REFINING THE BENCHMARKING OF NEW ZEALAND RCAs THROUGH THE DATA ENVELOPMENT ANALYSIS TECHNIQUE

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Abstract

Like the global community, New Zealand grapples with pressing economic and environmental challenges as it endeavours to achieve sustainability in the transport and infrastructure sector. A pivotal aspect of this pursuit lies in optimising road network maintenance and management practices across Road Controlling Authorities (RCAs) to bolster efficiency and sustainability. Employing statistical Data Envelopment Analysis (DEA) is a significantly prevalent strategy for performance benchmarking, transcending industries. While prior research underscores DEA's efficacy in the Transport and Infrastructure sector, the literature highlights its tendency to overlook crucial inefficiency indicators within decision-making units (DMUs), such as RCAs, potentially inflating efficiency ratings unrealistically.

Addressing this concern, this study iterated through model configurations, culminating in the development of a more realistic DEA benchmarking model using a limited number of critical performance variables. By imposing constraints on the weight allocation for the pivotal expenditure ($/km) input variable - the RCAs' sole controllable factor influencing maintenance performance - a more realistic portrayal of operational realities was obtained. Complemented by uncontrollable contextual variables such as Vehicle Kilometres Travelled (VKT/km) and Urban/Rural split (%UR), and a singular output variable, Pavement Health Index (PHI), each subjected to rigorous scaling and orientation procedures, this model facilitates realistic efficiency comparisons within DEA. This study's model is a sound basis to help highlight on-ground operational nuances and challenges encountered by RCAs, without distorted variable distributions and with significant potential for further development.

Furthermore, juxtaposing objective DEA scores with subjective asset management performance evaluations from Waka Kotahi NZTA and Te Ringa Maimoa (TRM) presents a unique, multifaceted understanding of RCA performance. This triangulated assessment offers insights into alignment or misalignment between evaluations, offering a holistic appraisal of maintenance practices and identifying potential areas for improvement. Focused on councils with high-quality data from the Consistent Condition Data Collection (CCDC) project, this research contributes to advancing road network maintenance practices by improving the framework for effective performance benchmarking and offering insights into asset management practices within the transport sector.

Dedication

"Tumhe chaad koe avar na dhiyaun. Joh bar chahun so tum te paun."

Sri Guru Gobind Singh Ji, the 10th Sikh Guru

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Glossary of Abbreviations

AADT	Annual Average Daily Traffic
AMP	Asset Management Plan
APF	Accident Prevention factor
ASF	Assignment (region) Size Factor
AT	Auckland Transport
ATS	Average Traffic Served
CCC	Christchurch City Council
CCDC	Consistent Condition Data Collection
CCI	Critical Condition Index
CEX	Capital Expenditure
CIPFA	Chartered Institute of Public Finance and Accountancy
CLF	Climatic Factor
CRS	Constant Returns to Scale
DCC	Dunedin City Council
DEA	Data Envelopment Analysis
DMU	Decision Making Unit
ED	Environmental Difficulty
EHF	Environmental Harshness Factor
ESAL	Equivalent Single Axle Load
FHWA	Federal Highway Administration
FNDC	Far North District Council
FWD	Falling Weight Deflectometer
FWP	Forward Works Plan
GDC	Gore District Council
GPS	Government Policy Statement
HCC	Hamilton City Council

HCV	Heavy Commercial Vehicle(s)
HDC	Hastings District Council
HKDC	Hauraki District Council
HSD	High Speed Data
HT	High-Traffic
HWDC	Horowhenua District Council
IDS	Infrastructure Decisison Support
IRI	International Roughness Index
KCDC	Kapiti Coast District Council
LOS	Level of Service
LT	Low-Traffic
LTPP	Long Term Pavement Performance
MEX	Maintenance Expenditure
NCC	Nelson City Council
NIWA	National Institue of Water and Atmospheric Research
NLTP	National Land Transport Programme
NOC	Network Operating Contract(s)
NPDC	New Plymouth District Council
NZ	New Zealand
NZDI	New Zealand Drought Index
NZTA	Waka Kotahi NZ Transport Agency
ONRC	One Network Road Classification
PCC	Porirua City Council
PCR	Pavement Condition Rating
PHI	Pavement Health Index
PII	Pavement Integrity Index
QA	Quality Assurance
QLDC	Queenstown-Lakes District Council
RAMM	Road Assessment and Maintenance Management database
RATA	Road Asset Technical Accord (Waikato)
RCA	Road Controlling Authority
RCF	Rating change factor
REG	Road Efficiency Group
RM	Routine Maintenance expenditure
SCI	Surface Condition Index
SCRIM	Sideway-force Coefficient Routine Investigation Machine
SFA	Stochastic Frontier Analysis
SH	State Highway
SRF	Soil Risk factor
STE	Smooth Travel Exposure
SWDC	South Waikato District Council
TAS	Total Area Served
TCC	Tauranga City Council
TCDC	Thames-Coromandel District Council
TDC	Taupo District Council
TE	Total Expenditure
dTIMS	Deighton Total Infrastructure Management System
TL	Treatment Length

TLA	Territorial Land Authority
TNZ	Transit New Zealand
TRM	Te Ringa Maimoa - Transport Excellence Partnership (formelry REG)
UK	United Kingdom
UKRLG	United Kingdom Roads Leadership Group
%UR	Percentage of Urban-Rural roads
US, USA	United States of America
VKT	Vehicle Kilometres Travelled
VRS	Variable Returns to Scale
WBOP	Western Bay of Plenty District Council
WCC	Wellington City Council
WDC	Waipa District Council
WGDC	Whanganui District Council

Chapter 1 - Introduction

1.1 Background and Purpose

New Zealand is experiencing a paradigm shift towards more sustainable practices and initiatives within transport and infrastructure. However, numerous challenges with unique opportunities exist, such as:

- Urban and rural growth.
- Economic and Infrastructure recovery post multiple natural disasters and COVID.
- Budget constraints due to inflation, construction costs and increased national debt.
- Climate change and targets of the Paris 2050 agreement from the government's policy statement on land transport (GPS 2021).

