vehicle may only be laden for part of a trip or may change loads, however, because the vehicles are permitted to carry indivisible loads, it is less likely. When it is possible to track a vehicle in this way, periods where data are inaccurate or lost at individual sites becomes less mission critical – value and redundancy are increased.

Due to the high volume of WiM movements observed each day over the TMR network, manually inspecting individual records to find common characteristics is time consuming and unsuited for most applications. To meet these aims, a methodology was developed to track vehicles from one WiM or classifier site to another. The approach uses an algorithm which automatically identifies records in the WiM and classifier dataset which could be from the same vehicle traveling across the network.

[15] Unless they are integrated with ANPR.

Matching records were identified by comparing the records of a reference vehicle of interest's axle spacing to all records of the same vehicle configuration within 10 days of the initial observation. Vehicle mass was not chosen for use in the matching algorithm, due to mass not being included in the classifier dataset.

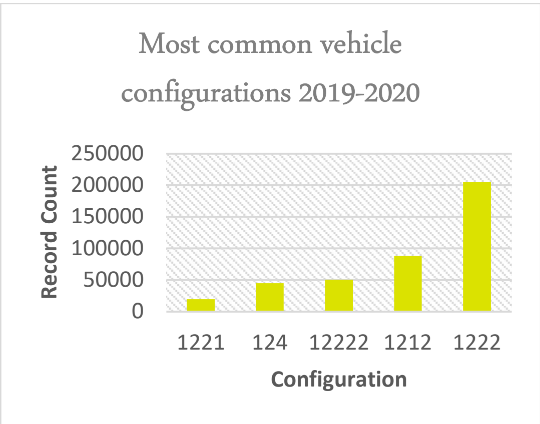
The performance of the algorithm was benchmarked using a representative dataset of WiM and classifier records in combination with a small sample of IAP data which contains unique vehicle identifiers.

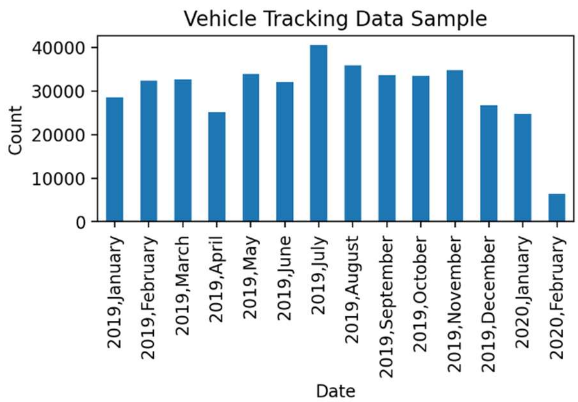
Lastly, the vehicle trips and the infrastructure crossings were inferred and presented as an application of WiM Class 1 heavy vehicle tracking.

Class 1 heavy vehicle WiM data characteristics

The likelihood of matching WiM records originating from the same vehicle is dependent on variation in axle spacing and configuration, referred to as the vehicle footprint. To investigate the general characteristics of low loader and load platform WiM records, a test dataset of Class 1 heavy vehicle configurations from January 2019 to February 2020 was used. The composition of this dataset is shown in Figure 5.28.

Figure 5.28: Most common low loader and load platform configurations 2019–2020





In the dataset 142 sites contained a minimum of 1,000 WiM record events and 293 different vehicle configurations were observed. Ninety-seven vehicle configurations had less than 1,000 records across all sites. While this indicates that for some vehicle types matching could be done solely with the vehicle configuration, between 10,000 and 200,000 records were found for the 5 most common configurations. Vehicles with these configurations are indistinguishable from each other using configuration alone. Therefore, to increase the uniqueness of the WiM records for matching purposes, the following additional characteristics were identified as likely candidates to be used as a pseudo-identifier:

- axle spacing
- time between records
- location of records.

Matching algorithm

Vehicle records were identified as potential matches to a reference record if the following conditions were satisfied:

- Records had the same configuration.
- The time between records was less than 10 days.
- The differences in all matching axle spacings between the reference and comparison records were within ± 200 mm.

For potentially matching records, the average variation between axle spacings for two records with matching configurations was evaluated to assess fitness of the match using Equation 2.

$$\Delta_s = \frac{\sum_{i=1}^{S} \left| s_{r,i} - s_{c,i} \right|}{S} \qquad (2)$$

where

Δ_s	=	the average variation in axle spacings between the comparison and reference vehicle
S	=	the number of axle spacings in the vehicle configuration
$s_{c,i}$	=	the ith axle spacing of the comparison vehicle
$s_{r,i}$	=	the ith axle spacing of the reference vehicle

If Δ_s is less than 200 mm, then the pair of records was considered a match. Pairs which shared a common record were then collected into trips which were sorted by time.

Matching results

To explore the value of the matching algorithm, a best-case scenario was created. Over the one-year period, records with configuration classes observed more than 1,000 times were excluded. The remaining 97 configurations are so unique that they are expected to originate from a small number of vehicles, significantly decreasing the chance of false positives. Using this filtered dataset matched records identified using the algorithm became WiM records pairs and were predicted to have the same vehicle source.

By combining these pairs which share a record, vehicle trips were constructed and shown in Table 5.5. These trips were calculated using shortest time routing over Queensland's road network. Bridge crossings highlighted in green were identified using the geospatial location to find intersecting road link identifiers. Out of 97 configurations and 11,095 WiM records, 723 unique trips were found. The best-case dataset of rare vehicle configurations represents 2.6% (11,095 out of 420,737) of all WiM and classifier records in the Class 1 heavy vehicle categories. Of these records, 34% were assignable to unique trips. Based on the characteristics of the WiM data, a lower bound of 34% of Class 1 heavy vehicle WiM activities can be tracked effectively using the vehicle footprint algorithm when not considering accuracy.

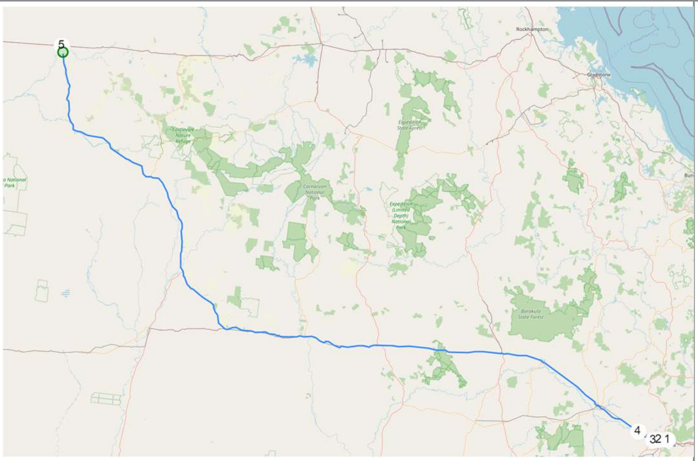
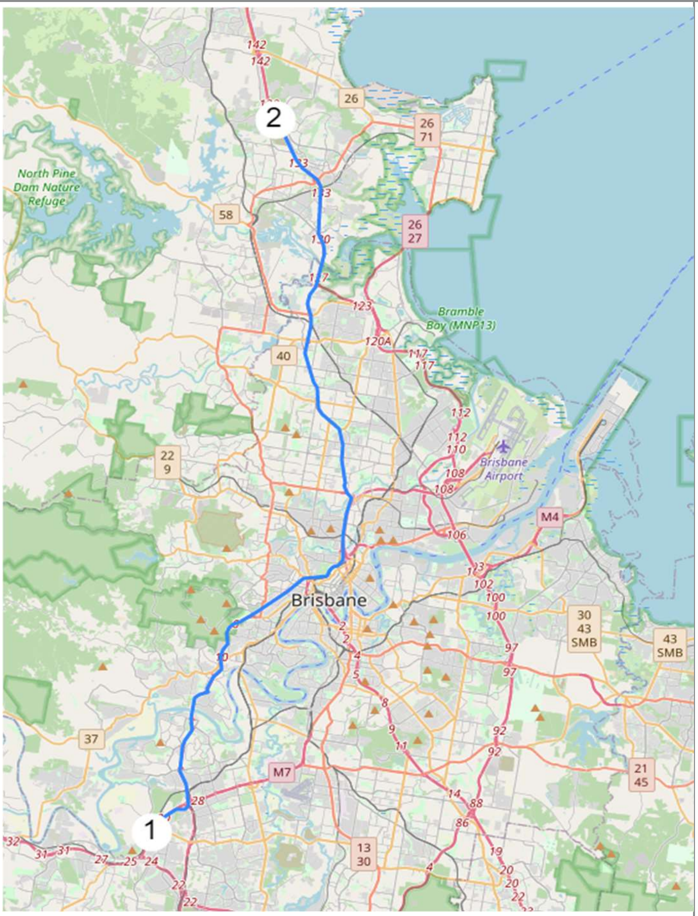
Algorithm routing and coverage

To determine the most likely trip of these matched records, map matching, in combination with a routing algorithm which was developed in NACOE R103 (Hore-Lacey et al. 2020) was used. The most likely trip is always considered to be the shortest trip by time when travelling at the speed limit. As the vehicles of interest are low loaders and load platforms, the networking was restricted to within 100 m of the 'Heavy Vehicle Routes' network (Queensland Department of Resources 2021).

By determining the vehicle's trip, infrastructure crossings of interest can be detected. In this example, it cannot be assumed that all vehicles detected at the north eastern WiM site crossed over the highlighted bridge. Using the tracking algorithm and routing methodology, bridge crossings can be inferred for individual vehicles based on the order of the movements.

Trips presented in Table 5.5 are merely meant to demonstrate the value of vehicle tracking for surfaces distant from WiM and classifier sites, and do not always reflect the true path of the vehicle. As the trip's complexity increases, the likelihood that the true trip is the same as the predicted trip decreases. For example, it is highly likely the first trip shown in Table 5.5 represents the true path of the vehicle, as there are few opportunities to deviate between the sightings. In the remaining trips there are many ways the vehicle can traverse the network between the sightings, reducing the likelihood that these predicted trips reflect the true trip.

Table 5.5: Summary of journeys for 3 sample trips

Count	Journey	Configuration
3		1229
5		1227
8		225

5.3.4 IAP Validation

While the total number of vehicles which are potentially trackable was shown in the previous sections, the accuracy of these tracked trips is unable to be determined with WiM and classifier data alone. In this context, accuracy refers to the number of times WiM and classifier records were correctly identified to originate from the same vehicle. To understand if matched sets returned by the algorithm all originate from the same vehicle, a separate IAP WiM merged dataset was used. IAP data is provided per vehicle over the entire network. By comparing IAP records from the same vehicle at WiM sites to vehicle trips generated via the tracking algorithm, the accuracy of the algorithm can be determined.

One month of IAP tagged vehicle records were matched to WiM movements at the Nudgee site, the same data used in Section 5.1. Using the same method from Section 5.1**,** IAP records were aligned with WiM movements using geospatial and temporal alignment. By synthesising the IAP and WiM data, unique vehicle identifiers were associated with WiM records. These identifiers were then used to validate the accuracy of the vehicle tracking algorithm. If a vehicle trip is accurate, then all records within the trip should have the same vehicle identifier. The matching algorithm was used to find pairs of records which crossed the Nudgee site and were predicted to be from the same vehicle. For each pair, a pass was assigned if the IAP vehicle IDs were identical. The pass rate is presented as the accuracy of the algorithm categorised by configuration in Table 5.6.

This IAP linked validation does not contain any low loader or load platform records, as none are enrolled in the IAP, and is therefore not necessarily representative of the vehicles of interest. A breakdown of the rate of accuracy of the alignment algorithm is shown in Table 5.6. **The average accuracy of the matching algorithm was 38%**. Based on these results, an accuracy statistic for the more common Class 1 heavy vehicle configurations described in Figure 5.28 is expected to be at most **38%**. This is based on the average rate of successful vehicle matches with the same IAP vehicle identifier from Table 5.6. **Interestingly, the rate of accuracy correlates with the number of vehicles in the vehicle configuration**, with rarer configurations having a higher accuracy than more common configurations. With an average accuracy of 38**%** it is expected that if all vehicle configurations were processed ~12.8% of all Class 1 heavy vehicle movements could be tracked using this methodology.

Table 5.6: IAP validation of tracking accuracy

Configurations	Accuracy (%)	Sample size
111	19.13	27,756
112	25.20	8,045
1212	50. 73	805
122	56.52	2,333
1222	46.34	4,123
12222	50.00	457
123	21.89	107,807
1233	47.05	6,895
Average	37.99	

This adjacent IAP validation demonstrates that vehicle matching using WiM footprints is only feasible when the vehicle configuration and axle spacings are significantly rare. For most vehicles, and even some low loader configurations, this is not the case. While low loaders and load platforms are relatively unique, the consistency of axle spacing and configuration measurements between sites was lower than expected. This resulted in fewer matches than what is possible using a vehicle footprint alone.

Two possible reasons for a lower-than-expected match volume and accuracy are:

- Variance in the axle spacing measurements between sites is greater than variance between different unique axle spacings.
- Vehicle configurations are not being classified in the same way or the classification windows are unsuitable for vehicle tracking.

Further investigation is needed into how IAP and alternative data sources could complement this tracking methodology to improve the volume and accuracy of the tracking algorithm. The validation was performed for only one site (Nudgee) and may not represent the accuracy of trips in different areas of Queensland.

5.3.5 Tracking Tools

As part of the project, PowerBI interfaces for visualising the detected trips were developed. These tools receive processed data from Python scripts, which output CSV files containing tracked trips, axle spacings and site locations. The static sites generated display 13 months worth of WiM and classifier data (Jan 2019 – Jan 2020), their respective trips and summary statistics.

These tools allow the user to interactively view the axle mass and axle spacings at sites where the vehicle was detected. In the PowerBI application, the following three pages detail the objectives required to interrogate WiM data and their trips, expanded upon in Table 5.7. Collectively, the tracking tools allow the user to find records of interest based on their configuration, mass, location and timings in the data control page. If this record of interest is part of a trip, the locations and axle masses can be viewed in the vehicle tracking page. The tracking and data control pages provide highly granular information on individual records and trips. In contrast, the WiM device map page provides aggregated statistics per site and is intended to be used to assess the quality of data coming from different WiM sites.

The following section covers the features and functionality of the tracking tools.

Table 5.7: PowerBI feature and function summary

Page name	Functionality	Objective
Data control	• Filter the entire WiM and classifier datasets based on vehicle type, time of day, record confidence, mass and site • See GVM distributions of all sites • See location of records which are included after data filtering • Identify vehicle trips from a known starting record	• To find a specific vehicle's WiM based on factors such as time of day, mass and vehicle configuration
WiM device map	• Filter map based on WiM device type • Visualise GVM against speed, speed histogram • See summary statistics such as vehicle count, GVM count, average steer and axle mass, and configuration frequency	• To compare the quality and reliability of WiM and classifier sites
Vehicle tracking	• Collect records which are part of a common trip • View the locations of WiM sites within the trip • Where available view axle mass distributions of records within the trip	• To investigate individual trips taken by specific vehicles • Highlight differences between the axle masses of the same vehicle at different sites

Data control page

The data control page provides filters to find individual WiM records, and subsections of WiM data which may be anomalous or unexpected, as shown in Figure 5.29. Both classifier and WiM data can be filtered. Data presentation windows are highlighted in orange, while data filter windows are highlighted blue. Adjusting the filters will alter the data presented in orange windows. Data can be filtered by:

- site location
- gross vehicle mass
- steer axle mass
- vehicle configuration
- steer axle type
- record confidence
- dolly type
- trip identifier
- trailer type.

The data is then visualised in the following windows:

GVM distribution – A histogram of the gross vehicle mass (tonnes) of all records encompassed by the filter. Minimum and maximum values can be set by dragging the slider.

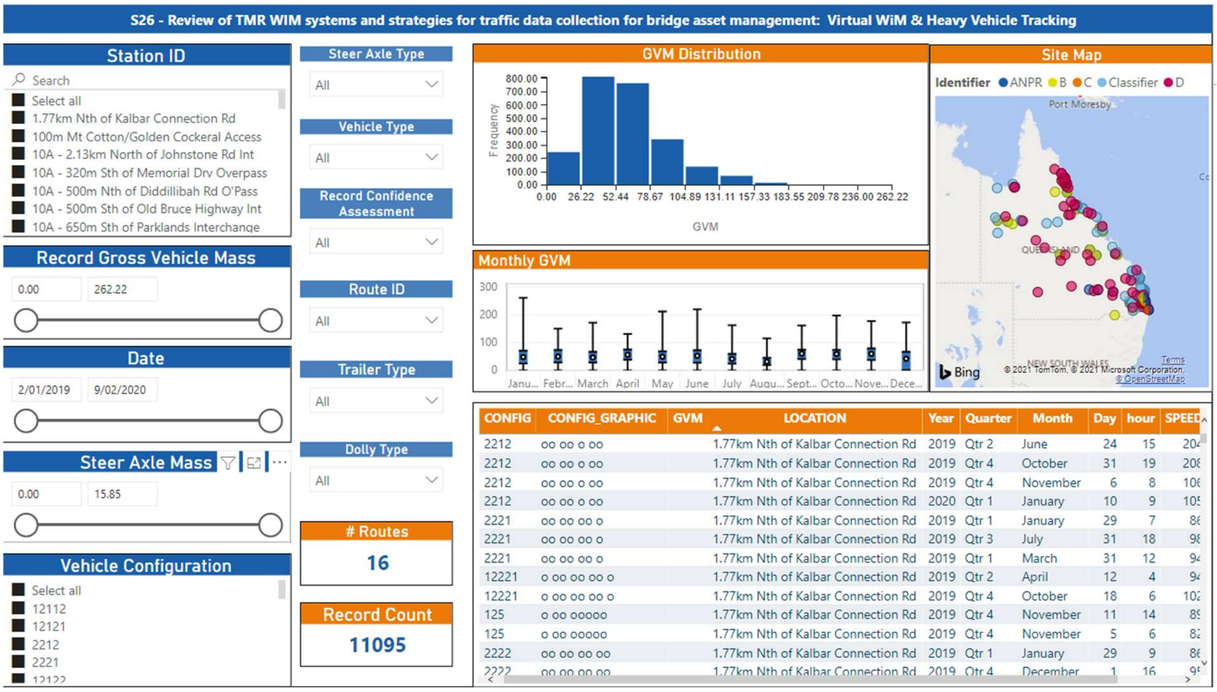
Site map – Locations of the data records categorised by type and quality of data. Clicking a site on the map will filter data displayed to only include records from this site.

Monthly GVM box and whisker

Box and whisker plot of the GVM by month. The mean is shown as a white dot. The shaded area shows data from the first to the third quartile, with whiskers showing the minimum and maximum values of the data. Classifier data is not included in the plot.

Record table – Shows individual records and any metadata, such as time of recording, location, GVM (if WiM record) and vehicle configuration.

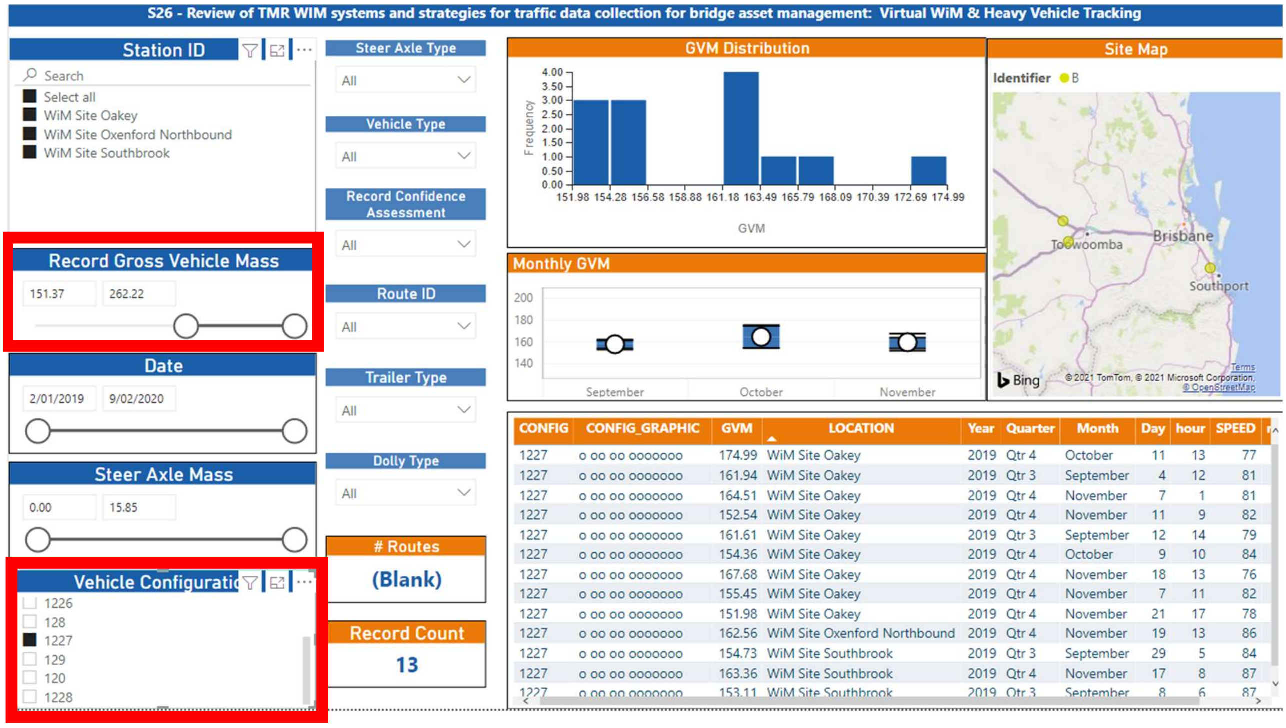
Figure 5.29: WiM and classifier data control page



Combining data filters

In Figure 5.30, two filters have been combined to view all records with a GVM greater than 151 t with a 1227 axle configuration. All the filters can be combined to focus on specific vehicles of interest or exclude vehicle populations which may be irrelevant to the analysis.

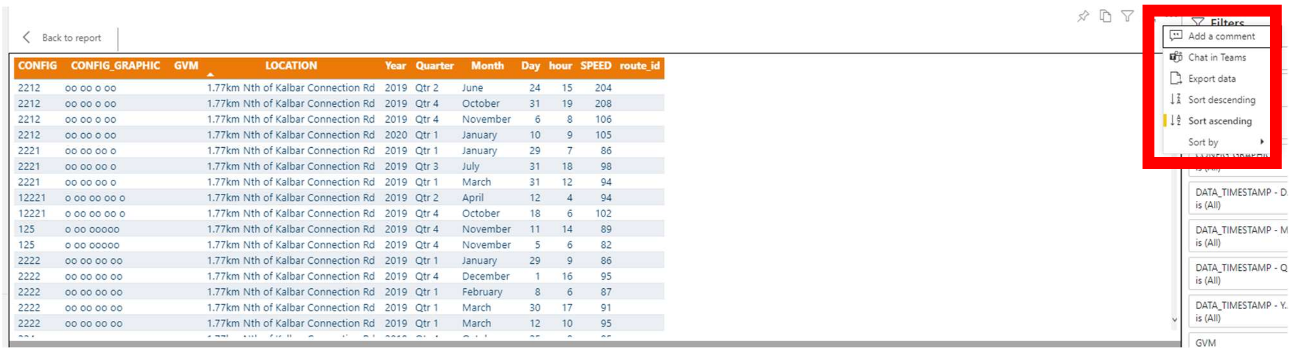
Figure 5.30: WiM and classifier data control page with filtering enabled, active filters are shown inside red boxes



Exporting data

The data control page can also be used to create segmented datasets of WiM and classifier data, by right clicking the table and selecting 'show as table', as shown in Figure 5.31. Using the ellipse in the top right-hand corner will allow the user to export the table as an Excel spreadsheet. Note that only 150,000 rows can be exported at a time.

Figure 5.31: WiM and classifier data control page with filtering enabled, active filters are shown inside Red boxes



WiM site data summary

The WiM data summary page visualises aggregated GVM, configuration and speed accuracy on a per site basis. By hovering over site locations on the map, the summary tooltip will appear. WiM sites of a specific type can also be filtered on the map.

Site map – Locations of WiM sites coloured based on the WiM device type are shown. Hovering over a WiM site will show the site tooltip.

Station filter – The station filter shows all WiM stations in the dataset. Users can search for specific stations using the station filter.

Site tooltip – The site tooltip will appear when the mouse hovers over a site, example tooltips for sites are provided in Figure 5.32 and Figure 5.33. The following information is provided in the tooltip for the site:

- **Speed histogram** – Frequency histogram of the speed at which records travel through the WiM site.
- **Gross vehicle mass against speed scatter plot** – The GVM against speed plotted for each record.
- **Vehicle configuration count** – Number of vehicles observed for the 8 most common configurations. Scrolling down in this window will show less common configurations.
- **Summary statistics –** A number of summary statistics are shown, which include:
  - average 123 steer axle mass
  - number of 123 steer axle records
  - 123 steer axle mass standard deviation
  - total vehicles recorded at site
  - speed limit of site.
- **Bar chart of record confidence** – This window shows the count of records and the confidence class per month, calculated based on the average (and deviation) in steer axle mass in 123 vehicles. All records within the month will have the same confidence value.

Figure 5.32: WiM Site Summary page, Barcaldine example

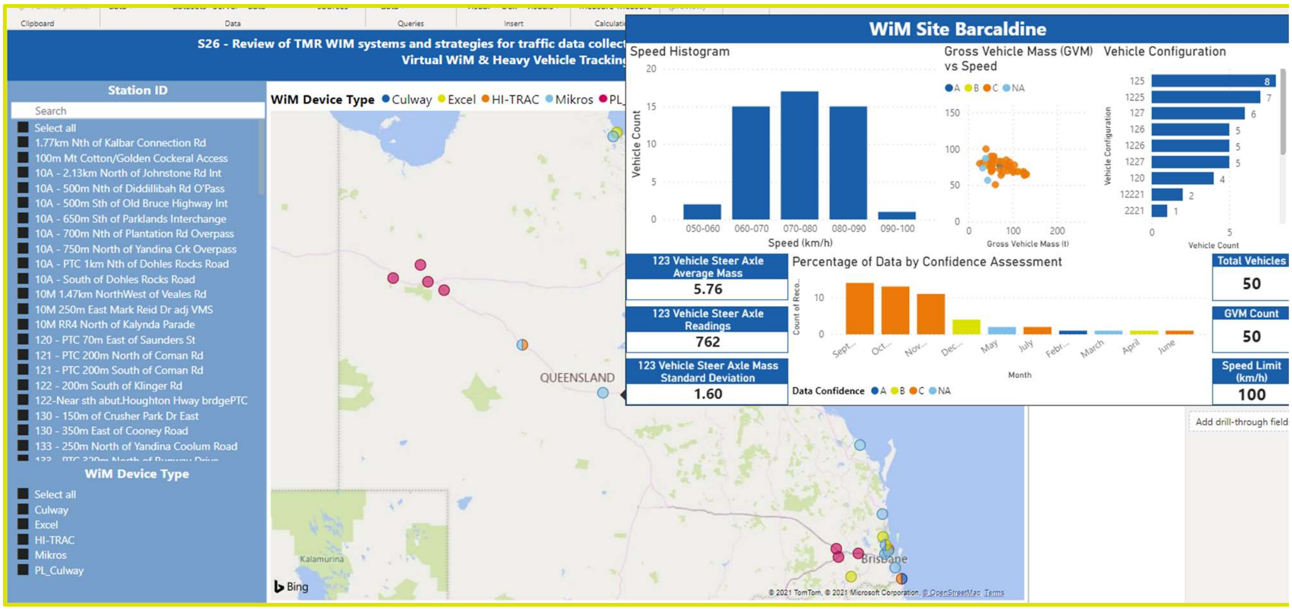
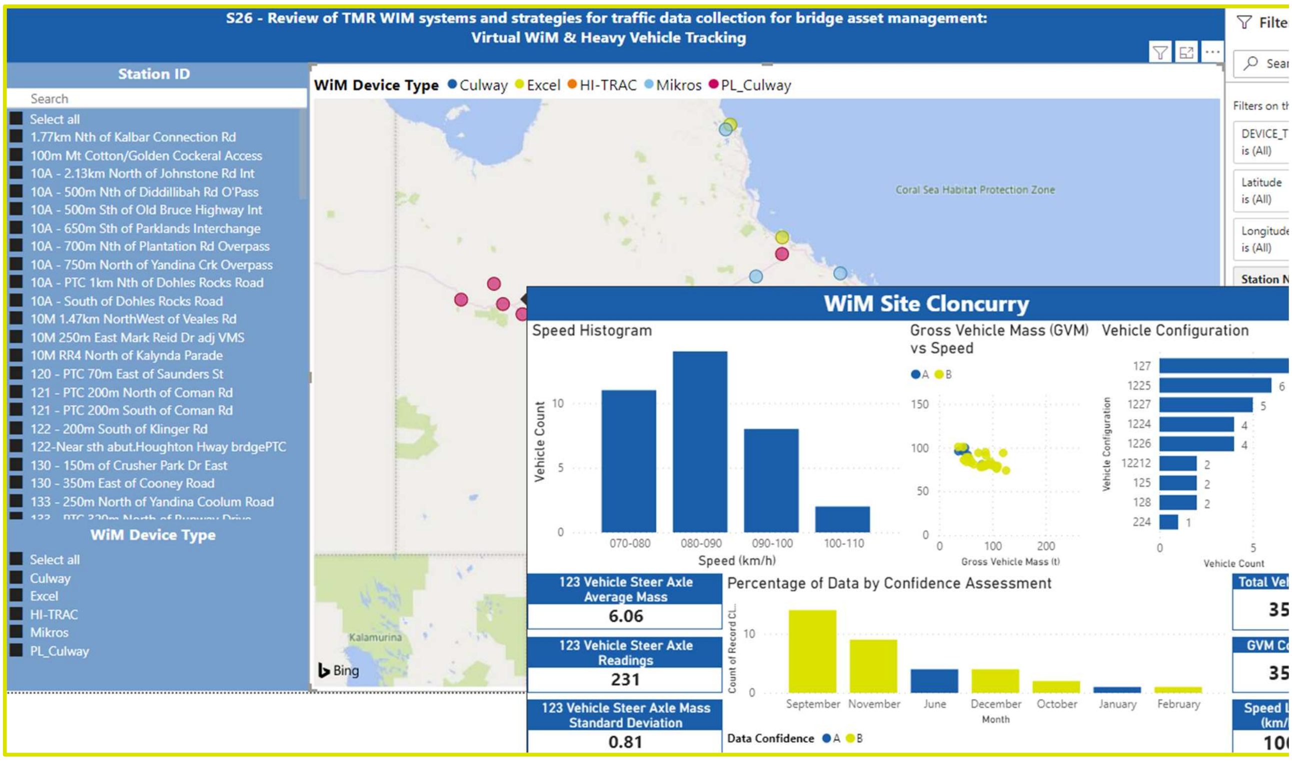


Figure 5.33: WiM Site Summary page Cloncurry example



Vehicle tracking page

The vehicle tracking page shows individual trips and the locations of WiM and classifier crossings. Specific trips can be selected using the trip filter, and trips which occurred within a specific date range can be found as well. Axle spacing and axle masses for every record in the trip are shown in the right-hand scatter plot. Examples of the vehicle tracking page are provided in Figure 5.34 and Figure 5.35.

Data filters

Similar to the data filter page, trips can be filtered based on the site location, date and vehicle identifier. These filters are useful if a user wants to find trips which pass through a specific location in a specific direction.

Trip map

The map of the observed location in the trip is displayed. Locations are coloured based on the WiM/classifier sites identified as being part of a trip.

Axle spacing and axle mass chart

This plot shows the distance of each axle from the steer axle in the X axis and the mass of each axle in the Y axis. This is used to confirm the similarity in records collected into the trip.

Record table

This record table shows the relevant information for the records in the trips.

Figure 5.34: Vehicle tracking example from Gatton to Southbrook, with class B confidence WiM masses

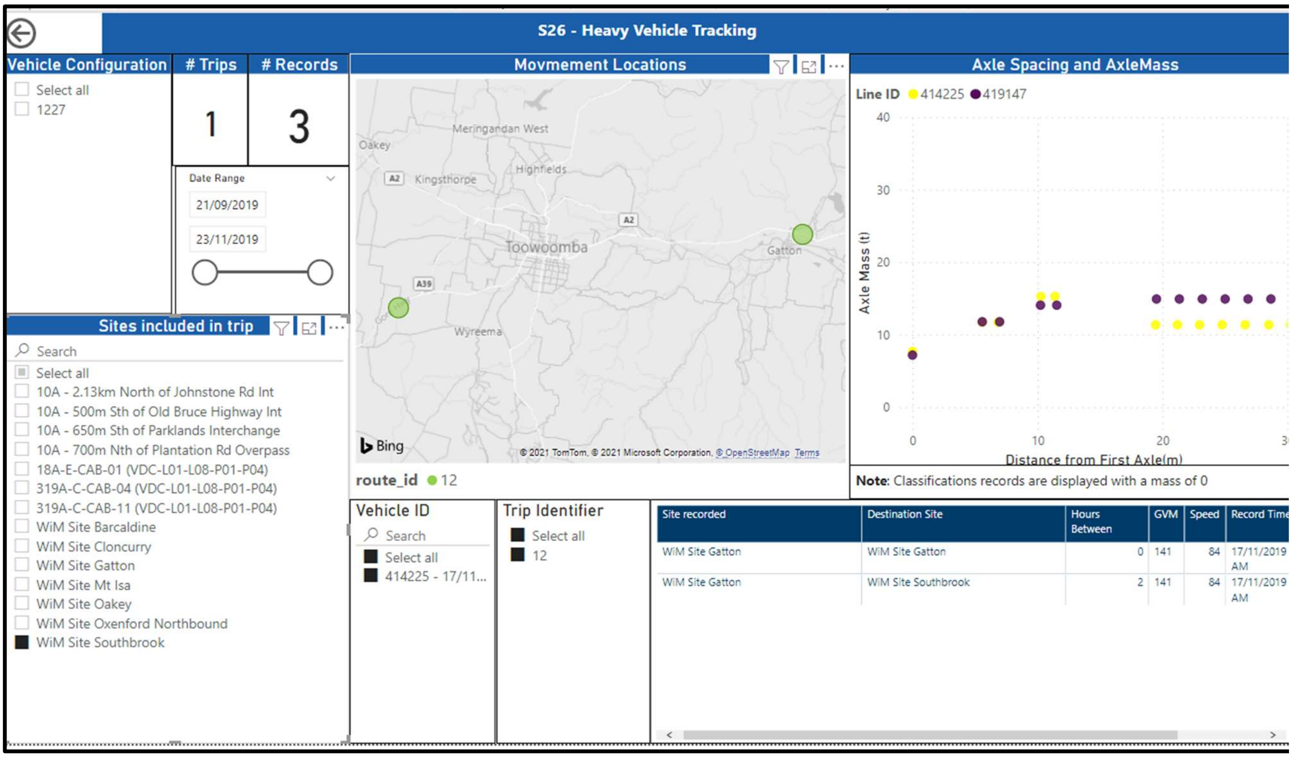
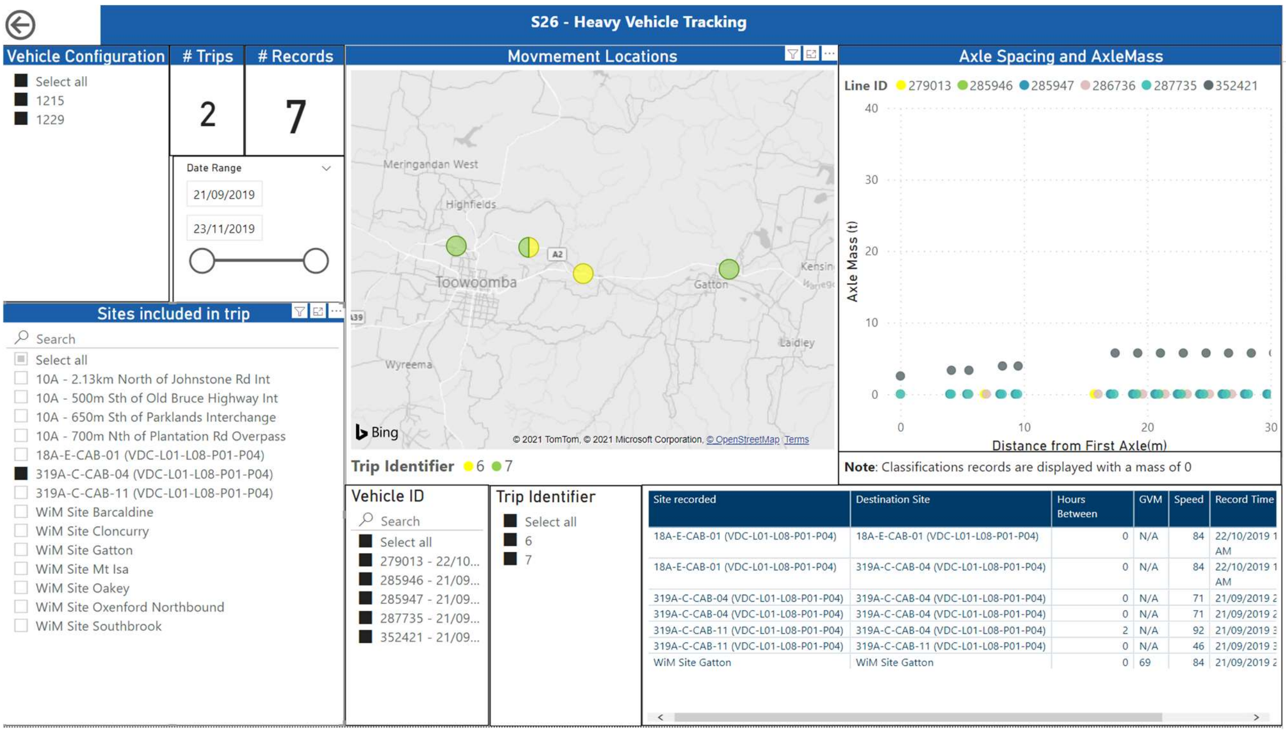


Figure 5.35: Another example of vehicle tracking which included classifier sites



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5.3.6 Limitations

Through the development of the tracking tool, some limitations to the tracking were noted, these include:

- Routing is a prediction, but not a true representation of the trips. With more information this may be less of a prediction for a percentage of the vehicles.
- The accuracy statistic was not able to be calculated for the low loader and load platforms as they did not have IAP installed.
- IAP validation was only able to be undertaken at a single site, so the accuracy was only able to be calculated at Nudgee. With IAP information at more sites, this may allow for a deeper understanding and improve the nuance of the tracking.
- The more unique the configuration of a vehicle, the more confidence that the vehicle being tracked is the same vehicle.