These are just some of the critical factors that territorial authorities within the country must consider (Ministry of Transport, 2020; Shah et al., 2021; The Treasury, 2023). New Zealand's unique geography and climatic variations across territories add another dimension to efficiently maintaining and managing New Zealand's ageing road networks, as explored through contextual soil and rainfall variables developed in Shivaramu et al. (2022a). Thus, for improving sustainability and overall performance, it is crucial that the Road Controlling Authorities (RCAs) within New Zealand identify areas of potential efficiency gains in their network maintenance and management practices. To this end, performance benchmarking, as conducted in this study, is a powerful and widely used tool across numerous industries to assess areas of performance improvements, under specific operating conditions and challenges (Codling, 1996; Shivaramu et al., 2022a, b).

Performance benchmarking involves the evaluation of available performance data against an organisation or entity's well performing peers to gauge how and where improvements are possible. Within the context of New Zealand transport, the national 'Road Assessment and Maintenance Management' database (RAMM) contains performance data recorded individually by RCAs for multiple parameters such as maintenance expenditure, total network lane kilometres, and the overall pavement performance measures, such as rutting and roughness. Benchmarking network performance would support better evidence-based decision making. It would provide greater transparency regarding cost-drivers for specific territories and promote equitable comparisons of councils' maintenance practices. Additionally, councils displaying best practices within particular operating environments could be identified, further highlighting opportunities for others to adapt and improve maintenance performance (IDS, 2023).

Shivaramu et al. (2022b) previously evaluated the efficacy of multiple performance benchmarking techniques across New Zealand's RCAs, considering the various operational, environmental, and geological factors that likely affect maintenance efficiency. Through comparison models and engineering judgement, it was determined that the Data Envelopment Analysis (DEA) technique would be the most suitable for such a purpose. However, while DEA is the most widely accepted benchmarking technique, it has an inherent tendency when unconstrained, to neglect influencing variables that suggest inefficiency (poor performance) for an RCA and give unrealistic weighting to variables suggesting efficiency (Cooper et al., 2011; Shivaramu et al., 2022a, b). Thus, to progress this benchmarking technique within the transport and asset management sector, it is critical that this DEA behaviour be mitigated and that the resulting DEA efficiency scores are evaluated in parallel with presently used performance assessments.

1.2 Problem Statement

DEA is the most popular and widely accepted benchmarking technique, mainly because it can consider the influence of multiple variables upon an RCA's efficiency, and automatically adjust the weighting, i.e., the 'priority', of any variable to give the best possible overall efficiency score to an RCA (Ozbek, 2007; Cooper et al., 2011; Shivaramu et al., 2022a, b). However, DEA's automated weight allocation can give RCAs an unrealistically high efficiency score if they have very strong performance in just one influencing variable, while neglecting poor performance in others. This inherent behaviour within DEA limits the robustness and practical value of its efficiency evaluations (Cook et al., 1994; Rouse et al., 1997; Dyson and Thanassoulis, 1988). This behaviour needs to be mitigated to ensure greater specificity in DEA efficiency evaluations and tailor benchmarking results to realistic RCA conditions.

However, within the transport and asset management sector no concrete guidance exists within literature regarding recommended weight constraints upon variables or how to determine them. The DEA software utilised throughout Shivaramu et al. (2022a, b) and this study allows manual weighting limit application on the chosen variables from either a minimum or maximum limit, or both together. Thus, it is crucial for this study to develop a sound methodology for applying weight restrictions upon selected variables.

Additionally, the evaluation of DEA efficiency scores is critical against currently used RCA performance assessments, to ensure that they have a practical value and add depth to understanding RCA performance. Assessments include regional on-ground maintenance performance scores collected by Waka Kotahi (NZTA), and the Asset Management Plan (AMP) scores by Te Ringa Maimoa (TRM), i.e., Transport Excellence Partnership. Such a comparison would ensure that the completely data-based and objective DEA scores are compared against subjective assessments of RCA performance, providing a completely new lens into RCA performance evaluation and highlighting potential misalignments across different assessments.

1.3 Objectives

The main aim of this study is to develop a more realistic RCA efficiency benchmarking model by controlling weight limits for critical factors influencing maintenance performance. It is also crucial that the DEA results are evaluated against currently utilised performance assessments, such as those previously mentioned. This would provide deeper understanding of actual RCA performance through the triangulation of performance assessments.

Thus, this study has three main objectives:

1. Choose appropriate variables for testing weight control in the DEA analysis.

2. Determine which variable(s) to control and by how much, subsequently making a recommendation for variable weight control.

3. Evaluate the DEA efficiency scores against known subjective assessments of asset management practices and quality of asset management plans.

1.4 Scope of Study

The councils chosen for this study were those with available high-speed data (HSD) from the Consistent Condition Data Collection (CCDC) project. Additionally, all included councils must have complete data, as DEA does not accept any blank cells. The DEA software from previous work done by Shivaramu et al. (2022a, b), will be used to ensure consistency and accuracy in analysis methods.

Fewer variables have been used in this study as compared to Shivaramu et al. (2022a) to fully understand the dynamics of DEA when variable restrictions are applied and to also limit the amount of 'moving parts' while a sound methodology was developed for applying restrictions. Future research will consider the impact of climatic and environmental variables on RCA performance under specific restrictions.

Additionally, all performance evaluations are conducted within New Zealand's geographical area. The most updated climate information from the National Institute of Water and Atmospheric research (NIWA) and the supplied NZTA and TRM performance scores have been used to conduct appropriate and up-to-date assessments within this study.

Chapter 2 – Literature Review

2.1 Introduction

This section discusses findings and knowledge relating to the practice of asset management and performance benchmarking with respect to road network maintenance and management. A knowledge base is established where current asset management practices, and efforts into performance benchmarking using DEA are discussed. This foundation will support this study by identifying sound guidance and research gaps, contributing towards the achievement of research objectives.

Additionally, this study has a specific focus on refining performance benchmarking in the transport sector using the DEA technique, within New Zealand's unique operating environment that has its associated challenges and nuances. Thus, this literature review draws guidance from a select group of studies that provide valuable insight to strengthen this research's knowledge base in relation to the niche focus area, particularly those studies that are relevant to advancing the transport asset management and performance benchmarking practice within New Zealand.

2.2 Road network management practices in New Zealand

This section describes the importance of asset management, the necessity of data collection for proper asset management, the current state of road maintenance performance reporting in New Zealand, utilisation of collected data for improving performance outcomes, and the main pavement deterioration defects.

2.2.1 The importance of asset management

The United Kingdom Roads Leadership Group (UKRLG) has stated that it is established good practice for organisations to develop, deliver and monitor strategies and plans for all services they deliver. This includes infrastructure asset owning and managing organisations, such as Waka Kotahi New Zealand Transport Agency (NZTA), as well as local Road Controlling Authorities (RCAs) within New Zealand. Additionally, the UKRLG states that those who have adopted these asset management principles demonstrate improvements in financial efficiency, accountability, asset stewardship, value for money and customer service (UKRLG, 2013).

According to the Federal Highway Administration (FHWA) of the United States (US), asset management is a strategic and systematic process of operating, maintaining, and improving physical assets while focusing on engineering and economic analysis based on robust information. This would help identify a thorough sequence of maintenance, preservation, repair, rehabilitation, and replacement activities that will achieve and sustain a desired state of good repair over the life cycle of the assets at minimum practicable cost (FHWA, 2019). Asset management also supports tracking the consumption of assets over time. It helps to better understand longer term implications of current decisions made about assets and ensure that costs are incurred at optimal periods of time (NZTA, 2011).

Additionally, the FHWA describes the relationship of asset management to performance management as:

> *Transportation performance management is an approach to managing transportation system performance outcomes. Asset management is the application of this approach to manage the condition of the infrastructure assets that are needed to provide for mobility and safety on the nation's transportation system. In short, asset management is the engine that drives infrastructure performance (FHWA, 2019).*

The FHWA conducted an international scanning report in 2005, where they assessed asset management practices across England, New Zealand, Canada, and Australia. Through this report, the FHWA sought to learn from leaders in asset management and apply learnings and best practice to the US environment. In 2005, NZTA existed as its two precursor entities, namely Land Transport New Zealand and Transit New Zealand. Transit New Zealand (TNZ) was the authority conducting all road network operations and planning. The FHWA noted that international transportation agencies, such as TNZ, reported that a major benefit of performance management was improved transparency as this enhanced understanding about transportation issues and led to greater trust between agencies and legislators (FHWA, 2005).

Figure 2.1 is taken from a 2021 Infrastructure Decision Support (IDS) report on the benefits of road condition data collection and summarises different elements of asset management. Additionally, this report states that, "best practice asset management does not always result in short-term direct savings in renewals and maintenance. However, if asset management becomes normal, the network's long-term costs will be minimised" (IDS, 2021a).

NZTA and the UKRLG have emphasised that an Asset Management Plan (AMP) informs target audiences, such as organisational boards, the Ministry of Transport, road user groups, stakeholders, and the government, about objectives and how they will be achieved, and also make the case for better funding. It links high-level statutory and strategic objectives with day-to-day business processes, operations on the network and investment decisions, facilitating a greater understanding of the contribution highway infrastructure assets make to economic growth and the needs of local communities (NZTA, 2011; UKRLG, 2013). After their international asset management scan, the FHWA also established that an AMP should demonstrate that authorities are exploiting their asset bases to their fullest potential and managing future maintenance liabilities efficiently (FHWA, 2005).

Additionally, the Chartered Institute of Public Finance and Accountancy (CIPFA) in the UK states that AMPs support consistency in information between authorities, further facilitating benchmarking and aggregated information to provide data at regional and national levels regarding spending patterns and needs. Thus, performance trends depicted through AMPs can be used to inform national decision making on both policy and resource allocation (CIPFA, 2013).