In addition to the tracking of the vehicle, there are limitations in regard to the tracking tool, these include:

- The tool does not dynamically update, so is reliant on a static database and connections to report on historical events.
- The tool is limited by the features of PowerBI, which means that the expansion of the tool is limited. This also means that functions cannot be created and embedded into PowerBI.

5.3.7 Summary

Tracking based on axle spacing and vehicle configuration data has been demonstrated to be effective when the configuration is sufficiently unique. When the estimated accuracy of the algorithm is combined with the total volume of tracked movements it is expected that 15% of low loader and load platforms were accurately tracked using WiM/classifier data. This is a significant volume of vehicle movements. Further improvements to the algorithm should be considered which would lead to a larger volume of accurately tracked movements.

One particularly useful benefit of vehicle tracking using this methodology is individual vehicle weight inference. When a vehicle crosses a classifier site, the resulting record does not contain mass data. Using a tracking methodology, the vehicle's weight can be inferred from either up or downstream WiM sites which are part of the trip. The value of classifier data is enhanced through extrapolation of WiM measurements, but in contrast to whole site extrapolation weight tracking inference can provide insight into specific vehicles of interest.

From a bridge asset management perspective, tracking the largest of these vehicles through the network provides a history of access data to inform bridge capacity assessments and enhance the credibility of decisions about access limits for routes.

Integrating ANPR technologies into the tracking and increasing the accuracy of the axle spacing data may increase the reliability and number of vehicles of interest that could be tracked through the network.

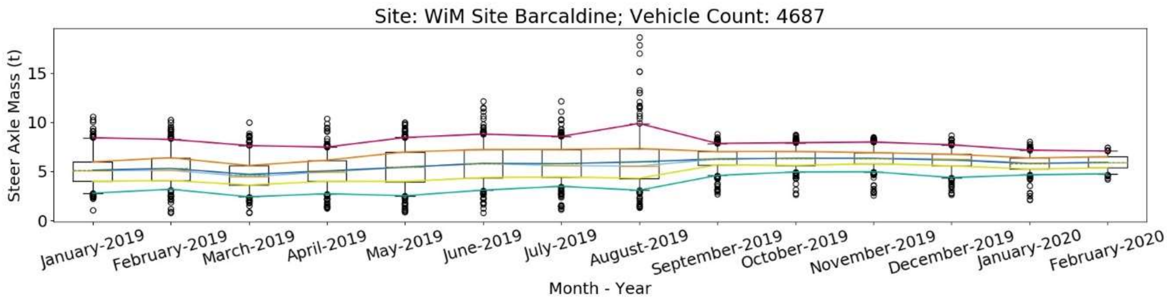
6. Future Considerations

NACOE S26 found that TMR would benefit from better data more often. This section outlines the possible enhancements to WiM, with a focus on the bridge perspective, which may be implemented with data fusion or added technology. Possible improvements are provided in the following sub-sections.

6.1 Axle Load Data

Ensuring quality axle load data over time lies at the core of the value proposition for WiM (Figure 6.1). Possible strategies for improving the axle load data measurements include valuing quality axle data highly and selecting WiM systems and sensors to provide value over the life of the sensors/system including regular road surface maintenance.

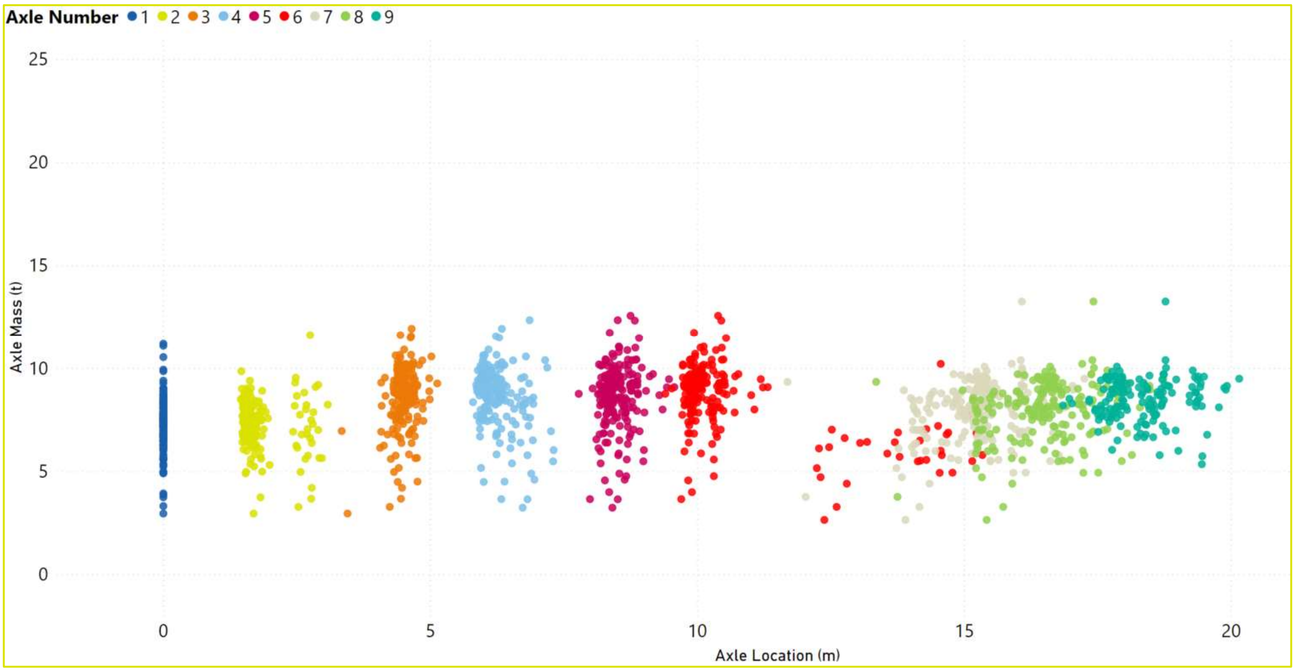
Figure 6.1: WiM monthly semitrailer 123 configuration steer axle mass statistics



6.2 Axle Spacing

The spacing of the axles for heavy vehicles can act as a signature for the larger vehicles on the network and can help differentiate vehicle types, identify routes taken, identify vehicles that may be suitable for live calibration of WiM sites, and to monitor compliance (Figure 6.2). Some possible strategies for improving the accuracy of axle spacing and speed data include quantifying the variability in axle spacing through case studies, investigating the causes of variability in recording of the axle spacing and implementing a continual improvement program, possibly in conjunction with suppliers of WiM and classifier systems.

Figure 6.2: Axle mass configuration for cranes with 6 or more axles

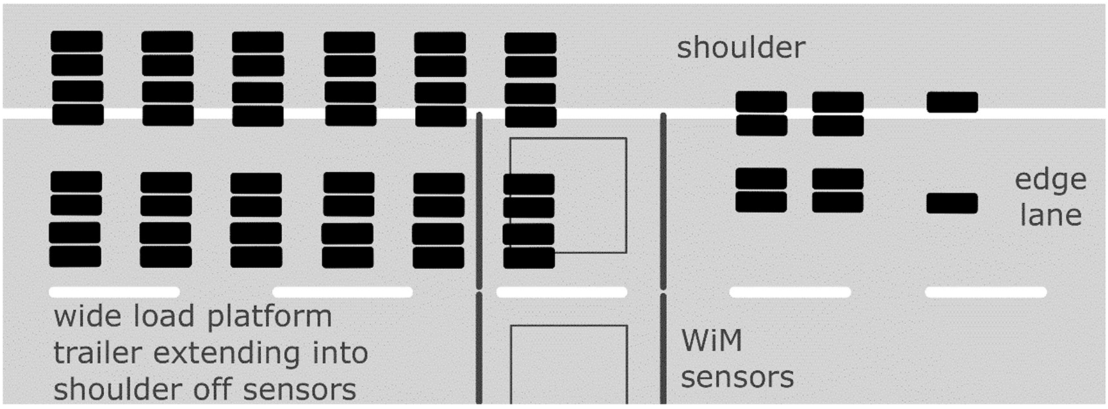


6.3 Coverage of Wide Vehicles

Pavement WiM and classifiers collect data for vehicles travelling in a lane, however wide vehicles such as low loaders and load platforms have a footprint such that it tends to straddle lanes or operate partly on the road shoulder. This means that while the detectors may collect data it may be nonsensical in terms of mass or configuration, leading to an underestimation of the actual loads on the road assets. When vehicles change lanes at WiM sites similar nonsensical inputs are provided. Where vehicles are operating partly on the road shoulder the mass operating on the shoulder is not recorded due to no sensors being in the shoulder (Figure 6.3). While vehicles such as prime movers may not straddle lanes, it is noted that their trailers may do.

The correct understanding of mass and configuration of these vehicles is critical as these are the largest vehicles on the network and they represent the largest risks to bridges.

Figure 6.3: The widest vehicles often run in the edge lane with tyres on the shoulder beyond the edge of the WiM sensors



Possible strategies for improving the coverage of wide vehicles include:

- upgrading algorithms to stitch together multi-lane WiM data (as was done for this project)
- extending the sensors to include the shoulder

- consider the use of bridge WiM, where the whole bridge span is the sensor such that data is collected for all drivelines, even on the shoulder.

6.4 Ground Contact Width & Permits

Lateral distribution of axle loads on permit vehicles such as low loaders and load platforms varies with the width of the ground contact. As ground contact width is currently not measured it is not possible to determine the lateral load distribution on structural components and hence acceptable loads or if overloading of a structure is occurring. In addition, the acceptable load per axle depends on the ground contact width and the number of wheels per axle.

Possible strategies to determine ground contact width and identify permit vehicles are to:

- investigate technologies such as permit vehicle details which are electronically readable, to enable measured data to be tied to permits and used for management of the network
- trial technologies for measuring ground contact width, such as TIRTL, Lidar, laser and in-pavement sensors
- adding sensors to measure ground contact width, the driveline of the truck and the number of tyres per axle.

6.5 Integration of ANPR Data with WiM

ANPR is important when using WiM as it provides confirmation that the vehicle type and configuration are as recorded in the WiM records. Possible strategies for improving the integration of ANPR with WiM data include:

- refining the integration of ANPR with WiM on multi-lane freeways
- trialling the use of emerging solar powered ANPR systems with 4G connectivity with CCTV capability, to facilitate the capture of number plates, CCTV and the ability to view still images of selected vehicles and their loading
- install front and rear facing systems where possible as well as ensuring that an angled view of the vehicle can be achieved, to allow for an identification of all the components of the configuration
- continue the development of the integration of ANPR with WiM in association with monitoring projects.

6.6 Geographical Coverage of WiM

There are currently some portions of the road network where there are no WiMs or classifier stations which transmit data back to the central data repository. These black spots in WiM or classifier stations include:

- urban freeway vehicle sensing technologies that do not provide 'axle spacing signatures' (e.g. loops)
- highways where no WiM stations have been installed.

Possible strategies for extending the geographical coverage of classifiers and WiM include updating classifiers to report data via telemetry, installing WiM sites at critical locations and progressing the concepts of virtual WiM (vWiM) by integrating WiM and classifier data via 'axle spacing signatures' and or ANPR data to extrapolate WiM data to other locations on the network.

6.7 Bridge WiM

Bridge based WiM systems are not commonly used. It has the potential advantage of being more stable over time as less pavement maintenance is required. Advantages also include that the sensors are generally not removed when pavement upgrades are undertaken. This ensures that all heavy vehicles are recorded. Additionally, the system and sensors are relocatable.

6.8 On-Board Mass (OBM) Measurement

On-board mass (OBM) measurement has been emerging for decades in parallel with WiM and is now becoming more common in Queensland. Data is currently available to TMR for a limited subset of freight vehicles. As the heavy vehicle fleet is becoming increasingly sophisticated, there will likely be an increasing take-up of these technologies by transport companies.

Possible strategies relating to OBM include:

- Cease the collection of WiM and classifier data and rely on OBM and related technologies. From a bridge perspective this only works if all vehicles are fitted with OBM and all axle spacing and axle loads are reported.
- Utilise the OBM data to validate WiM station calibrations and support TMRs calibration of OBM data.
- Continue to use WiM and classifier data to ensure coverage of all vehicles.
- Merge the WiM, classifier and OBM datasets.

6.9 Bridge Response Monitoring

Bridge response monitoring provides both the performance data for components as well as the load model data for the traffic stream. The bridge response monitoring systems are best utilised when integrated with other datasets such as AVIS, WiM, classifier, OBM, permit and authority to operate data.

Possible strategies for bridge response monitoring include continuing to utilise, to:

- inform structural behaviour
- identify vehicles accessing the network and their effects on structures
- support due diligence
- refine assessment load models to support risk and asset management
- safely extend lives of bridges, inform rehabilitation and improve utilisation of the bridge asset.

6.10 Uncommon Heavy Vehicle Tracking

Potential enhancements to the tracking tool include:

- integration of the heavy vehicle network into the matching algorithm
- mapping of potential heavy vehicle trips undertaken by vehicles
- integration with IAP to validate and improve tracking
- exploring methods to aggregate routing data of all vehicles which cross the same bridge.

From a bridge asset management perspective, tracking the largest of these vehicles through the network provides a history of access data to inform bridge capacity assessments and enhance the credibility of decisions about access limits for routes.

7. Conclusions and Recommendations

The overall aim of the project was to review TMR's WiM systems and to identify opportunities for improvement with an emphasis on technologies and systems that could improve input to the credible risk-informed management of the bridge stock.

Benchmarking TMR's WiM systems nationally concluded that the systems are mature and would benefit from the generation of more accurate WiM data with less down time while reliably recording information on Class 1 heavy vehicles such as cranes, low loaders and load platforms. Approaches that may facilitate this outcome include:

- installing WiM stations in pavements with slow rates of deterioration to improve data quality over the life of the WiM station
- measuring ground contact width to improve the understanding of the loads and compliance levels of the Class 1 heavy vehicles
- improving data analytics to extract more knowledge from available data
- monitoring and continually improving the data quality.

This project's recommendations complement similar findings from NACOE R103, which explored the concept and development of a vWiM model focused on providing network-wide information. In that project a vWiM framework was proposed that comprised of three modules to combine the data types of interest. All the modules apply network allocation and extrapolation techniques to build the vWiM network-wide. Module 1 proposed to use data from WiM sites and classifiers. Module 2 was based on combining with ANPR data sources and Module 3 proposed to use truck telematics (GPS and OBM) data.

7.1 Conclusions

The project demonstrated that there are increasing opportunities for WiM and related technologies to support evidence-based decisions by TMR. Internal engagement, national and international reviews also found that the value proposition for WiM data is not well articulated because the focus is on collecting data to inform compliance rates rather than the optimal management of the road and bridge network and the heavy vehicles that provide transport services for the community.

A draft Strategic Asset Management Plan (SAMP) for TMR WiM was developed. The draft SAMP proposed a program of continual improvement and investment in data quality, accessibility and the application of WiM and related datasets over 10 years to respond to identified stakeholder needs.

The vehicles posing the greatest risk to bridges across the network were investigated to understand their characteristics and enable them to be tracked through the network. The applications of WiM expand with increasing data quality and data coverage.

While it is possible to extract value from imperfect data, it is also the case that some applications require improved quality and reliability of data. It was concluded that there are many means for improving data quality, including updating specifications for WiM and classifiers, continuous improvement of data post-processing with a network-level focus, and live calibration of existing WiM sites using vehicles of known and consistent mass, identified in the traffic stream.

Data coverage can be improved through strategic maintenance of existing WiM systems, identifying and addressing data black spots, using the WiM data extrapolation methods developed as part of this project to provide virtual WiM data at classifier sites, combining complementary datasets, incorporating the connection between WiM and other heavy vehicle data sources, including bridge monitoring, ANPR, IAP, ATO, OBM, and classifier data. The more independent complementary data sources that can be effectively combined, the more opportunities that will arise.

7.2 Recommendations

It is recommended TMR adopt the vWiM concepts of integrating multiple datasets and supporting a program of continual improvement. The program should target the quality, coverage, accessibility, and linking of datasets. Further development of the engineering and analytics to translate the data into information and knowledge are also necessary to support informed decisions that benefit the Queensland community.

References

Austroads 2000, Development of an Austroads heavy vehicle nomenclature system: discussion paper, AP-R174-00, Austroads, Sydney, NSW.

Austroads 2006, *Automatic vehicle classification by vehicle length*, AP-T60-06, Austroads, Sydney, NSW.

Austroads 2016, *National strategic weigh-in-motion network*, AP-R535-16, Austroads, Sydney, NSW.

Eskew, E, Ward, D, Heldt, T, Heywood, R, Karl, C, Lewis, K & Dann, E 2021, 'S26: review of TMR WiM systems and strategies: virtual WiM & heavy vehicle tracking: feasibility & value (year 3 2019/20)', contract report 014932, prepared for Queensland Department of Transport and Main Roads under the NACoE program, ARRB, Brisbane, Qld.

Heldt, T, Heywood, R, McDonnell, A, Pathirage, T & Mahagamage, V 2019, 'S26: review of TMR WiM systems and strategies for traffic data collection for bridge asset management (year 2 – 2018/19)', contract report PRG18026, prepared for Queensland Department of Transport and Main Roads under the NACoE program, ARRB, Brisbane, Qld.

Hore-Lacey, W, Germanchev, A, Eastwood, B & Shackleton, D 2020, *R103: virtual weigh-in-motion and Queensland freight movement study,* contract report 015302, prepared for Queensland Department of Transport and Main Roads under the NACOE program, ARRB, Brisbane, Qld.

Karl, C, Lewis, K, Dann, E, Eskew, E & Irannezhad, E 2021, 'S26: virtual WiM & heavy vehicle tracking – feasibility & value (year 4 2020/21)', contract report 015696, prepared for Queensland Department of Transport and Main Roads under the NACoE program, ARRB, Brisbane, Qld.

Liebherr n.d., *LTM 1070-4.2: a small 4-axle crane with giant potential*, Liebherr, Adelaide, South Australia, viewed 10 January 2022, <https://www.liebherr.com/en/aus/products/mobile-and-crawler-cranes/mobile-cranes/liebherr-mobile-cranes/ltm-1070-4.2.html>.

Manitowoc 2015, *GROVE TMS9000E product guide,* Manitowoc, WI, USA.

Manitowoc 2020, *GROVE GMK7550 product guide,* Manitowoc, WI, USA.

National Heavy Vehicle Regulator 2016a, *Glossary of common terms*, version 1.1, NHVR, Brisbane, Qld.

National Heavy Vehicle Regulator 2016b, *National heavy vehicle mass and dimension limits*, NHVR, Brisbane, Qld.

National Heavy Vehicle Regulator 2019, *Classes of Heavy Vehicles in the Heavy Vehicle National Law*, NHVR.

National Heavy Vehicle Regulator 2021, *Intelligent access program (IAP)*, NHVR, Brisbane, Qld, viewed 12 January 2022, < https://www.nhvr.gov.au/road-access/access-management/intelligent-access-program-iap>.