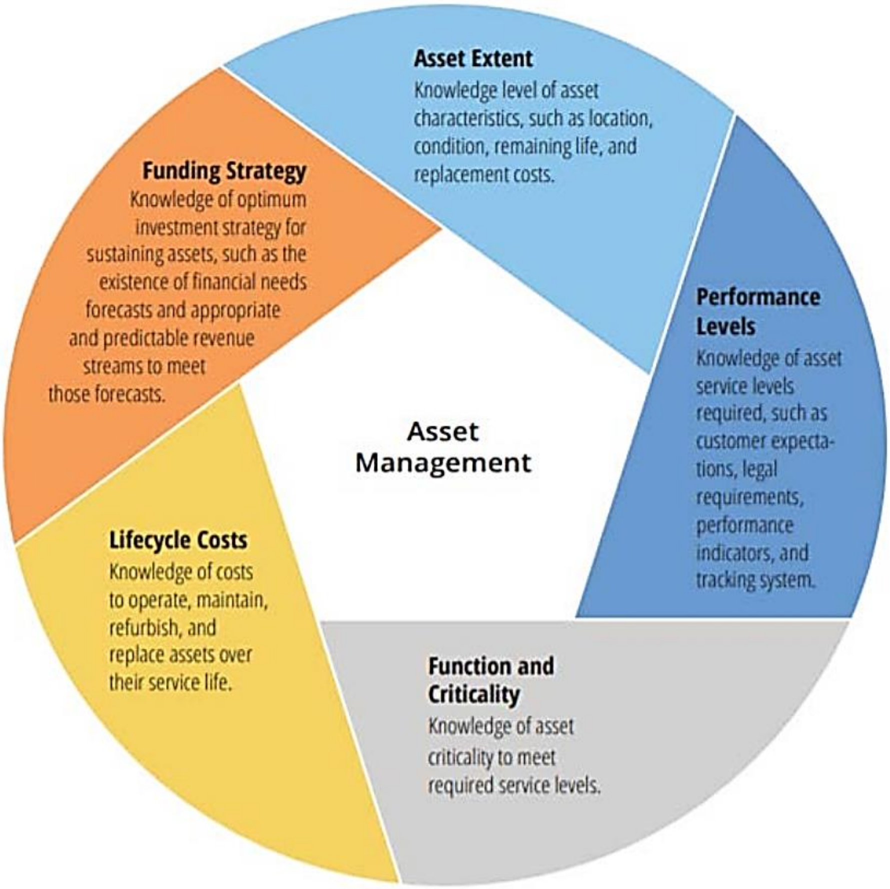


Figure 2.1: Elements of asset management (IDS, 2021a)

2.2.2 Road condition data collection and utilisation in asset management

The ability to demonstrate that infrastructure is being preserved and to demonstrate the consequences of not investing in asset management are critical, especially in constrained funding environments such as present-day. Thus, greater information availability regarding network performance is crucial, as robust data serves as the decision-making foundation for accurate asset management. This data, in turn, depends on the quality and efficiency of supporting databases (FHWA, 2005; IDS, 2021a). All elements in Figure 2.1 directly link back to the necessity of good quality data for all asset management processes. Moreover, along with efficiency and economical gains, more resilient networks and improved customer satisfaction are additional beneficial outcomes resulting from robust evidence inputs into an asset management process, as depicted in Figure 2.2.

Significant developments have been made in the analysis and interrogation of condition data, placing greater emphasis on data collection techniques and practices, i.e., “the analysis technology is pushing the adoption of smarter collection techniques” (IDS, 2021a). However, data collection must be more consistent across New Zealand, and councils must follow thorough data collection strategies. The FHWA states that while “data collection is critical to successful asset management, too much inaccurate, unfriendly data is worse than having none at all” (FHWA, 2005). Data collection strategies must ensure that accurate data is collected at appropriate frequencies using robust technology. Furthermore, better standards are required for data management and storage, as practicing historical processes may prevent full utilisation of upcoming data collection technologies (IDS, 2021a).

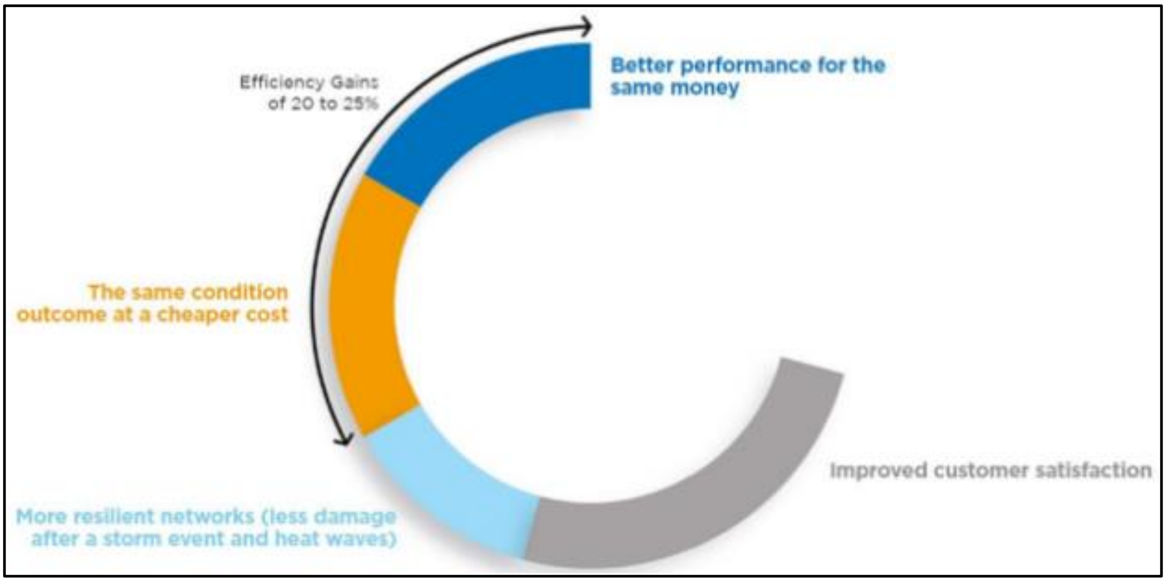


Figure 2.2: Benefits from road network asset management (IDS, 2021a)

Table 2.1 lists the strengths and weaknesses of various road condition data collection techniques within New Zealand (NZ), as identified in IDS (2021a).

Table 2.1: Strengths and weaknesses of road condition data collection techniques in NZ (IDS, 2021a)

Data Collection Technique	Main Purpose and Application	Strengths	Weaknesses
Visual Rating (RAMM Surveys)	• RAMM rating survey originally meant to understand priorities for resurfacing works. • Later developments refined visual rating surveys into current format. • For several years, RAMM surveys were the only condition description available to RCAs. • In most cases, RAMM rating surveys included roughness surveys, either using laser or response type measurements	• Comprehensive surveys that include visual defects and drainage assessment • Nationally standardised survey methodology	• Uses a sampling method, which cannot provide full picture of entire network. • Subjective survey gives variable results from different raters (See NZTA Research Report 528) • Only picks up surface defects, i.e., if no faults show on the surface, it suggests there is nothing wrong with the pavement.
Defect Assessments (All faults and defects)	• Used mostly by contractors, defect is an initial windshield survey. • Followed by more detailed on-foot inspection of defects to quantify all visual defects that need addressing through routine maintenance work. • Contractors use these surveys to determine extent of maintenance required. • New technology utilising LiDAR and photographic surveys overlaid by artificial intelligence will replace visual assessment in coming years.	• Useful indicator for routine and early preventive interventions. • 100% coverage survey. • Severity and extend of faults are captured on an ongoing basis.	• Currently, only picks up visual defects. • Long-term limitations for asset management analytics and planning processes. • Subjective inspection gives variable results from different inspectors. • Not standardised nationally so inspection methodology varies between contractors

Automated Condition Surveys, e.g., • Roughness • Rutting • Texture • SCRIM	• Many New Zealand networks have been surveyed using automated survey equipment. • Properly calibrated and quality assured (QA) surveys produce very reliable data for trend monitoring, advanced optimisation modelling and monitoring the overall state of networks and individual sites.	• Relatively inexpensive for the data it produces. • Provides continuous information.	• Quality subject to robust calibration and QA processes. • Could give variable results in wet weather. • Not effective in some urban environments and winding geometry.
Scanning Lasers	• High-frequency scanning lasers used to capture 'images' of road surface. • Images are post-processed using algorithms that identify and quantify defects. • Becoming more widely used around the world for full network surveys and inputs to the asset management process.	• Gives very consistent results (although it may be biased). • Could be used for 100% network surveys	• Prone to false positive identification. • Limited in the type of defects it picks up (developing area). • Not as robust on chip-seals compared to asphalt surfaces.

Numerous case studies across New Zealand discussed in IDS (2021a) show that high-confidence data yielded significant maintenance performance improvements, financial savings, and asset management decision making advantages to respective local councils. Key problems and outcomes from these case studies have been summarised in Table 2.2.

Table 2.2: Case studies showcasing the value of data in asset management (IDS, 2021a)

Problem Description	Actions	Outcomes
CASE STUDY 1 Central Otago District Council could potentially have financial savings in maintenance work, but greater certainty regarding pavement life and realistic value depreciation was required.	• RAMM data inventory cleaned up and High-Speed Data (HSD) collected across the network. • Falling Weight Deflectometer (FWD) testing across at least 5-10% sample of network. • Deterioration modelling to find minimum network preservation investment level.	• Cost to undertake FWD testing, HSD survey, and modelling was a maximum of $65,000. • Optimisation efforts yielded savings in next fiscal year budget of almost $290,000. • Overall reduction of 13% on regular spending due to sufficient data.
CASE STUDY 2 Wellington City Council wanted to conduct long-term assessments and risk valuations of pavement assets, worth $800 Million, but asset data was not robust, and the Forward Works Plan (FWP) inaccurately reflected maintenance works required.	• Full network FWD testing was highly economically priced and was a means to improve confidence in pavement asset data. • FWD testing enabled data validation for pavement strength and remaining network life, and improved capability to measure Heavy Commercial Vehicle (HCV) pavements impacts.	• Night FWD surveys conducted in busy areas. • Network now has data-supported life and pavement strength assessments to support decision making. • FWP treatment selection and deterioration modelling has network-wide data support. • $5M savings in planned ten-year maintenance forecast.
CASE STUDY 3 During the 2013 National Long-Term Programme (NLTP) analysis, NZTA wanted proof that an optimised maintenance programme would be beneficial compared to the typical field-based 'worst-first' approach.	• Deighton Total Infrastructure Management System (dTIMS) model undertaken on a State Highway (SH). • Two scenarios modelled for identical budget levels, i.e., an optimised programme, and a typical 'worse-first' approach. • Comparisons made across forecasted condition outcomes and routine maintenance required.	• 20-30% improvements for 75^{th} percentile rutting and cracking condition outcomes over the next 20 years. • Average reactive routine maintenance costs over next 20 years for the optimised programme were 80% of the 'worst-first' costs. • Overall, 10% investment cost saving.

CASE STUDY 4 Assessing the difference in cracking information using different network sample sizes across Whangarei District Council.	• RAMM cracking data assessed for 100% of all Treatment Lengths (TLs) within Whangarei District Council. • Random sample of 20% of TLs taken to compare statistical outcomes against the 100% TL sample group.	• Mean crack length was 0.68m less in the 20% TL sample group compared to the 100% TL group. • Shows that bias often exists in data taken from a sample of an overall network.
CASE STUDY 5 Different Wellington Network TL sample sizes used for strength analysis (FWD testing).	• 5% and 66% network sample sizes taken for FWD testing. • 5% FWD testing predicted a $5M greater 10-year rehabilitation investment and also a $1M lesser Year 20 asset value, as compared to the 66% FWD tests.	• Smaller representative values would likely always be conservative. • A $60,000 increase in FWD testing costs to cover 66% of the network resulted in a $5M planning saving.
CASE STUDY 6 Frequent condition surveys are required to have confidence in trends.	• Study conducted at the onset of the Long-Term Pavement Performance (LTPP) programme to understand confidence of the HSD surveys. • Each LTPP site underwent 4 repeated HSD surveys, with expected variation.	• Accurate HSD surveys will always have some variability in measurements. • Variability may be greater than expected yearly change. • Series of measurements needed over time to make confident conclusions on actual condition trend.
CASE STUDY 7 Improving understanding of condition changes through trend analysis.	• Modelling suggested significant renewals for a council's access roads, but this was weakly supported through available roughness data.	• New Zealand councils would significantly benefit from complete HSD parameter data. • Meaningful trends require at least annual data points.