Queensland Department of Resources 2021, *Queensland spatial catalogue: state controlled roads bridges,* catalogue, DoR, Brisbane, Qld, viewed 10 January 2022, <https://qldspatial.information.qld.gov.au/catalogue/custom/detail.page?fid={14D6B946-F361-4CE7-B156-EA8C324866DC}>.

Queensland Department of Transport and Main Roads 2017, *Transport and Main Roads specifications: MRTS251 traffic counter/classifier*, TMR, Brisbane, Qld.

Queensland Department of Transport and Main Roads 2018, *Queensland transport and logistics workforce: current and future trends report*, TMR, Brisbane, Qld.

Queensland Department of Transport and Main Roads 2019, *Queensland transport and roads investment program 2019-20 to 2022-23*, TMR, Brisbane, Qld.

Queensland Department of Transport and Main Roads 2020a, *Department of Transport and Main Roads: 2019-2020 Annual Report*, TMR, Brisbane, Qld.

Queensland Department of Transport and Main Roads 2020b, *Transport and Main Roads specifications: MRTS203 provision of weigh-in-motion system*, TMR, Brisbane, Qld.

Queensland Department of Transport and Main Roads 2020c, *Standard drawing 1906: WiM Piezo sensor installation details*, TMR, Brisbane, Qld.

Song, Y, Wang, X, Wright, G, Thatcher, D, Wu, P & Felix, P 2019, 'Traffic volume prediction with segment-based regression kriging and its implementation in assessing the impact of heavy vehicles', *IEEE Transactions on Intelligent Transportation Systems*, vol. 20, no. 1, pp. 232-43.

Vanderstaay, AGB 2006, 'A methodology to remove unwanted variability in Queensland WiM data', *ARRB conference: research into practice, 22nd, 2006, Canberra,* ARRB Group, Melbourne, Vic, 13 pp.

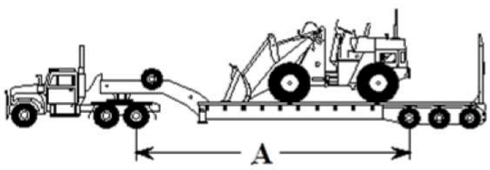
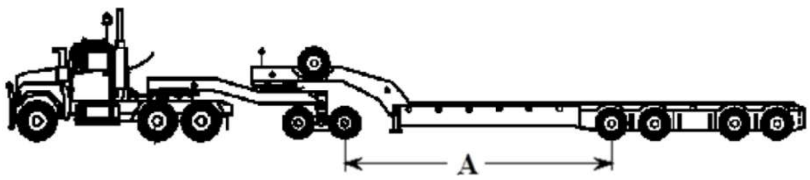
Zanardo, G & Heldt, T 2018, 'S26: review of TMR WiM systems and strategies for traffic data collection for bridge asset management (year 1 – 2017/18)', contract report PRG17025, prepared for Queensland Department of Transport and Main Roads under the NACoE program, ARRB, Brisbane, Qld.

Appendix A Definitions and Terminology

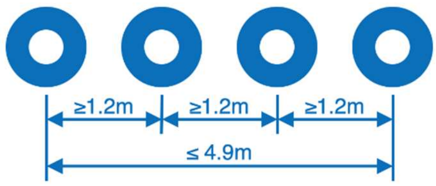
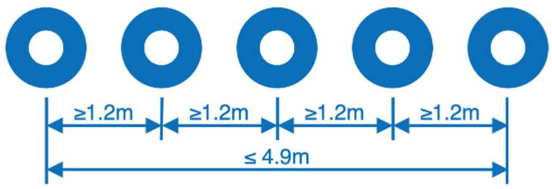
The key terms, acronyms and mathematical symbols used throughout the report are provided to facilitate understanding of the outcomes for a range of stakeholders. Where applicable, definitions relating to heavy vehicles are taken from the National Heavy Vehicle Regulator (2016a). The terms, acronyms and mathematical symbols defined in this appendix are used throughout this report and its associated appendices.

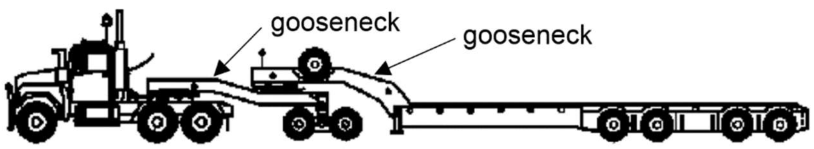
A.1 Key Terms

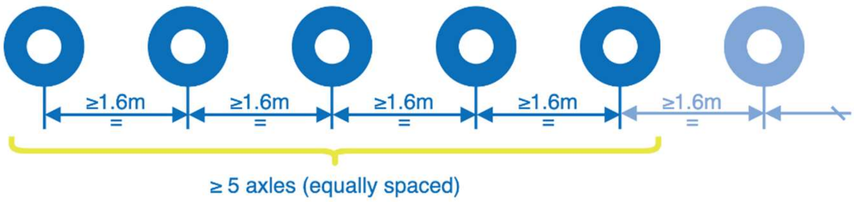
The following are key terms and their meaning in the context of this report.

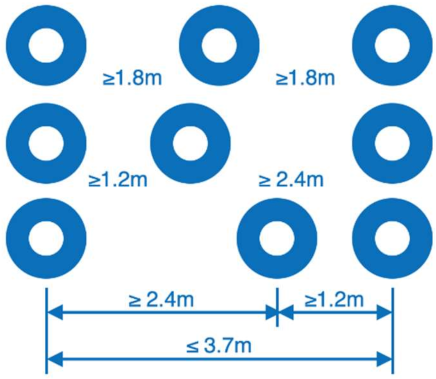
Term	Definition
123 vehicle	A vehicle (most commonly a **semi-trailer**) comprising a single steer axle, tandem drive axle group and tri-axle trailer group with **configuration** '123'.
'A' distance	The length between the centreline of the last axle of the prime mover and the first axle of the trailer.  Source: HVNL Multi-State Class 1 Load Carrying Vehicles Dimension Exemption Notice 2016 Amendment Notice 2019 (No. 1). For the purpose of the **project** the 'A' distance for combinations with a single or tandem **dolly** in **combination** was the distance between the last axle of the dolly and the first axle of the low loader or load platform trailer:  Source: HVNL Multi-State Class 1 Load Carrying Vehicles Dimension Exemption Notice 2016 Amendment Notice 2019 (No. 1).
Austroads class 6+	A vehicle with ≥ 3 axle groups and ≥ 3 axles. *Refer* Figure A.1 *for more details.*
Axle	One or more shafts positioned in a line across a vehicle on which one or more wheels which are intended to support the vehicle turn. *Source: NHVR (2016a).*
Axle group	An axle or group of axles where each axle in the group is ≤ 2.1 m from the adjacent axle in the same group. **Note:** This is based on the implemented logic in WiM and classifiers which is based on Austroads vehicle classes.
Axle spacing	The spacing between two axles of a vehicle. For classifier and WiM records, the spacing is indexed by the number of spaces between axles on the vehicle. For example: Axle space 1 would represent the distance between the first axle of the vehicle to the second axle; whereas axle space 2 would be the distance from the second axle to the third.

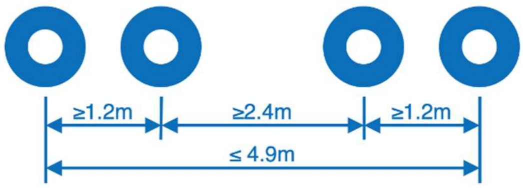
Term	Definition
Boom dolly	A device for distributing mass connected behind a **heavy mobile crane** in travel mode which supports part of the crane boom.  Source: NHVR (2019).
Calibration concerns *(WiM)*	WiM data from a site during a period of time where, based upon a statistical analysis of the **123 vehicle** configuration steer axle mass, the data has been assessed as likely being out of calibration.
Class 1 heavy vehicle	A vehicle classed by Heavy Vehicle National Law as being a class 1 vehicle. These include Special Purpose Vehicles (SPV), Oversize Overmass Vehicles (OSOM) and Agricultural Vehicles. *Refer to* Figure A.2 *for more details.*
Class A confidence data *(WiM)*	When referring to a WiM site, indicates that the site was assessed as having confident data according to the class A confidence 123 vehicle configuration steer axle mass thresholds during the specified period of time. When referring to a vehicle of interest record, indicates that the record came from a period of time at a site that was deemed to be confident based upon the class A confidence 123 vehicle configuration steer axle mass limits, and that the records steer axle mass was within the class A confidence vehicle of interest steer axle mass limit (if a low loader or load platform).
Class B confidence data *(WiM)*	When referring to a WiM site, indicates that the site was assessed as having confident data according to the class B confidence 123 vehicle configuration steer axle mass thresholds during the specified period of time. When referring to a vehicle of interest record, indicates that the record came from a period of time at a site that was deemed to be confident based upon the class B confidence 123 vehicle configuration steer axle mass limits, and that the records steer axle mass was within the class B confidence vehicle of interest steer axle mass limit (if a low loader or load platform).
Class C confidence data *(WiM)*	When referring to a WiM site, indicates that the site was assessed as having confident data according to the class C confidence 123 vehicle configuration steer axle mass thresholds during the specified period of time. When referring to a vehicle of interest record, indicates that the record came from a period of time at a site that was deemed to be confident based upon the class C confidence 123 vehicle configuration steer axle mass limits, and that the records steer axle mass was within the class C confidence vehicle of interest steer axle mass limit (if a low loader or load platform).
Classification	The type of vehicle which is identified (e.g. truck, crane, truck and dog, low loader, load platform, B-double, etc.) based on a vehicle classification scheme, e.g. the Austroads 1994 12-bin vehicle classification scheme (Austroads 2000), HVNL classification scheme.
Classifier data	In this report, the term 'classifier data' refers to the classifier portion of the data from both classifier and WiM sites.
Classifier footprint OR **Axle-spacing footprint OR** **Axle spacing signature**	The configuration and axle spacings from a specific WiM or classifier record. Often unique and consistent (within axle spacing measurement tolerances) for rare vehicles including many **Class 1 heavy vehicles** such as **load platforms** and **heavy mobile cranes.**
Configuration *(of a vehicle)*	A string representing the number of axles in each successive **axle group** of a vehicle **combination**. The numbers within the configuration have the following meanings: 1 = a single axle (≥ 2.1 m from the nearest adjacent axle) 2 = tandem-axle group 3 = tri-axle group 4 = quad-axle group 5 = quin-axle group Groups represented by numbers ≥ 6 are most commonly **load platform trailers:** 6 = six-axle group 7 = seven-axle group 8 = eight-axle group 9 = nine-axle group

Term	Definition
	0 = ten-axle group A = eleven-axle group B = twelve-axle group C = thirteen-axle group (and so on for higher letters) A vehicle comprising a **prime mover** with a tandem **dolly** towing a ten-axle **load platform trailer** would have the configuration '1220'. The arrangement of the axles may be: O OO OO OOOOOOOOOO The front of the vehicle is always denoted by the first number in the configuration. The vehicle above, for example, is travelling to the left. Similarly, a '123' may be a **semitrailer** with the following arrangement of axles: O OO OOO NOTE: Alphanumeric identifiers for axles were revised after this report such that ten-axle group changed from 0 to A, the proceeding axle groups identifiers has changed, such that B represents eleven-axle group, etc.
Closed quad	A quad-axle group with the following geometry:  In **configurations**, this axle group is represented by a '4'.
Closed quin	A quin-axle group with the following geometry:  In **configurations**, this axle group is represented by a '5'.
Combination	A group of vehicles consisting of a motor vehicle such as a **prime mover** or rigid truck towing one or more other vehicle units such as a **semi-trailer** or trailer. Source: NHVR (2016a).
Confident *(WiM)*	WiM data from a site and during a period of time where, based upon a statistical analysis of the 123 vehicle configuration steer axle mass, the data has been assessed as being a confident representation of the expected traffic.
Cumulative distribution/cumulative probability	The cumulative probability or distribution is the probability that an observation will be less than or equal to a given number. For example, a cumulative probability of 60% that a steer axle mass is 6.0 t, means that 60% of the vehicles in the dataset have a steer axle mass which is less than or equal to 6.0 tonne.
Data filtering	Selecting subsets of data based upon key parameters in the data, to support objectives of specific investigations.
Data processing	Modification of data from its original form to support the needs of specific investigations and/or allow implementation into visualisations.
Data analysis	Detailed examinations performed on **raw, processed** and or **filtered data** to identify key trends in the records and determine the findings of this **project** and associated **investigations**.
Data visualisation	The presentation of data in visual or tabulated form to: • communicate ideas and insights and make information easier to understand and retain • identify trends and outliers • present the results of data analytics • guide the data analytics.

Term	Definition
	For example, dashboards were developed to assist in visualisation and manual exploration of the large datasets, allowing the user to pose and answer questions related to the data.
Dog trailer	A trailer that has two axle groups with the front axle group steered by connection to the towing vehicle. In the **project**, only 4-axle dog trailers (sometimes called 'super dogs') are considered in an attempt to distinguish between these trailers and **spread quad** trailer groups from low loaders.
Dolly	A device for distributing mass that: a. is usually coupled between a prime mover and a low loader *trailer or load platform trailer*; b. consists of a rigid frame of a **gooseneck** shape c. does not directly carry any load d. is equipped with 1 or more axles, a kingpin and a fifth wheel coupling. Source: HVNL Heavy Vehicle (Mass, Dimension and Loading) National Regulation. For the purposes of the **project**, (a) has been updated to include the italicised text.
Dynamic mass	The observed mass (applied force divided by acceleration due to gravity) of the moving vehicle (rather than the **static mass** of the vehicle). May refer to the observed mass of an **axle**, **axle group**, vehicle or **combination**.
Expected traffic	Representation of the traffic which is likely to be observed at a location over a period of time, based upon observed data. Does not account for outliers.
Fifth wheel coupling	A device (other than an upper rotating element and a kingpin) used with a prime mover, semi-trailer or converter dolly to permit quick coupling and uncoupling; and provide for articulation. Source: NHVR (2016a).
Filtered data	A subset of data (usually **processed data**) obtained by **data filtering**. Typically, this is the data used as input to **data analysis** which is aimed at testing hypotheses or answering questions generated through the various **investigations** of this **project**.
Full dataset	All of the **supplied data** without any filters.
Gooseneck	A rigid connection frame between a **load platform**, **low loader** or **dolly** which is cranked by necessity to make the connection with the part of the **combination** which is in front (a **prime mover** or **dolly**).  Source: HVNL Multi-State Class 1 Load Carrying Vehicles Dimension Exemption Notice 2016 Amendment Notice 2019 (No. 1).
Ground contact width	In relation to an axle, the distance between the outermost point of ground contact of the outside tyres on each end of the axle. In relation to an axle group, the greatest ground contact width of all the axles in the group.  Source: NHVR (2016a).
Heavy mobile cranes	Mobile cranes (also commonly referred to as 'all terrain cranes') with more than 4 axles.
Investigation	A part of this **project**.
Logger	A computer on site at a WiM or classifier which receives and processes **raw sensor data** and subsequently sends **raw data** for collation in TMR's database.
Load platform	For the purposes of this **project**, this is any vehicle combination which includes a **load platform trailer**.

Term	Definition
Load platform trailer	A trailer specifically designed for the movement of large loads with the trailer having all of the following features: • at least five rows of axles • a minimum of 1.6 m longitudinal spacing between axle rows • at least 8 tyres per axle row • all axle rows are steerable • may be constructed of multiple platform modules. Source: HVNL Multi-State Class 1 Load Carrying Vehicles Dimension Exemption Notice 2016 Amendment Notice 2019 (No. 1). For the purposes of this **project** a load platform trailer is defined as a trailer consisting of one or more modules having the following features. ≥ 5 equally spaced axles ≥ 1.6 m longitudinal spacing between axles  In **configurations** this axle group may be represented by '5','6','7',…,'A','B','C' depending on the number of axles, or if the axle spacings are ≥ 2.1 m, would be denoted by a series of '11111…'.
Low loader	For the purposes of this **project**, a low loader is considered to comprise a tandem-drive **prime mover** with a **low loader trailer** with or without a single or tandem **dolly**.
Low loader trailer	A semi-trailer by with a loading deck no more than 1.2 m above the ground. Source: HVNL Amendment Notice 2019 No 1. For the purposes of this **project** a low loader trailer includes **spread tri**, **closed quad**, **spread quad** or **closed quin**-axle group trailer.
Prime mover	A motor vehicle designed to tow a **semitrailer**. Typically comprising a steer (or **twinsteer**) axle group and a **tandem drive** axle group. Source: NHVR (2016a).
Probability distribution	A probability distribution presents the probability of an observation having a specific value or a value in a specific range. For example, a probability of 15% that a steer axle mass is between 6.0 t and 6.5 t, means that 15% of the vehicles have steer axle mass in this range.
Processed data	Data obtained as the result of **data processing**.
Querying	Identifying sub-datasets relevant to this **project** from TMR WiM and classifier databases.
Raw data	Data which has been transferred directly from the weigh-in-motion and classifier sites to TMR's database without any post-processing by TMR. It has been processed by on-site data loggers each with their own classification algorithms developed by various suppliers to MRTS251 and MRTS203 technical specifications. This is different to **raw sensor data** which is data from the actual sensors and is independent of classification algorithms.
Raw sensor data	Signals produced by the various sensors that make up weigh-in-motion and classifier systems including from loops, tubes, piezoelectric and strain sensors. This is the data which is interpreted by the proprietary loggers onsite using bespoke logic developed by the supplier.
Semi-trailer *(axle group type)*	A trailer that has 1 axle group towards the rear and a way of attaching to a prime mover that results in some of the load being imposed on the prime mover. Source: NHVR (2016a).
Semi-trailer *(vehicle type)*	A combination comprising a **prime mover** and a **semi-trailer**.