The case studies further highlight that sufficient sampling size and frequency is paramount to effective trend analysis and proactive maintenance programmes, especially for high volume or nationally significant roads (IDS, 2021a). To summarise the practical value of asset management, Figure 2.3 shows the efficacy of proactive renewal measures, such as resurfacing, to mitigate significant complete rehabilitation costs and user discomfort at a more advanced pavement deterioration stage.

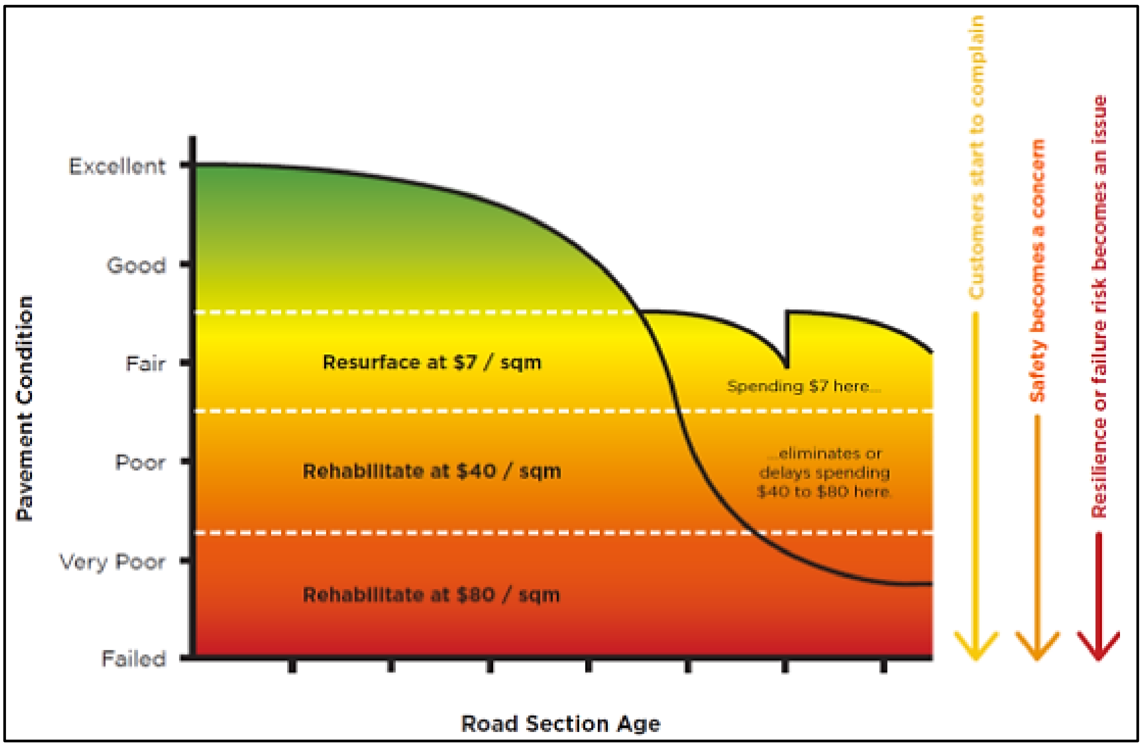


Figure 2.3: Relationship between road deterioration and the timing of treatments (IDS, 2021a)

2.2.3 Main pavement deterioration defects

The aim of condition data collection is to determine the degree of pavement decay occurring and to direct maintenance planning towards the appropriate treatment strategy for a road section. Figure 2.4 has been taken from IDS (2021a) and summarises interactions between fundamental pavement failure modes and the development of visible defects as a road deteriorates. The figure highlights that a particular defect being measured could be a 'symptom' of a particular failure mode or a secondary defect occurring because another defect had worsened, causing further damage of a different nature. Moreover, if certain defects become visible, it is possible that significant pavement deterioration would already have occurred. Conversely, significant pavement deterioration may have occurred without any marked visible signs (IDS, 2021a).