<table>
<tr><th>Term</th><th>Definition</th></tr>
<tr><td>Spread tri
(axle group type)</td><td>A tri-axle group complying with one of the following three sets of geometries:


In configurations the above would be denoted '3', '21' and '12' respectively.</td></tr>
<tr><td>Spread quad
(axle group type)</td><td>A quad-axle group with the following geometry:


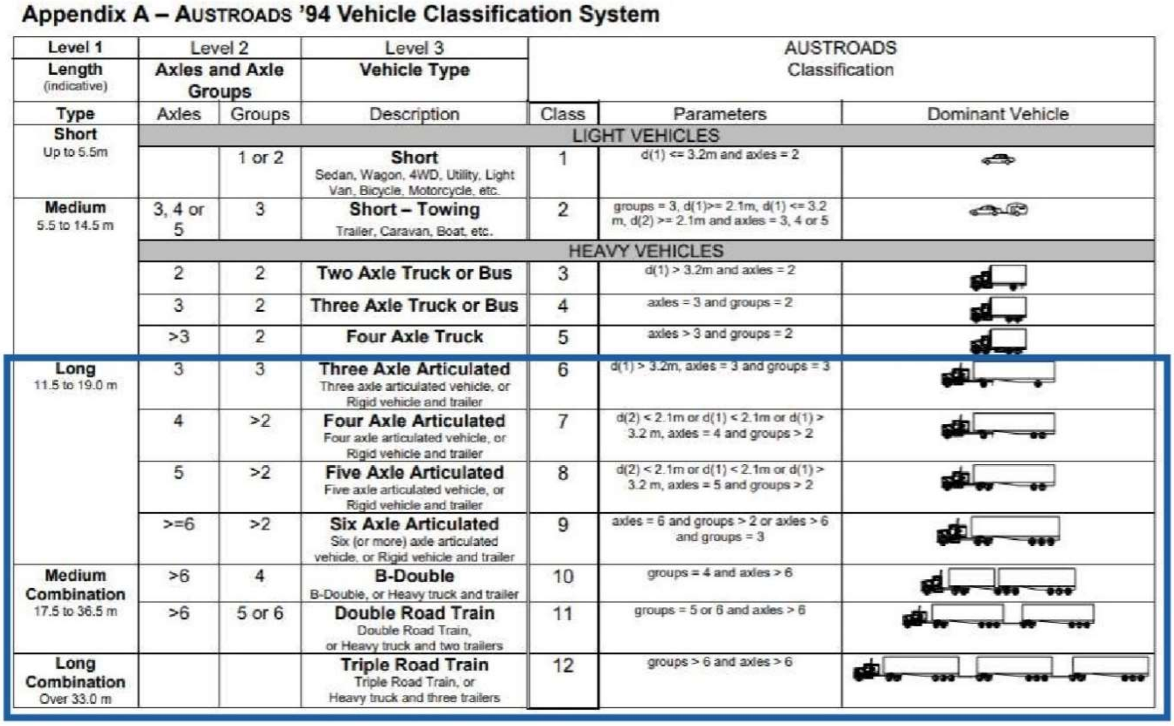
In configurations the above would be denoted '22'.</td></tr>
<tr><td>Site</td><td>Location of a WiM or classifier.</td></tr>
<tr><td>Static mass</td><td>The actual mass of a vehicle (as opposed to the dynamic mass) as would be determined by the standing vehicle on an accurate set of scales.
May refer to the actual mass of an axle, axle group, vehicle or combination.</td></tr>
<tr><td>Steer axle</td><td>The front steerable axle used to steer the vehicle.</td></tr>
<tr><td>Project</td><td>This NACOE research project.</td></tr>
<tr><td>Supplied data</td><td>Data supplied to this project.</td></tr>
<tr><td>Tandem drive
(axle group type)</td><td>A drive axle group with two axles in a prime mover.</td></tr>
<tr><td>Target data</td><td>Data of concern to an investigation which is extracted from the supplied data through logic and rules.</td></tr>
<tr><td>Tolerance
(axle spacing)</td><td>An amount by which any dimension can deviate from the nominal dimensions or dimension limits and still be classified as a particular axle group type, trailer or vehicle type.

Unless noted otherwise, a tolerance of ± 200 mm has been considered.</td></tr>
<tr><td>Truck and dog</td><td>A combination consisting of a rigid truck with 3 or 4 axles towing a dog trailer with 3 or 4 axles.

Source: NHVR (2019).
Source: HVNL National Class 3 Truck and Dog Trailer Mass Exemption Notice 2018 (No.2).
For the purpose of this project the focus has been on truck and dogs which have 4-axle dog trailers.</td></tr>
<tr><td>Twinsteer
(axle group type)</td><td>A group of 2 axles connected to the same steering mechanism on a motor vehicle, the axle spacing of at least 1 m but not more than 2 m.</td></tr>
<tr><td>Unconfident (WiM)</td><td>WiM data from a site and during a period of time where, based upon a statistical analysis of the 123 vehicle configuration steer axle mass, the data has been assessed as not being a confident representation of the expected network traffic.</td></tr>
<tr><td>Vehicles of interest</td><td>Low loaders, load platforms and heavy mobile cranes.</td></tr>
</table>

Term	Definition
Vehicle type	The common language description of the vehicle (e.g. truck, crane, truck and dog, low loader, load platform, B-double, etc.), closely aligned to a vehicle classification scheme.
Virtual Weigh in Motion *(vWiM)*	Virtual Weigh-in-Motion (vWiM) is an emerging concept targeted at providing enhanced evidence about the heavy vehicles that access the road network to support access and planning decisions by (i) providing 'virtual' WiM data and related information at locations without a WiM station, and (ii) enhancing the credibility and application of heavy vehicle data by merging data subsets from different technologies to provide a richer picture of heavy vehicle journeys and vehicle characteristics.

Figure A.1: Austroads vehicle classifications with Austroads class 6+ vehicles identified

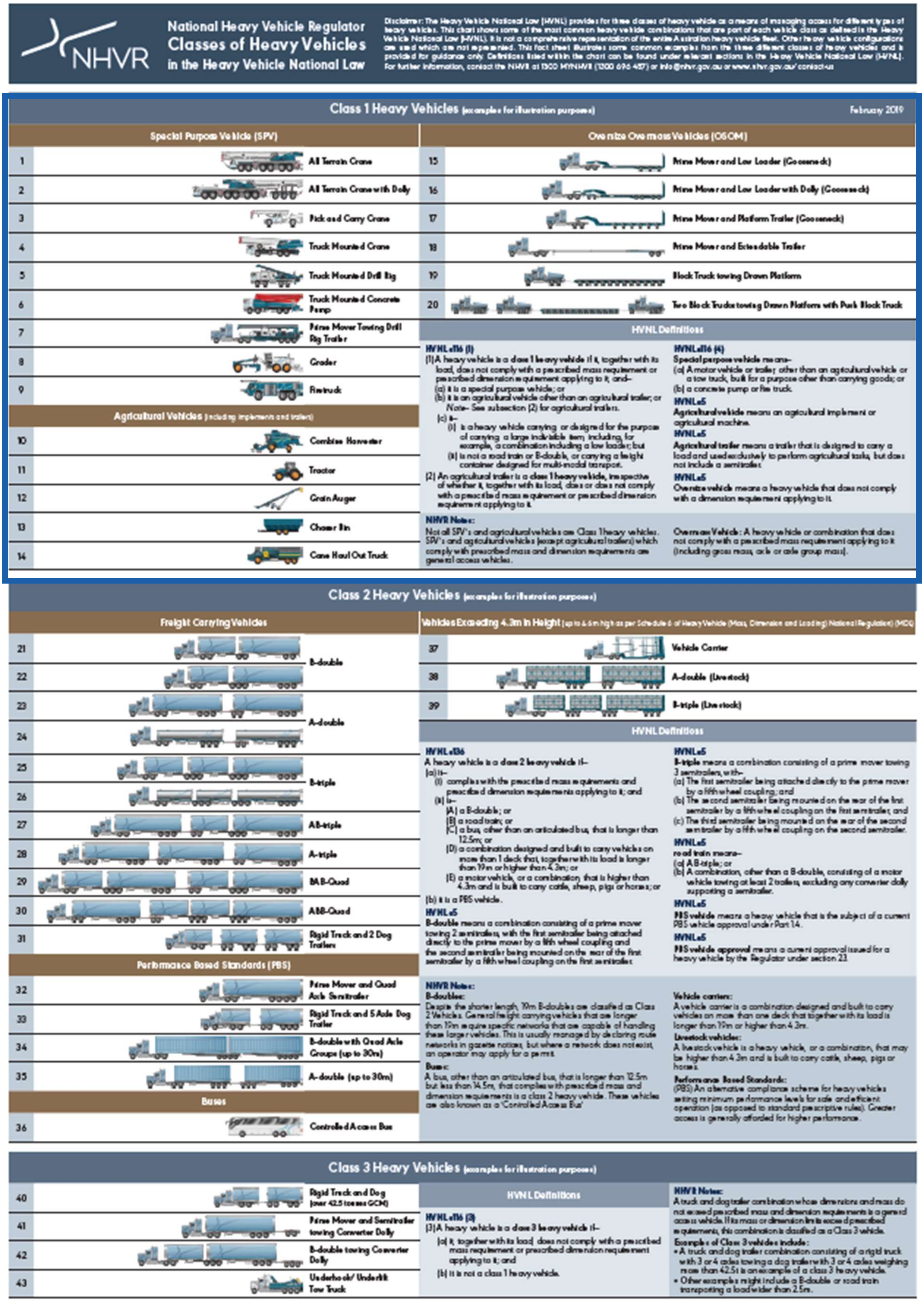


Appendix A – AUSTROADS '94 Vehicle Classification System

Level 1 Length (indicative)	Level 2 Axles and Axle Groups		Level 3 Vehicle Type	AUSTROADS Classification		
Type	Axles	Groups	Description	Class	Parameters	Dominant Vehicle
Short Up to 5.5m	LIGHT VEHICLES					
		1 or 2	**Short** Sedan, Wagon, 4WD, Utility, Light Van, Bicycle, Motorcycle, etc.	1	d(1) <= 3.2m and axles = 2	
Medium 5.5 to 14.5 m	3, 4 or 5	3	**Short – Towing** Trailer, Caravan, Boat, etc.	2	groups = 3, d(1)>= 2.1m, d(1) <= 3.2 m, d(2) >= 2.1m and axles = 3, 4 or 5	
	HEAVY VEHICLES					
	2	2	**Two Axle Truck or Bus**	3	d(1) > 3.2m and axles = 2	
	3	2	**Three Axle Truck or Bus**	4	axles = 3 and groups = 2	
	>3	2	**Four Axle Truck**	5	axles > 3 and groups = 2	
Long 11.5 to 19.0 m	3	3	**Three Axle Articulated** Three axle articulated vehicle, or Rigid vehicle and trailer	6	d(1) > 3.2m, axles = 3 and groups = 3	
	4	>2	**Four Axle Articulated** Four axle articulated vehicle, or Rigid vehicle and trailer	7	d(2) < 2.1m or d(1) < 2.1m or d(1) > 3.2 m, axles = 4 and groups > 2	
	5	>2	**Five Axle Articulated** Five axle articulated vehicle, or Rigid vehicle and trailer	8	d(2) < 2.1m or d(1) < 2.1m or d(1) > 3.2 m, axles = 5 and groups > 2	
	>=6	>2	**Six Axle Articulated** Six (or more) axle articulated vehicle, or Rigid vehicle and trailer	9	axles = 6 and groups > 2 or axles > 6 and groups = 3	
Medium Combination 17.5 to 36.5 m	>6	4	**B-Double** B-Double, or Heavy truck and trailer	10	groups = 4 and axles > 6	
	>6	5 or 6	**Double Road Train** Double Road Train, or Heavy truck and two trailers	11	groups = 5 or 6 and axles > 6	
Long Combination Over 33.0 m			**Triple Road Train** Triple Road Train, or Heavy truck and three trailers	12	groups > 6 and axles > 6	

Source: Austroads (2000).

Figure A.2: HVNL vehicle classifications with class 1 vehicles identified



Source: NHVR (2019).

A.2 Acronyms

Acronym	Definition
ANPR	Automatic number plate recognition
ARRB	Australian Road Research Board
ATO	Authority to operate
CDF	Cumulative distribution function
GAF	Gateway Arterial Flyover
GCM	Gross combination mass (applies to combinations of vehicles and trailers but often, and in this report, used interchangeably with GVM)
GCW	Ground contact width
GPS	Global Positioning System
GVM	Gross vehicle mass (applies to heavy vehicles without trailers but often, and in this report, used interchangeably with GCM)
HVNL	Heavy Vehicle National Laws
IAP	Intelligent Access Program The IAP is a national program developed in partnership with all Australian road agencies. It allows participating operators access, or improved access, to the road network in return for IAP monitoring and compliance with access conditions imposed by road agencies or road managers. Heavy vehicles are monitored using telematics services with an in-vehicle unit (IVU). The IVU is supplied and operated by an IAP service provider. IVUs use satellite tracking and wireless communication technology to remotely monitor where, when and how heavy vehicles are being operated on the road network. Source: NHVR (2021).
NACOE	National Asset Centre of Excellence
OBM	On-board mass monitoring
OSOM	Over size and over mass
PDF	Probability distribution function
TETS	Traffic Engineering, Technology and Systems
TMR	Queensland Department of Transport and Main Roads
vWiM	Virtual weigh in motion
WiM	Weigh in motion

A.3 Mathematical Symbols

Mathematical symbol	Definition
$>$	Greater than
$\geq$	Greater than or equal to
$<$	Less than
$\leq$	Less than or equal to
$\pm$	Plus or minus
$=$	Equal to
$\sum$	Sum of
$\sqrt{}$	Square root
^{2}	Squared
max(x)	Maximum of dataset *x*
$\lvert(x)\rvert$	Absolute value of dataset *x*
F(x)	Cumulative distribution of dataset x

Appendix B Project S26 Dataset

B.1 Context

TMR collects traffic data for a range of purposes, including understanding the heavy vehicle usage of the network. Several data collection technologies are used by TMR including WiM, classifiers, ANPR cameras and permanent weighbridges. TMR's data collection network has developed in tandem with technological improvements, with much of their data centrally stored and managed. Access to this data is tightly controlled for a range of reasons, including the privacy of road users, with TMR carefully considering the data usage before providing access. Activities associated with the TMR Gateway Arterial Flyover (GAF) project – focused specifically on bridge protection – led to modifications to data processing algorithms which exposed a new dataset of oversize overmass (OSOM) vehicles enabling the systematic analysis and understanding of these vehicles which had not been possible historically. The project was provided access to the improved dataset for the purposes of its investigations into vWiM for the vehicles of interest.

B.2 Objective

The objective of this section is to define the datasets used in this project to inform the investigation of the vehicles of interest.

B.3 Methodology

Using the updated WiM algorithm developed during the GAF project, approximately 1 year of raw WiM data was analysed for a limited number of sites.

B.4 Data Review

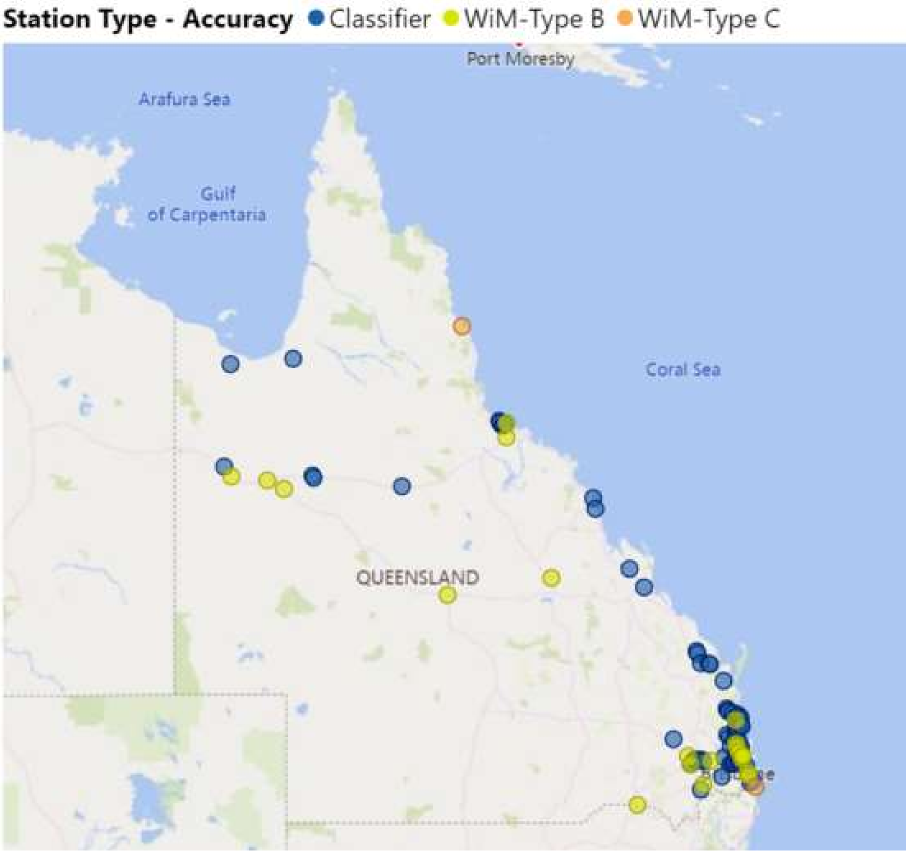
B.4.1 Data Source (WiM and Classifier)

The project sourced input from both WiM and classifier data collected over the period from 01/01/19 to 09/02/2020. Across the Queensland network TMR has 60 WiM installations and 126 networked classifier installations. For the purposes of this project data was acquired from:

- 23 WiM installations
- 97 networked classifier installations.

The locations of the WiM and classifiers are indicated on Figure B.1. Data from this asset base is continually uploaded into a TMR database, which formed a key input to the project.

Figure B.1: Locations of TMR WiM and classifier sites used by the project[16]



TMR WiM stations are comprised of a combination of Culway WiM stations and piezometer technologies, and are classified as Class A, Class B and Class C based on their accuracy as shown in Table B.1. An additional category, Class D, defines WiM stations which fall outside of the Class A, B or C accuracy levels. The project only utilised data from Class C or higher WiM sites, to ensure the accuracy of its derived analyses. The accuracy class of each WiM site used in this project is shown in Table B.2. Accuracy specifications for classifiers, as specified in MRTS251, are shown in Table B.3, with details on each classifier used in the project in Table B.4.

Table B.1: TMR WiM accuracy types

Function	Accuracy Tolerance		
	Class A	Class B	Class C
Single axles	± 15%	± 20%	± 30%
Axle groups	± 10%	± 15%	± 20%
Gross vehicle mass	± 6%	± 10%	± 15%
Speed	± 2 km/h		
Axle spacing	± 15 mm		

Source: MRTS203 (TMR 2020b).

[16] The Kuranda Rainforest Station is identified as a Class C WiM site however, due to issues with data quality, is treated for the purposes of the project as a classifier.

Table B.2: TMR WiM sites and accuracy

Location	Road name	Road section ID	Class 6+ records	Vehicles of interest	Latitude	Longitude	Device	Accuracy class
WiM Site Barcaldine	Landsborough Highway (Barcaldine – Longreach)	13E	33,190	1,589	−23.6	145.3	Mikros	B
WiM Site Belmont (north)	Gateway Motorway (Eight Mile Plains – Nudgee)	N239	1,216,621	17,500	−27.5	153.1	Mikros	B
WiM Site Belmont (south)	Gateway Motorway (Eight Mile Plains – Nudgee)	N239	1,207,279	18,705	−27.5	153.1	Mikros	B
WiM Site Boggabilla	Newell Hwy – (NSW)	-	178,250	2,941	−28.6	150.3	Mikros	B
WiM Site Burpengary	Bruce Highway (Brisbane – Gympie)	10A	85,160	1,923	−27.1	153.0	Excel	B
WiM Site Calcium	Flinders Highway (Townsville – Charters Towers)	14A	20,956	647	−19.6	146.8	Culway	B
WiM Site Capella	Gregory Highway (Emerald – Clermont)	27B	27,879	820	−23.1	148.0	Culway	B
WiM Site Cloncurry	Barkly Highway (Cloncurry – Mt Isa)	15A	55,153	1,087	−20.7	140.4	Culway	B
WiM Site Freestone	Cunningham Highway (Ipswich – Warwick)	17B	286,499	1,979	−28.1	152.1	Excel	B
WiM Site Gatton	Warrego Highway (Ipswich – Toowoomba)	18A	587,346	8,963	−27.5	152.3	Mikros/ Culway	B
WiM Site Hemmant	Port of Brisbane Motorway	U27	655,853	8,582	−27.4	153.1	HI-TRAC	B
WiM Site Hotham Ck southbound	Pacific Highway (Pacific Motorway)	12A	34,584	907	−27.8	153.3	Mikros	B
WiM Site Lytton	Port of Brisbane Motorway	U27	242,289	3,425	−27.4	153.2	HI-TRAC	B
WiM Site Middle Creek	Landsborough Highway (Kynuna – Cloncurry)	13H	2,003	32	−20.9	140.9	Culway	B
WiM Site Mt Isa	Barkly Highway (Mt Isa – Camooweal)	15B	30,504	751	−20.6	139.5	Culway	B
WiM Site Narangba	Bruce Highway (Brisbane – Gympie)	10A	222,724	4,414	−27.2	153.0	Excel	B
WiM Site Nudgee	Gateway Arterial Road (Gateway Motorway – north)	U13C	1,501,235	33,116	−27.3	153.1	Mikros/ Excel	B
WiM Site Oakey	Warrego Highway (Toowoomba – Dalby)	18B	260,264	4,866	−27.4	151.7	Culway	B
WiM Site Oxenford northbound	Pacific Highway (Pacific Motorway)	12A	318,857	5,704	−27.9	153.3	Mikros	B
WiM Site Southbrook	Gore Highway (Toowoomba-Millmerran)	28A	157,815	1,615	−27.6	151.8	Culway	B
WiM Site Townsville Port Access Road	Townsville Port Road	841	91,013	124	−19.3	146.8	Excel	B
WiM Site Tugun	Pacific Highway (Pacific Motorway)	12A	444,516	6,050	−28.2	153.5	Culway/ HI-TRAC	C
WiM Site Yandina Bypass	Bruce Highway (Brisbane – Gympie)	10A	470,639	7,841	−26.6	153.0	Mikros	B

Table B.3: TMR classifier accuracy

Function	Accuracy tolerance
Traffic volume	± 2%
Traffic classification accuracy	> 95%
Axle spacing	Not specified
Speed	Not specified

Source: MRTS251.

Table B.4: TMR classifier sites

Location	Road name	Road section ID	Class 6+ records	Vehicles of interest	Latitude	Longitude
1.77 km north of Kalbar Connection Rd	Cunningham Highway (Ipswich – Warwick)	17B	307,326	2,103	−27.9	152.6
100 m Mt Cotton/Golden Cockeral Access	Mount Cotton Road	111	18,516	575	−27.6	153.2
10A – 2.13 km north of Johnstone Rd Int	Bruce Highway (Brisbane – Gympie)	10A	476,605	6,824	−26.9	153.0
10A – 500 m north of Diddillibah Rd O'Pass	Bruce Highway (Brisbane – Gympie)	10A	225,748	3,596	−26.7	153.0
10A – 500 m south of Old Bruce Highway Int	Bruce Highway (Brisbane – Gympie)	10A	495,526	4,324	−26.4	152.9
10A – 650 m south of Parklands Interchange	Bruce Highway (Brisbane – Gympie)	10A	547,138	7,384	−26.6	153.0
10A – 700 m north of Plantation Rd Overpass	Bruce Highway (Brisbane – Gympie)	10A	1,199,139	21,097	−27.2	153.0
10A – 750 m north of Yandina Crk Overpass	Bruce Highway (Brisbane – Gympie)	10A	346,182	4,448	−26.5	153.0
10A – PTC 1 km north of Dohles Rocks Road	Bruce Highway (Brisbane – Gympie)	10A	629,710	11,792	−27.3	153.0
10A – South of Dohles Rocks Road	Bruce Highway (Brisbane – Gympie)	10A	302,401	5,821	−27.3	153.0
10M 1.47 km north-west of Veales Rd	Bruce Highway (Townsville – Ingham)	10M	170,583	3,089	−19.2	146.6
10M 250 m east Mark Reid Dr adj VMS	Bruce Highway (Townsville – Ingham)	10M	222,145	4,775	−19.3	146.8
10M RR4 north of Kalynda Parade	Bruce Highway (Townsville – Ingham)	10M	38,068	964	−19.3	146.7
120 – PTC 70 m east of Saunders St	Redcliffe Road	120	78,171	3,647	−27.3	153.0
121 – PTC 200 m north of Coman Rd	Deception Bay Road	121	14,810	593	−27.2	153.0
121 – PTC 200 m south of Coman Rd	Deception Bay Road	121	14,810	593	−27.2	153.0
122-Near south abut.Houghton Hway brdgePTC	Brighton – Redcliffe Road	122	14,498	1,261	−27.3	153.1
122 – 200 m south of Klinger Rd	Brighton – Redcliffe Road	122	1,440	103	−27.2	153.1
126 – 270 m east of Browns Rd/Volz Rd	Caboolture – Bribie Island Road	126	20,888	398	−27.1	153.1

Location	Road name	Road section ID	Class 6+ records	Vehicles of interest	Latitude	Longitude
130 – 150 m east of Crusher Park Dr	Nambour – Bli Bli Road	130	18,136	404	−26.6	153.0
130 – 350 m east of Cooney Road	Nambour – Bli Bli Road	130	25,293	2,272	−26.6	153.0
133 – 150 m north of Clarkes Rd	Maroochydore – Noosa Road	133	6,283	299	−26.6	153.0
133 – 250 m north of Yandina Coolum Road	Maroochydore – Noosa Road	133	2,895	17	−26.5	153.1
133 – PTC 320 m north of Runway Drive	Maroochydore – Noosa Road	133	3,122	227	−26.6	153.1
134 – 30 m west of Short Street	Mooloolaba Road	134	574	22	−26.7	153.1
136 – 500 m west of Sunshine Motorway	Maroochydore Road	136	32,894	882	−26.7	153.1
140 – 250 m west of Emu Mountain Rd	Eumundi – Noosa Road	140	18,053	795	−26.4	153.0
14C Ch 17.22 – West Hughenden	Flinders Highway (Hughenden – Richmond)	14C	226,985	52	−20.9	144.0
14E Ch 6.33 - 2.7 km west of Int 14E/78A	Flinders Highway (Julia Creek – Cloncurry)	14E	17,817	185	−20.7	141.7
150B – 150 m north of 150A Overpass	Sunshine Motorway (Mooloolaba – Peregian)	150B	14,789	236	−26.7	153.1
150B – 740 m north of Maroochy Blvd	Sunshine Motorway (Mooloolaba – Peregian)	150B	51,005	991	−26.7	153.1
150B – Under Havana Rd Foot Bridge	Sunshine Motorway (Mooloolaba – Peregian)	150B	11,675	142	−26.5	153.1
150B – Under West Coolum Rd Overpass	Sunshine Motorway (Mooloolaba – Peregian)	150B	35,778	331	−26.6	153.1
153 – 200 m north of Waterview Street	Nicklin Way	153	5,833	103	−26.7	153.1
15B Ch 50.9 km (west of Gunpowder Int)	Barkly Highway (Mt Isa Camooweal)	15B	418,112	180	−20.4	139.3
17A west of Church St Ramps Goodna MIM764	Cunningham Highway (Ipswich Motorway)	17A	4,476	52	−27.6	152.9
17B – 20 m east of Acacia Ave (PS) Loop/Piezo	Cunningham Highway (Ipswich – Warwick)	17B	134,599	1,413	−28.2	152.0
17B – South of Barclay St Overpass PTC	Cunningham Highway (Ipswich – Warwick)	17B	348,540	8,854	−27.6	152.8
180 m West of Macgregor Street	Griffith Arterial Road	U20	354,036	4,885	−27.6	153.1
18A-E-CAB-01 (VDC-L01-L08-P01-P04)	Warrego Highway (Ipswich – Toowoomba)	18A	318,896	4,739	−27.5	152.1
18B-W-CAB-17-L04-P02_Lanes 2 & 4	Toowoomba Second Range Crossing (Warrego Highway)	319A	124,452	2,339	−27.5	151.9
220 m south of Slatyer Av & Thomas Dr	Southport – Burleigh Road	103	6,334	104	−28.0	153.4
280 m north Worongary Creek VCS13	Pacific Highway (Pacific Motorway)	12A	693,425	7,978	−28.1	153.4
30 m east of Estoril St intersection	Griffith Arterial Road	U20	244,281	2,682	−27.6	153.1
319A-C-CAB-04 (VDC-L01-L08-P01-P04)	Toowoomba Second Range Crossing (Warrego Highway)	319A	241,543	3,621	−27.5	152.0
319A-C-CAB-05 (VDC-L01-L08-P01-P04)	Toowoomba Second Range Crossing (Warrego Highway)	319A	64,962	748	−27.5	151.9
319A-C-CAB-11 (VDC-L01-L08-P01-P04)	Toowoomba Second Range Crossing (Warrego Highway)	319A	253,869	4,244	−27.5	151.9
319A-C-CAB-13 (VDC-L01-L08-P01-P04)	Toowoomba Second Range Crossing (Warrego Highway)	319A	225,062	3,503	−27.5	151.9
319B-W-CAB-01 (VDC-L01-L04-P01-P02)	Toowoomba Second Range Crossing (Gore Highway)	319B	128,940	1,510	−27.5	151.8

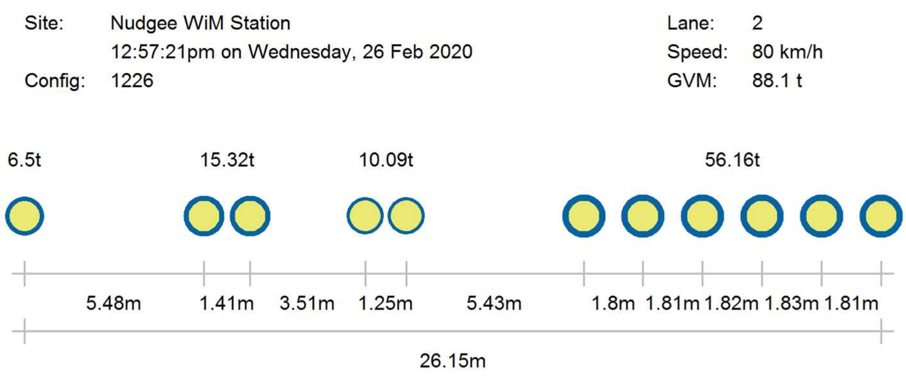
Location	Road name	Road section ID	Class 6+ records	Vehicles of interest	Latitude	Longitude
319B-W-CAB-04 (VDC-L01-L04-P01-P02)	Toowoomba Second Range Crossing (Gore Highway)	319B	91,668	1,248	−27.6	151.8
401 – 150 m south of Kremzow Rd	Brisbane – Woodford Road	401	83,574	1,426	−27.3	153.0
401 – PTC at Terrors Creek Dayboro	Brisbane – Woodford Road	401	5,652	743	−27.2	152.8
40A – 200 m east of Mason Rd	D'Aguilar Highway (Caboolture – Kilcoy)	40A	15,339	229	−27.0	152.8
40A – 200 m west of Smith Rd O'Pass PTC	D'Aguilar Highway (Caboolture – Kilcoy)	40A	151,439	3,584	−27.1	152.9
40A – 2 km west of Kilcoy-Beerwah Road	D'Aguilar Highway (Caboolture – Kilcoy)	40A	34,154	640	−26.9	152.7
42A – 50 m north of Beeston Dr	Brisbane Valley Highway (Ipswich-Harlin)	42A	65,009	1,236	−27.5	152.7
45A (N) @ Kaths Rd/Pirrinuan Malakoff Rd	Bruce Highway (Dalby – Kingaroy)	45A	241,543	3,621	−27.0	151.3
45A (S) @ Pirrinuan Malakoff Rd/Kaths Rd	Bruce Highway (Dalby – Kingaroy)	45A	318,896	4,739	−27.0	151.3
489 – 90 m north of Keil Mountain O'Pass	Nambour Connection Road	489	11,881	394	−26.7	153.0
490 – 500 m south of Big Kart Track Entry	Glasshouse Mountains Road	490	27,445	689	−26.8	153.0
490 – 300 m north of Mooloolah Connection Rd	Glasshouse Mountains Road	490	34,824	889	−26.8	153.0
492 – 50 m East of Blackbutt St	Kilcoy – Beerwah Road	492	13,662	243	−26.9	153.0
500M south of Sandgate Road	Gateway Arterial Road (Gateway Motorway – North)	U13C	141,266	2,926	−27.3	153.1
5807 Ch 4.88 km – south of Julia Creek	Julia Creek – Kynuna Road	5807	1,580,575	307	−20.7	141.7
78A Ch 488.064 – 12 km south of Bourketown	Wills Dev Road (Julia Creek-Burketown)	78A	974	42	−17.8	139.5
78A Ch 9.0 – north of Julia Creek	Wills Dev Road (Julia Creek-Burketown)	78A	114,689	9	−20.6	141.7
835 100 m south of Illuta St	Garbutt – Upper Ross Road	835	7,503	644	−19.4	146.7
89A Ch 371.26 – 200 m south of Int 89A/92A	Burke Dev Road (Cloncurry – Normanton)	89A	95	0	−17.7	141.0
89B Ch 7.23 500 m north of Melville Creek	Burke Dev Road (Normanton – Dimbulah)	89B	2,599	92	−17.7	141.1
900 – PTC 200 m south of Keong Road	Everton Park – Albany Creek Road	900	40,700	1,117	−27.4	153.0
Adjacent Apple Tree Ck RA T/dist 62.31	Bruce Highway (Maryborough – Gin Gin)	10C	209,329	2,423	−25.2	152.2
Adjacent to Jervis St	Cunningham Arterial Road (Ipswich Motorway)	U16	186,461	2,315	−27.6	152.9
At Booyal School T/dist 84.855	Bruce Highway (Maryborough – Gin Gin)	10C	270,165	3,676	−25.2	152.0
At Coles Creek – Bruce Hwy (Motorway)	Bruce Highway (Brisbane – Gympie)	10A	45,168	310	−26.4	152.8
Bruce Hwy 100 m south Knight St	Bruce Highway (Rockhampton-St Lawrence)	10F	24,482	416	−23.4	150.5
Bruce Hwy 40 m south Mountain Ck (Kunwarara)	Bruce Highway (Rockhampton-St Lawrence)	10F	72,388	1,160	−22.9	150.1
Cathedral School	Ross River Road	612	4,245	144	−19.3	146.8
Childers Rail Xing T/dist 56.00	Bruce Highway (Maryborough – Gin Gin)	10C	269,582	2,708	−25.2	152.3
City Gates to Lagoon Street	Bruce Highway (St. Lawrence – Mackay)	10G	208,279	2,887	−21.2	149.2

Location	Road name	Road section ID	Class 6+ records	Vehicles of interest	Latitude	Longitude
Kuranda Rainforest station	Kennedy Highway (Cairns – Mareeba)	32A	37,976	637	−16.8	145.7
Kybong Ck to Cobb's Gully FC12	Bruce Highway (Brisbane – Gympie)	10A	463,498	3,877	−26.3	152.7
North of Jensens Road T/dist 9.562	Bruce Highway (Gin Gin – Benaraby)	10D	517	3	−24.9	151.9
On Ramp to 319-C-CAB-15-L04-P02	Toowoomba Second Range Crossing (Warrego Highway)	319A	31,250	529	−27.5	151.9
Pac Mway south side Paradise Rd overpass	Pacific Highway (Pacific Motorway)	12A	647,984	9,926	−27.6	153.1
Pine River Bridge	Gympie Arterial Road	U14	302,401	5,821	−27.3	153.0
Rd 10A – Between Cooroy Int and Old 10A	Bruce Highway (Brisbane – Gympie)	10A	507,630	4,894	−26.4	152.8
Riawena	Griffith Arterial Road	U20	413,649	6,062	−27.6	153.0
Sichter Street – Broad Street	Bruce Highway (St. Lawrence – Mackay)	10G	210,718	3,808	−21.4	149.2
South of Progress Rd on Ipswich Motorway	Cunningham Arterial Road (Ipswich Motorway)	U16	582,247	10,234	−27.6	152.9
South of Roadtek Depot Gin Gin T/dist2.012	Bruce Highway (Gin Gin – Benaraby)	10D	56,383	679	−25.0	151.9
South side Glenorchy Straight T/dist 72.22	Bruce Highway (Gympie – Maryborough)	10B	128,914	1,189	−25.6	152.6
Strathpine/Gympie Rd/School Entrance	Brisbane – Woodford Road	401	83,574	1,426	−27.3	153.0
U13C 250 m south of Wyampa Road	Gateway Arterial Road (Gateway Motorway – North)	U13C	744,447	12,743	−27.3	153.0
U13C Gateway Motorway north	Gateway Arterial Road (Gateway Motorway – North)	U13C	4,032	37	−27.4	153.1
U13C north of Barrett St Ped Overpass	Gateway Arterial Road (Gateway Motorway – North)	U13C	923,038	14,877	−27.3	153.1
U21 – 20 m north of Cemetery Entrance	Nathan Connection Arterial Road	U21	19,887	292	−27.6	153.1
West of Gateway Mwy at Wishart	Redland Sub-Arterial Road	U91	306,808	4,883	−27.5	153.1

B.4.2 Data Characteristics

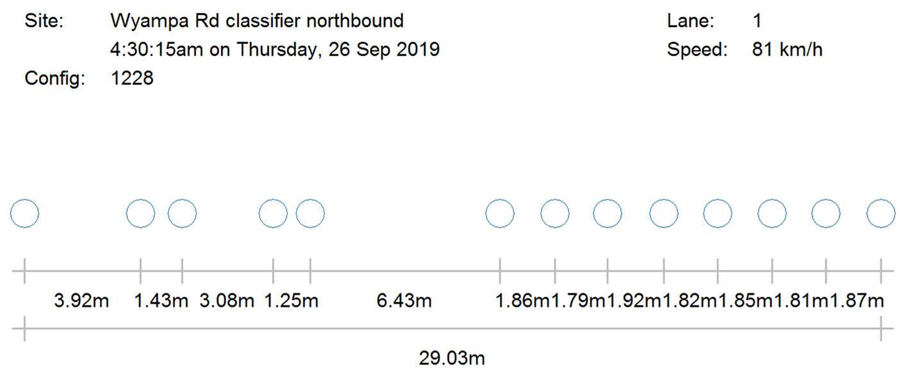
The data in a WiM record includes site location, date and time stamp, lane number, configuration, axle group masses, GVM, speed and axle spacings. An example of a typical WiM record is graphically illustrated in Figure B.2, where the colour on the axle wheel indicates a mass recorded and line thickness represents the relative magnitude of the mass for the axle (distributed evenly within the group).

Figure B.2: Graphical representation of typical WiM record



Classifier records are identical to the WiM records except for the mass data (axle group mass and GVM) as illustrated graphically in Figure B.3.

Figure B.3: Graphical representation of typical classifier record



B.4.3 Data Summary

The supplied data from TMR databases included WiM and classifier records for all Austroads class 6+ vehicles, as summarised in Table B.5. The project used an algorithm to extract the records of low loaders and load platforms from the Class 6+ dataset based upon the record's axle geometry, as described in Appendix N of Eskew et al. (2021). The algorithm also included an axle spacing tolerance of ± 0.2 m to allow for the measurement accuracy range, per TMR's procedures based upon observations. Axle masses were not included in the selection criteria, as they are only measured at the WiM sites. The low loaders and load platforms identified by the project represented approximately 2% of all heavy vehicle records in the Austroads class 6+ dataset.