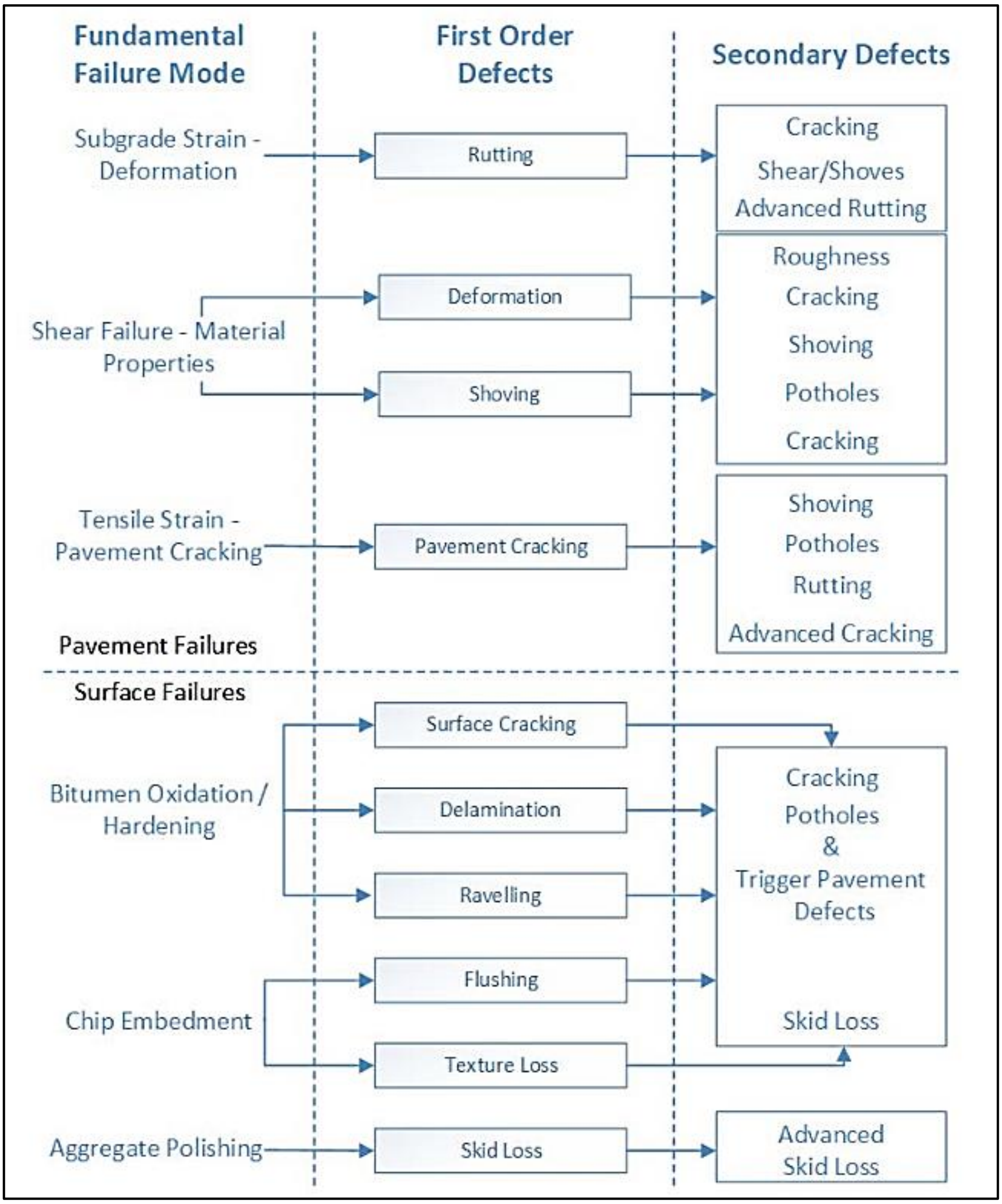


Figure 2.4: Failure modes and defects across pavements and surfaces (IDS, 2021a)

Subsequent sections discuss the usage of available network condition and performance data to conduct performance benchmarking for network maintenance and management practices amongst peers, such as RCAs. The benefits of performance benchmarking for better outcomes have been discussed, and techniques that can equitably consider RCA performance efficiency across different influencing factors have been evaluated for suitability.

2.3 Benchmarking & its techniques

2.3.1 Usage and purpose of benchmarking

Codling (1996) states that in business terms, "benchmarking is an ongoing process of measuring and improving products, services and practices against the best that can be identified worldwide". Bhutta and Huq (1999) also state that benchmarking is a tool for improvement, achieved through comparison with other organisations recognised as the best within a particular sector. Philosophically, it is understood that benchmarking involves being humble enough to admit that someone else is better at something and being wise enough to learn how to match them and even surpass them at it (Andersen, 1999; Bhutta and Huq, 1999). Overall, benchmarking can help an organisation develop a critical attitude towards its operational processes and practice an active learning process to attain measurable improvement (Andersen, 1999; Shivaramu et al., 2022b).

As an example, Codling (1996) explains that a pioneering application of benchmarking was undertaken by the Xerox company in the USA during the 1970s. When threatened by the loss of shares in the printing market from much cheaper Japanese competitors, the company successfully identified opportunities in its manufacturing and production systems allowing it to cut unnecessary costs and match Japanese prices. This allowed it to retain significant market share all throughout the 1980s and become leaders in the application of benchmarking.

Performance benchmarking is now widespread across private and public sectors across numerous industries, such as hospitality, manufacturing, mining, banking, healthcare, tourism, airlines, insurance, and primary industries, to name a few (Shivaramu et al., 2022b). New Zealand, like many countries, is faced with ageing road networks, budget constraints and challenging environmental conditions. These factors contribute towards roading authorities being unable to meet the level of service (LOS) requirements and facing increasing maintenance costs.

Several organisations in the transport sector have tested and implemented benchmarking programmes to improve their performance. Also, benchmarking, when collaborative, results in transparency and improved economic performance in public sector organisations. Thus, benchmarking the performance of New Zealand's local Road Controlling Authorities (RCAs) could potentially improve pavement maintenance outcomes across the country, leading to overall better managed road networks and a better user experience (Shivaramu et al., 2022b; Rouse et al., 1997; Costello et al., 2014). Costello et al. (2017) further state that there may be instances where infrastructure asset owners, such as RCAs, would need to establish appropriate investment and service levels without having all necessary information for guidance. In such cases, benchmarking across similar organisations or even other countries, with appropriate practices, may help in critical asset management decision making.

2.3.2 Types of benchmarking

Numerous types of benchmarking methods are applied globally to different situations, such as performance benchmarking, strategic benchmarking, and internal benchmarking, to name a few. Various benchmarking types have been described by Ajelabi and Tang (2010) to assist practitioners and organisations in identifying which method would be most relevant for their goals. These various types have been given in Table 2.3 below. This study is concerned with benchmarking the pavement maintenance efficiency demonstrated by RCAs across New Zealand. Thus, performance benchmarking is relevant for this study.