Table B.5: Summary of low loaders and load platform data

Parameter		Information
Sites		22 Class B WiM stations 1 Class C WiM station 97 classifier stations
Date range		01/01/19 – 09/02/20
Austroads class 6+ vehicle data	Total supplied data	27,025,531 records
	Total target data	393,552 low loader and load platform records

Records of heavy mobile cranes (cranes with four or more axles) were extracted from the raw WiM and classifier data using a similar algorithm to the one used for the low loads and load platforms, further described in Appendix O of Eskew et al. (2021), which identifies the rules used to interrogate the dataset based on the vehicle type. Filter criteria were developed for the 83 crane models found in the Intelligent Access Program (IAP) crane register using their unique axle spacings based on manufacturers' specifications. It was determined that several 4 axle twin-steer rigid trucks were identified as cranes due to similarities in their axle spacing and configurations (models TADANO GT550/E-1 and GT550/E-2, LINKBELT HTC86100, GROVE TMS9000E, and KATO NK500, NK550 and SL-700R). These crane models were filtered out of the crane dataset to limit the pollution of the results caused by the twin-steer rigid truck records. Crane data used in this project is summarised in Table B.6.

Table B.6: Summary of selected (crane) data

Parameter	Information
WiM sites	Belmont (south) Belmont (north) Nudgee Hemmant
Date range	01/01/19 – 09/02/20
Total crane data	2,860 crane records

B.4.4 Data Quality

Issues with raw data

A review of the data revealed that the vehicle records found at the classifier site 5807 Ch 4.88 km – south of Julia Creek contained records which were implausible, configurations which do not exist. The data from this site is known within TMR to be of lower quality. The data from this site is excluded in parts of the analysis to improve confidence in the results.

While issues were noted with individual records, most of the records from the remaining sites were deemed plausible for the low loader and load platform dataset. The approach used to identify vehicles of interest (based on axle spacing alone) may result in some vehicles being identified incorrectly. Further discussion on misidentification of vehicles can be found in Section 4.2 and Appendix K 4.2 in Eskew et al (2021).

Changing configurations

During the project, it was noted that some models of vehicles within the vehicles of interest have the capacity to change their configuration by hydraulically lifting axles. This would change the recorded configuration at the WiM or classifier sites, making identification of the vehicles difficult and causing ambiguity on the impact of these vehicles on the roadway.

Appendix C SWOT Analysis of vWiM

A SWOT (Strengths, Weaknesses, Opportunities and Threats) analysis was performed by Eskew et al. (2021) to assess the potential for vWiM for TMR. The results are summarised in Figure C.1.

Figure C.1: vWiM SWOT analysis

Strengths

- Uses existing infrastructure for data capture and storage
- TMR has used a consistent WiM and classifier data capture procedure over time.
- Steer axle mass of articulated vehicles are relatively constant with time providing a basis for benchmarking and assessing confidence in data quality.
- Growing appetite among stakeholders for access to data to improve and support decisions.
- Cost of data collection and storage is decreasing over time due to emerging technology.
- Improved confidence in the data can be generated through better understanding.
- Meaning can be extracted from multiple data lenses focussed data on specific questions.

Weaknesses

- Gaps in understanding due to key parameters that are currently not monitored::
  - Ground contact width (which affects permitted mass)
  - Records from vehicles occupying multiple lanes
  - Records from vehicles with wheels in the shoulder or median (off sensors)
- Data is not currently collected or presented with a decision support focus
- Uncertainty in the data
- Size of the datasets (can present challenges to the effective combination and analysis of data)
- Poor track record going from insight to action – need for better demonstration of value propositions
- Current allocations of operational and intelligence expenditure (OPEX and INTELLIGEX) are rarely adequate to support the optimal management of the data assets in the long term

Opportunities

- Large amounts of historical data collected with a consistent data capture procedure allow new methods to be applied to historical data with little additional effort.
- Ability to interrogating individual events using multiple data sources, leverage value in understanding important questions around compliance to help optimise management of the network.
- Active control of loads (providing the feedback loop for access management decisions).
- Data driven decision making.
- Culture of credible collaboration with industry based upon knowledge of risks to assets.
- Augment TMR's existing data capture infrastructure to meet specific use case requirements, (for example installing a TIRTL to capture ground contact width and driveline to better understand wide load platforms and low loaders).
- Increased public visibility of their road network through data applications.

Threats

- Data quality and availability (need more data, more often, of a higher quality)
- Data literacy and awareness at an organisational level needs to be developed, this affects both awareness and understanding of opportunities and inherent limitations in datasets
- Need for a stronger more effective link between the data and the decisions it can support
- Legislative framing – many relevant datasets are protected under privacy laws which stand in the way of possible applications, privacy issues need to be resolved before many valuable applications can be developed
- As the reliance on data increases, data security and integrity becomes increasingly important

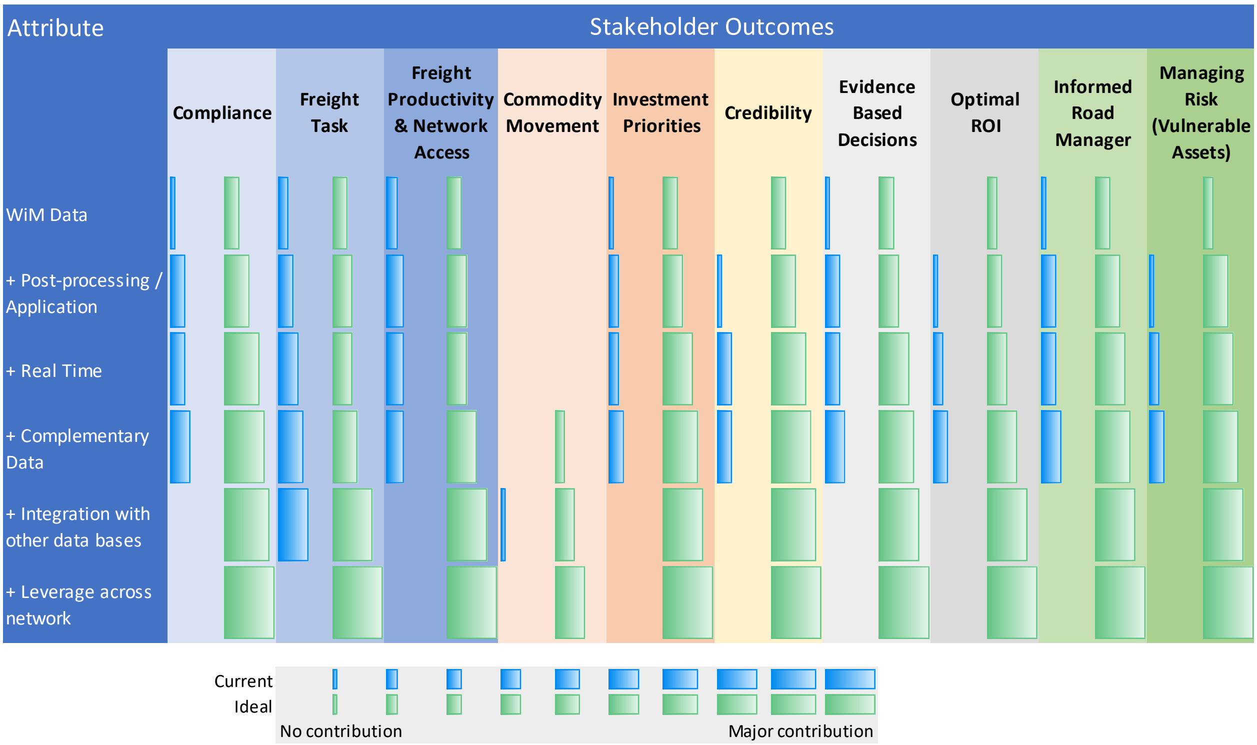
Appendix D Stakeholder Engagement

D.1 Overview

A major component in the second year of this project was to engage with TMR internal stakeholders to investigate the existing and potential use of WiM data. Through discussions with relevant stakeholders, the aim was to determine how WiM is currently used, as well as to explore additional potential uses and how those identified uses align with localised business requirements and TMR's broader organisational objectives and policies.

Analysis of the feedback has been used to identify perceived and actual gaps or deficiencies in the existing dataset, and the barriers that prevent more effective and widespread utilisation and application of the data, both in terms of functional and locational performance requirements. The feedback has been mapped to the desired business and stakeholder outcomes expressed both explicitly and implicitly throughout the engagement exercise. A trend map (Figure D.1) was developed to demonstrate the extent to which WiM data (and associated technologies) contribute to achieving these desired outcomes both now, using the existing available data, and in the future, assuming that the 'ideal' dataset identified by stakeholders is available. The methodology and findings from the stakeholder engagement are discussed in further detail below.

Figure D.1: Trend map of stakeholder outcomes



The findings from the stakeholder engagement have been used to document TMR's current (implicit) strategy for WiM and formed an input to the development of the draft *Strategic Asset Management Plan (SAMP)*. The methodology for stakeholder engagement included the following:

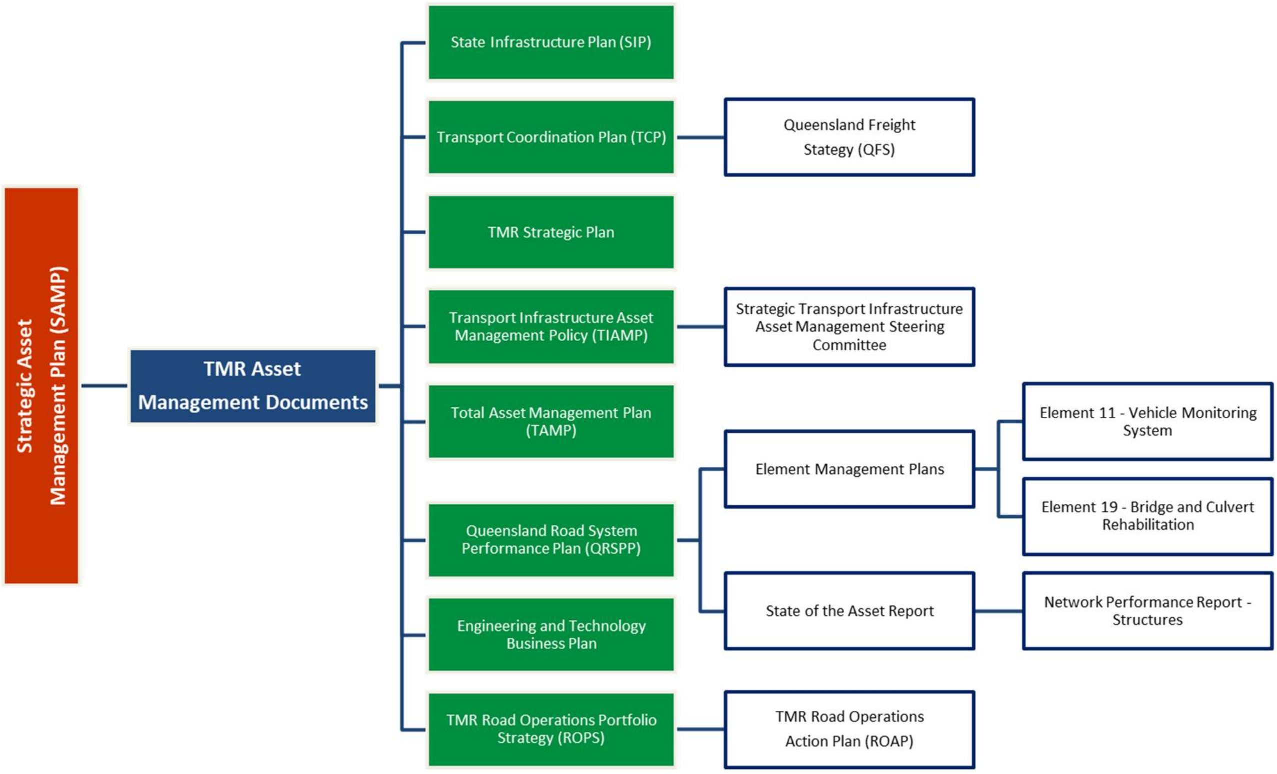
- review of existing TMR policy and strategy documentation to confirm the project context and alignment of a proposed draft WiM SAMP within the existing strategic framework (Appendix C of Heldt et al. 2019)
- initial stakeholder engagement to seek input and strategic alignment from the WiM managers within TMR (Road Operations) and to identify stakeholders for detailed follow up engagement

- detailed stakeholder engagement to seek to understand the existing and potential uses and values of WiM data to their business needs, and to identify the technical data requirements and barriers for effective implementation of the currently available data.

D.2 Initial Stakeholder Meeting with Road Operations

An initial stakeholder meeting was held with the Acting Manager of Road Operations, who is the manager of weigh-in motion (WiM) assets throughout the state. The purpose of this meeting was to present a summary of the review of TMR's strategic documentation (Appendix D and Figure D.2) to demonstrate the proposed alignment of the draft WiM SAMP with the existing *Road Operations Portfolio Strategy* and the *Road Operations Action Plan*, and to seek endorsement from Road Operations for the proposed draft WiM SAMP to form an input to these existing strategic documents.

Figure D.2: Core TMR policy/strategy document hierarchy



In addition, this meeting was intended to seek advice and confirmation regarding the proposed stakeholder engagement methodology, the general questions to be addressed and the specific individuals and functional areas within TMR that should be consulted during the detailed follow-up engagement.

D.2.1 WiM SAMP Alignment

Road Operations confirmed that the draft WiM SAMP should form an input to the *Road Operations Portfolio Strategy* and the *Road Operations Action Plan*. The Strategy describes the aspirational view of the road network to 2022 and beyond and the existing *Action Plan (2016–2018)* sets out the specific tactical initiatives to be addressed over the two years from 2016. This document was under review at the time of this investigation and there may be an opportunity to include the draft WiM SAMP in the next document revision.

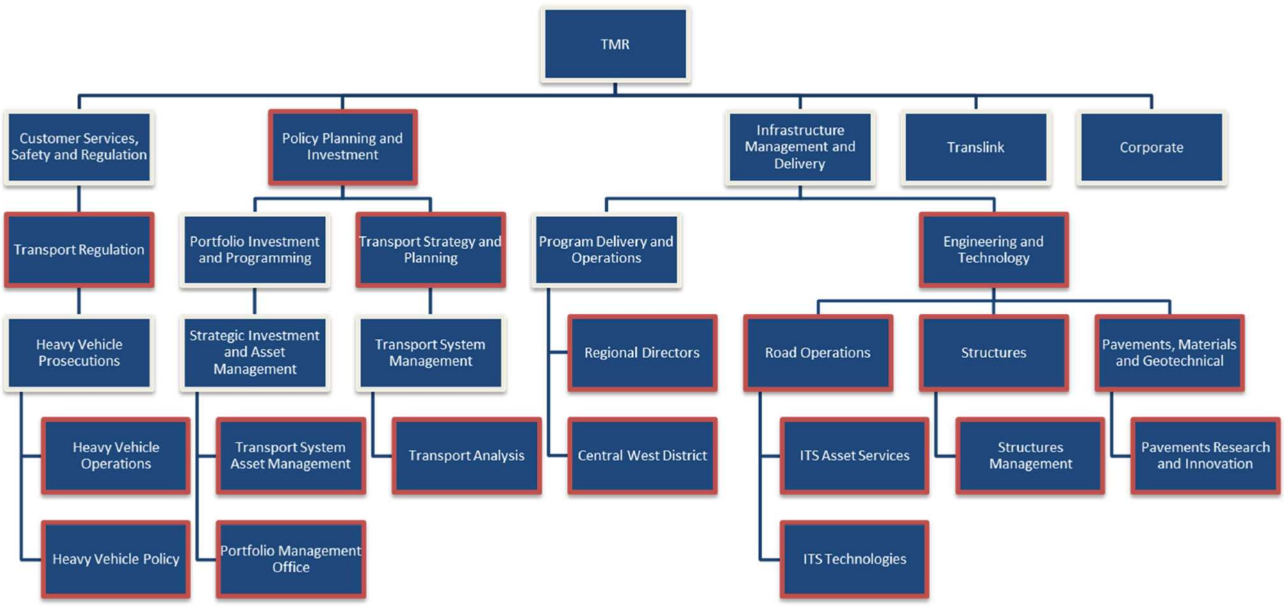
D.2.2 Stakeholder Identification

It is recognised that WiM data has varied existing and potential uses across TMR, and as such it was critical to ensure that development of a WiM data strategy included input from a broad range of users. Discussions with Road Operations identified that the broad functional areas that should provide input to development of the WiM strategy included:

- Engineering and Technology – Structures, Pavements and Road Operations
- Program Delivery and Operations – specifically District Director (Central West) who is the nominated Champion for Element 11 (Vehicle Monitoring System), as well as Regional Directors
- Transport Strategy and Planning – Transport Analysis
- Portfolio Investment and Programming – Strategic Investment and Asset Management
- Transport Regulation – Heavy Vehicles Operation and Policy.

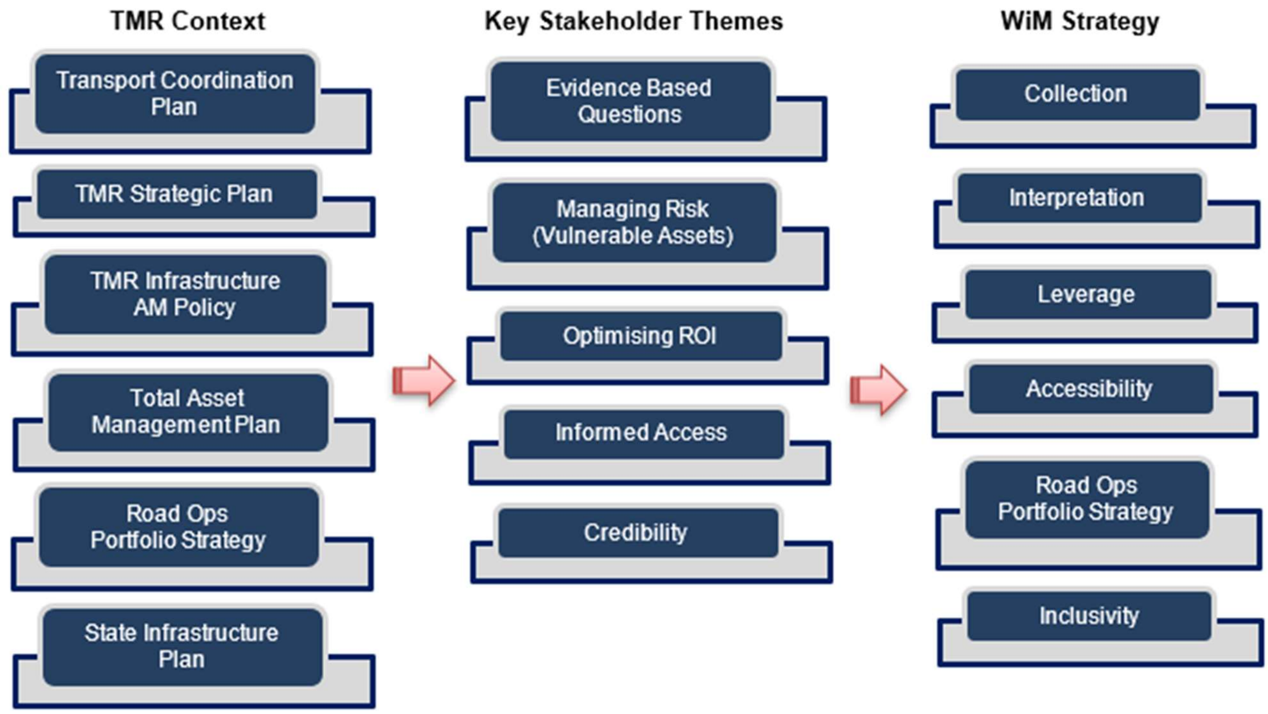
Within these areas, specific individuals were recommended by Road Operations for detailed consultation, based on current, previous or potential involvement with WiM data. In addition, throughout the course of the detailed stakeholder engagement, additional officers were suggested, who were included in the list of potential stakeholders and where possible, were also interviewed. Figure D.3 shows the relative positions of these personnel within TMR (highlighted with a red border). Note that this is not a complete organisational chart of TMR, but, is intended to show the relationships between the branches and units that were consulted, the extent of engagement across TMR and the various levels of management that have contributed to this review. Engagement included meetings with officers at various levels including: General Managers/Chief Engineer, Executive Directors/Deputy Chief Engineers, District Directors, Directors, Managers, Principal Engineers, Project Managers, and Principal & Senior Analysts.

Figure D.3: Relative positions of stakeholders engaged across TMR (highlighted with red border)



Key TMR context documents are summarised in Figure D.4, along with key stakeholder themes and proposed WiM strategy elements.

Figure D.4: WiM strategy development workflow



D.2.3 Development of Focus Questions for Detailed Stakeholder Engagement

A series of detailed questions were provided to Road Operations as the suggested basis for the detailed stakeholder engagement, including:

- Why do we collect WiM data?
- How is WiM data used to make/support decisions?
- What data/reports are available and how are they used?
- Who is utilising WiM data?
- Who could utilise WiM data?
- What data/reports could be valuable to you?
- Why don’t you/TMR utilise WiM data more?
- How would an absence of WiM data affect your business?
- Could linking WiM data with other databases and data analytics enhance value?
- What evidence do you require for infrastructure investment decision making?
- How do you manage risk within a constrained budget?
- Why is WiM data valuable to you and how is it valued?
- What would happen with x% more or less investment in WiM?

Imagine that in 10 years’ time, TMR is operating an evidence-based business. Then:

- What data would be required?
- How would it be used?
- What needs to happen now to get there?

After discussion with Road Operations, it was agreed that a concise set of five or six focus questions, a collation of the detailed questions stated above, would be preferable, and are as follows:

1. Imagine that in 10 years' time TMR is operating an evidence-based business where decisions need to be based on traceable data. Assuming no constraints – What HV data is important to your business? What do you really want to know and how would you use it? – ('Ideal')
2. What HV data are you using now? How do you use it? ('Current')
3. Is the 'current' only a subset of the 'ideal'? Why?
4. Would you be prepared to pay for the 'ideal' dataset? How much? How could it be funded?
5. How important is it to your business to move from the 'current' to the 'ideal' over the next 10 years?

D.3 Detailed Stakeholder Engagement Methodology

The detailed stakeholder engagement meetings included a brief overview of the project background and Year 1 findings, as well as a discussion outlining the review of TMR's strategic documentation and the proposal to develop a draft WiM SAMP to align with the existing *Road Operations Portfolio Strategy* and the *Road Operations Action Plan.* This was followed by a brainstorming session to explore the heavy vehicle data inputs to the relevant business area, based around the five focus questions summarised in Section D.2.3. Each stakeholder was also asked to comment on the range of stakeholders being consulted and advise whether they had any additional suggestions.

D.4 Stakeholder Engagement Findings

While the focus questions were intended to guide the discussions, in most cases, the discussion was allowed to flow freely in order to explore all issues that were relevant to the particular business area. The findings from the stakeholder engagement are presented as a summary of the general themes and issues that were raised rather than a definitive compilation of answers to the specific focus questions.

Road Operations provided detailed feedback regarding the available WiM data, and how it is intended to support decisions across TMR including: pavement design and maintenance, freight planning studies (to understand commodity movements and trends in mass on routes), monitoring of over mass vehicles to assist with compliance and analysis of the road network to support design life forecasts.

D.4.1 Answers to the Question WHY Do We Need WiM at All?

Group	Subgroup	Key response
Transport Regulation	Heavy Vehicle Policy	• Classifiers quantify types of vehicles and speed, and are cheap and mobile. WiM gives axle spacing and mass as well, ANPR can then identify specific vehicles. • OBM only provides data for participating vehicles but WiM will be able to provide data for vehicles that we don't know about. • It will also assist with categorising vehicles depending on the weight such as livestock vehicles and tankers. • WiM data could also help with validating Performance Based Standard (PBS) vehicles.
	Heavy Vehicle Operations	• Use some WiM data now, but coverage and content not adequate. Transport industry knows more about our asset usage than we do.
Portfolio Investment and Programming	Transport Systems Asset Management	• WiM is an enabler, not an asset in its own right which provides a service to the public. • WiM provides data to enable us to understand overloading. Need to optimise the use of heavy vehicles or WiM data but understand that we are in transition to sourcing data from alternative sources.
	Portfolio Management Office	• We have the methodology to use the data but not the data to use. • If we have the data and the reliability is good, then data-based decision making is possible.
Transport Strategy and Planning	Transport Analysis	• WiM is not currently operational or calibrated. • If it was fully operational, some of the possible data required include axle, mass, spacing and speed which would be used to generate bending moment, shear and pier reactions of a bridge. • Statistical variations can feed into live load factors.
Program Delivery and Operations	Central West District	• Reliable WiM data could assist operation of assets and help address known issues.
Engineering & Technology	Road Operations	• WiM data is collected to provide information on the makeup of the heavy vehicle fleet. • The information collected is at a vehicle by vehicle level and includes axle weights and spacings.
	Pavements Materials & Geotechnical	• WiM data would help to develop performance relationships for rutting and the diagnostics would assist with understanding of pavement behaviour. • It will also provide a greater understanding of pavement response to actual loading and the damage relationships would assist with the determination of potential additional capacity.
	Structures	• Don't currently use WiM data, and don't have established methodologies to do so, because it doesn't inform key parameters.

D.4.2 Ideal Dataset/Requirements

Group	Subgroup	Key response
Transport Regulation	Heavy Vehicle Policy and Heavy Vehicle Operations	• Ideal scenario is operating vehicles across full routes – manage truck routes by reducing need to break down vehicles – e.g. issue from Toowoomba to the Port • Knowing what vehicles are using a route and whether they comply with the route restrictions • Know what the routes are and what they've been approved for • Understanding which vehicles are interstate and which ones are intrastate • Mass of heavy vehicles which helps to categorise the vehicles e.g. live freight, tankers etc. • Need to know if it is a regulation vehicle or a permit vehicle
Portfolio Investment and Programming	Transport Systems Asset Management	• Need reliable information and need to communicate that the data is reliable. Also need data analytics to go with it. • Reliable link between the WiM data and the vehicle class/category/permit class which is currently missing • A network-wide view by using smaller number of calibrated WiM sites but expand/extrapolate to the wider network using vehicle classifiers

Group	Subgroup	Key response
		• Essentially, ideal dataset includes knowing every load, the distance it has travelled and origin/destination • Demonstrating a hard link between the load and performance • Short term goal is to increase the number of reliable WiM systems and achieve integration of information and systems
	Portfolio Management Office	• Vehicle classifiers • The number of vehicles that are over the limit
Transport Strategy and Planning	Transport Analysis	• Major freight routes for planning • Where are new commodities/crops being developed? • What type of vehicles are used for different commodities? Different commodities, e.g. livestock use different vehicle configuration to bulk commodities • All data should be real time and has to have human interaction only by necessity. • Needs to include push notification
Program Delivery and Operations	Central West District	• Need to know the growth rate of freight and how the freight task changing over time. If it was integrated with the traffic data, it would give a better picture of usage across the network • Hard data to back up theories e.g. loads on volumetrically loaded cattle trucks – are they 5% over? 10% over? Hard evidence would be useful. • The actual growth of the freight task for example every 10 years. This would provide valuable inputs to the business case for road projects • Integration with other ITS applications would be highly beneficial. e.g. Bruce Highway is installing Bluetooth trackers, if WiM data could be integrated with such systems it would provide a network-wide view of where the loads are travelling. This could also be integrated with the ANPR data or tracking technology. By seeing where the loads are travelling it expands the value of a single WiM station to broader sections of the network. • Integration with weather data • An annual report that goes out to the districts summarising the data, availability and accuracy. When people know what information is available, they are more likely to use it • Ideal future is having completely integrated real time ITS, traffic counts and heavy load data

Engineering & Technology	Road Operations	• A sustainable network of WiM sites producing reliable and accurate data
		How the ideal data would be used?
		• A fully functional overload surveillance system that assists in altering the behaviour of heavy vehicle operators to:
		  – minimise heavy vehicle overloading, resulting in maximum road and bridge asset life
		  – significantly reduce heavy vehicle related crashes

	Pavements Materials & Geotechnical	• Data needs to be reliable and calibrated – errors in load are magnified because in pavement design the load is raised to a minimum power of 5 (for asphalt pavements). Inaccuracies in input data therefore lead to overly conservative designs. • Axle load group types, masses, spacing, number of groups • Reliable classification of vehicles • Image processing - combined photo/video technology with WiM data • Vehicle type/class/identification combined with axle masses and spacing • Where is the vehicle travelling – in combination with other technology • Linking WiM systems together and to other systems such as ANPR and permit systems – this would allow a network overview to be developed • Continuous spectrum of group masses • Forecast of growth rate • Tyre pressures, pressure distribution and ground contact area (currently using an assumed value of 750 kPa) • Lateral position – damage is magnified when wheel loads are closer to the edge, potential for channelisation/wander in autonomous vehicles • Frequency – existing relationships assume there is a recovery time between loads, platooning and autonomous vehicles may affect this

Group	Subgroup	Key response
		• Research – horizontal forces – how can we assess damage caused by horizontal forces – this is more relevant for seals than for asphalt • Research – consider WiM in different pavement types - the more bound a pavement is, the more sensitive it is to overload • Research – connect WiM data to weather sensors/moisture monitoring in the pavement • Look at whether required data can be sourced from vehicle telematics instead of from WiM • It is hard to link failure to a particular cause • Needs to be able to cope with line marking changes **Usage of the ideal dataset** • Develop performance relationships for rutting related to the WiM data • Question re autonomous vehicles – potentially more frequent but smaller vehicles • Diagnostics would assist with understanding of pavement behaviour • Greater understanding of pavement response to actual loading and the damage relationship would assist with determination of potential additional capacity. If we understand the damage relationship this may facilitate more efficient use • Research – design is based on a general mechanistic procedure. It is challenging to develop performance relationships for new materials – better data would assist with this
	Structures	• A system to detect the mass of the heavy vehicle prior to being driven over a structure which alerts the driver to divert in order to avoid the structure being overloaded • Ideal dataset, including axle mass spacing which could recommend the driver to drive slower • A system to detect the speed of all vehicles on a bridge, which vehicles have gone over the bridge and how often • Data on the history of the permits already issued to detect heavy vehicle outliers which have been approved previously however has caused harm to the deck wearing surfaces of bridges • Data on past performance without relying on freight data • WiM needs to be more network-wide and needs to be relevant to a specific structure

D.4.3 Current Dataset

Group	Subgroup	Key response
Transport Regulation	Heavy Vehicle Policy and Heavy Vehicle Operations	• Intelligent Access Program (IAP) data informs compliance intelligence data • This is tracking the OBM, where they are tracking and how heavy they are • There are restrictions on what you can and can't use the data for (IAP/OBM) • Mandatory IAP is linked to registration so you know which vehicle it is • Currently, this is predominantly used for education
Portfolio Investment and Programming	Transport Systems Asset Management	• Currently getting data from the internet, On-Board Mass (OBM) and Intelligent Access Program (IAP) • Drawback of OBM is that you can only get data from those who choose to take it on whereas WiM can give you data on all traffic that passes a particular site • IAP uses satellite tracking and telematics to remotely monitor where when and how heavy vehicles are being operated on the road network. The IAP can also include on-board mass monitoring to record the mass of the vehicle in some areas • IAP does not identify the driver of the vehicle • Use ANPR cameras to detect whether a vehicle is registered or insured, in conjunction with the Queensland Police Service
	Portfolio Management Office	• Current dataset facilitates network reporting
Transport Strategy and Planning	Transport Analysis	• No current dataset

Group	Subgroup	Key response
Program Delivery and Operations	Central West District	• WiM data not being used at the moment but very interested in obtaining the data since it can be used as an input to pavement design and seal design
Engineering & Technology	Road Operations	• Date/time location of GVM and freight numbers • Standard Axle Repetitions (SARS) for impact assessment on pavements and bridges • ESA calculations for planning and asset protection • Over mass and oversize reports for compliance planning • Vehicle configuration noncompliance on approved routes • Speeding heavy vehicles • Imbalance loading of heavy vehicles **Current data used by:** • Pavement and structural engineers both internal and external • Freight and heavy vehicle planning studies • Transport compliance • National Heavy Vehicle Regulator • Consultants • Asset managers **Current data could be used as follows:** • Improved data could be utilised for identification of vehicle in lane placement • Local governments could use data to inform their decisions
	Pavements Materials & Geotechnical	• Loads and axle groups – if there is a WiM in close proximity to the design location – this data has to be specifically requested, and then an assessment is made, based on the load distribution and engineering judgement, as to the validity or accuracy of the data. It would be beneficial if this data was easier to access, ideally in real-time. In addition, it would be preferable to be able to access the raw data to assist with determinations as to the data accuracy. The variation in data from a site can vary significantly from year to year. It is unclear whether this is due to calibration issues or accurately represents variations in actual loading. • Classifier data is more readily available and more likely to be available for sites close to the design site.
	Structures	• Currently WiM has no useful visibility in the bridge space, more so in the compliance space

D.4.4 Barriers Stopping Getting to the Ideal

Group	Subgroup	Key response
Transport Regulation	Heavy Vehicle Policy & Heavy Vehicle Operations	• Lack of reliability of data
Portfolio Investment and Programming	Transport Systems Asset Management	• Lack of accessibility to the required data, reliability of the data quality and integration between the data sources. • Lack of reliability of the data quality is another issue. Therefore, it is better to have fewer, better calibrated, more reliable WiM sites. • Linking the WiM information to be an enabler for the type of payback for the user
	Portfolio Management Office	• Low reliability of obtained data with constrained funding • Less effective maintenance of the heavy vehicle standards
Transport Strategy and Planning	Transport Analysis	• Low reliability of data therefore cannot be used for prosecutions
Program Delivery and Operations	Central West District	• WiM sites are unreliable and data quality is low • WiM data not readily available unless you know who to contact • Districts are requesting new WiM sites but E11 reluctant to install any new sites as they have insufficient operational funding
Engineering & Technology	Road Operations	• Approximately 80–100 reports are generated a month from the self-service web tools • Need to assess the WiM network state-wide – identify strategic needs and gaps

Group	Subgroup	Key response
		• Ongoing assessment of equipment and site performance – programmed site maintenance and calibration equipment and infrastructure upgrades • The main challenge is the value of the data. Replacement cost of WiM asset can be handled but it is the value of the data that is high **What needs to happen now to get to the ideal** • Overload management cannot be achieved without the significant input of CSB resources to enforce mass compliance. Funding provision for these resources should be considered. • Assessment of the need for additional, and/or required changes to, the WiM networks across the state (by periodically identifying strategic needs, gaps and duplications etc.) • Ongoing assessment of equipment and site performance with a view to programming site maintenance, site recalibrations, and equipment/infrastructure upgrades where necessary
	Pavements Materials & Geotechnical	–
	Structures	• If cost of getting the data exceeds the cost of existing efficiency, then there is no beneficial value • Essentially, the business hasn't identified the need for data, so no barriers are present

D.4.5 Importance/Value of the Idea Dataset and How it is Valued

Group	Subgroup	Key response
Transport Regulation	Heavy Vehicle Policy and Heavy Vehicle Operations	• Yes, WiM data could be used to validate Performance Based Standards (PBS) – are the vehicles within the envelope? • Philosophy of 'run, build, maintain' is difficult without the inputs being known. • 'Lean' asset management and 'lean' access management needs a good knowledge of the inputs
Portfolio Investment and Programming	Transport Systems Asset Management	• No question that we need heavy vehicle data
	Portfolio Management Office	• Important since reliable data will lead to data-based decision making
Transport Strategy and Planning	Transport Analysis	• Better WiM data means better calibration of the model and more reliable estimates. In turn this leads to improved decision making and smarter spending • Even better static data would be helpful compared to what is currently available • It's more than aspirational – we have no choice; industry has the data and we don't
Program Delivery and Operations	Central West District	• If there is no WiM, we would lose the ability to quantify arguments. • Could continue to conduct business but lack of data would compromise the ability to do it effectively • Would lose sight of what the loads are and how they are changing, especially important if loading regimes change and you would end up in a best guess scenario
Engineering & Technology	Road Operations	• Reduce significant risks for the management of bridges and pavements • A quality system for mass management of heavy vehicles will mitigate the risk and likely deliver productivity improvements from improved access to infrastructure • Increase support of compliance to Transport Operations (Road Use Management) Act 1995 • Optimising transport productivity can significantly reduce the cost of business and cost of living for consumers, and enhance our international competitiveness in key export markets • Restricted access to the network limits productivity improvements
	Pavements Materials & Geotechnical	**Value** • Without knowing how much better the data can be it is difficult to quantify the value

Group	Subgroup	Key response
		• The gross replacement value of the State Controlled Network (as at 30 June 2017) is approximately $76 billion (State of the Asset Report 2016–2017), approximately $1 billion is spent annually on maintenance, preservation and operations (MPO) – (from TMR annual report – operating budget $5.8 billion, capital budget $2.8 billion, managed assets worth $76 billion) – If you could get 10% better life – what does that look like? – If your distribution changed by x% then the pavement thickness changes by y%, then apply $/m^2? **Importance** • Very important but there are currently workarounds • Without accurate data designs are suboptimal
	Structures	**Value of the ideal dataset** • Current dataset not systematically used and no current methodologies to use data if it was available. Essentially, limited value **Importance of the ideal dataset** • We don't know the importance right now • It's a challenging time to be doing the project • Business hasn't identified the need for the data • Appetite within organisation is for tangible offsets to demonstrate the cost and benefit

D.4.6 Fund Collection for the Ideal Dataset

Group	Subgroup	Key response
Transport Regulation	Heavy Vehicle Policy and Heavy Vehicle Operations	–
Portfolio Investment and Programming	Transport Systems Asset Management	–
	Portfolio Management Office	–
Transport Strategy and Planning	Transport Analysis	–
Program Delivery and Operations	Central West District	–
Engineering & Technology	Road Operations	• Prioritise the site maintenance base on safety risk and compromising the risks for the management of bridges and pavements
	Pavements Materials & Geotechnical	• The data could be used to facilitate user access – e.g. for PBS applications a percentage of the application fee is directed towards calibration of WiM sites • Major projects exceeding defined value required to include a WiM site, including ongoing funding for maintenance/calibration • Fund it through enforcement – how much 'damage' is saved through better enforcement
	Structures	• Until you know how it would change your business it's very hard to put a value on it • Currently getting by without it but need a change of focus