Table 2.3: Types of Benchmarking (Ajelabi & Tang, 2010)

Type	Definition
Performance Benchmarking	Comparison of measures to determine the relative performance of the organisation
Process Benchmarking	Comparison of methods and processes to improve the processes in an organisation
Strategic Benchmarking	Comparison of an organisation's strategy with successful strategies from other organisations to help improve capability to deal with a changing external environment
Internal Benchmarking	Comparisons of performance made between department/divisions of the same organisation solely to find and apply best practice information
Competitive Benchmarking	Comparison made against the "best" competition in the same market to compare performance and results
Functional Benchmarking	Comparisons of a particular function in industry. The purpose of this benchmarking is to become the best in the function
Generic Benchmarking	Comparison of processes against best process operators regardless of industry

2.3.3 Evaluated techniques of performance benchmarking

For any endeavour, it is critical to understand the purpose, type of data, and the adaptability of benchmarking techniques to the desired application. To identify the most suitable technique for pavement management performance benchmarking with respect to a New Zealand context, Shivaramu et al. (2022b) compared the advantages, disadvantages, limitations, and suitability of multiple techniques found in literature. The incorporation of the fundamental concepts of productivity and efficiency within each technique has been used as a basis for comparison. Productivity has been described as a ratio between Outputs and Inputs, as shown in the equation below:

Productivity = Output/Input Equation 2.1

With regards to highway maintenance, Rouse et al. (1997) have described Outputs to be activities such as general or routine maintenance, resealing, and rehabilitation. Inputs, such as materials or labour, enable output production. Another item, Outcomes, can be seen as the end results of Outputs and Inputs. For example, with regards to highway maintenance, Outcomes could be the state of the road network condition as measured by roughness levels and other surface defects such as rutting and cracking. Outcomes, outputs, and inputs can be presented as a trichotomy, where their relationships define Effectiveness, Economy, and Efficiency, i.e., the '3Es', as shown in Figure 2.5 below.

Effectiveness is the relationship between outputs and outcomes, for example, the network condition post maintenance would be an indicator of effectiveness within pavement management. Economy is a relationship between cost (an input) and outcomes. Understandably, better, and multiple outcomes from lower or a fixed amount of costs and other inputs would be ideal. Efficiency is a relationship between outputs and inputs, wherein, the goal is to have maximum outputs from any inputs. Different combinations such as maximum output and minimal input, or fixed input but maximum output, etc. are possible to gauge efficiency (Shivaramu et al., 2022b; Rouse et al., 1997).

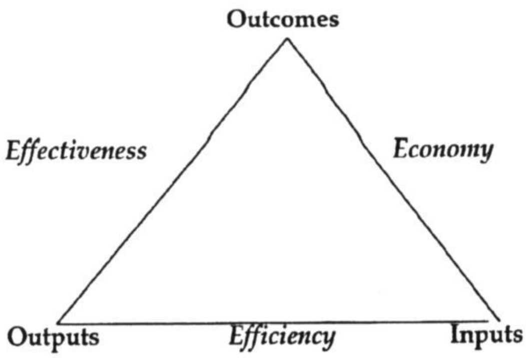


Figure 2.5: The '3Es' and their relationships (Rouse et al., 1997)

Shivaramu et al. (2022b) have evaluated the applicability of six statistical techniques suitable for pavement maintenance performance benchmarking. They are, Partial Efficiency Measure (or Ratio Analysis), Total Factor Efficiency Measure (or Total Factor Productivity approach), Balanced Scorecard, Regression Analysis (or Multivariate Statistical Analysis), Stochastic Frontier Analysis (SFA), and Data Envelopment Analysis (DEA). The ratio or productivity techniques are simpler than the more complex frontier-based methods involving variable weighting optimisation, such as SFA and DEA.

Realistically, road maintenance activities involve multiple input and output variables, as well as several uncontrollable factors, i.e., uncontrollable contextual variables, such as environmental conditions and vehicle kilometres travelled per lane kilometre (VKT/km) within an RCA's territory. Thus, an ideal benchmarking approach would incorporate not only input and output variables, but also multiple uncontrollable contextual variables to account for unique working conditions within each RCA (Rouse et al., 1997; Shivaramu et al., 2022b; de la Garza et al., 2009; Ozbek et al., 2009).

The six aforementioned techniques have been evaluated against specific criteria to select the most suitable technique for pavement maintenance purposes. The results found by Shivaramu et al. (2022b) are given in Table 2.4.

2.3.4 Why frontier-based methods are more appropriate for pavement maintenance performance benchmarking

Based upon the selection criteria in Table 2.4, the two frontier-based methods, SFA and DEA, were considered most appropriate for pavement benchmarking due to their ability to overcome limitations of other methods. SFA and DEA can incorporate multiple input and output variables in their analyses when analysing the efficiency of each Decision Making Unit (DMU), which in this case are the RCAs across New Zealand. Non-economic factors such as environmental conditions, pavement ages, accident rates, etc., can also be included as variables in the modelling. Weights for these variables do not need to be pre-determined by the user, thus avoiding errors due to subjectivity when comparing RCAs. Notably, frontier-based methods may also reveal relationships between input and output variables which would not be evident in non-frontier methods. Moreover, DEA can interpret the efficiency of RCAs without requiring formulated assumptions and variations, as would be required in linear and non-linear regression models. This attribute would be especially valuable in a complex task such as pavement management due to multiple influencing factors acting upon RCA performance (Shivaramu et al., 2022b; Copper et al., 1994; Cooper et al., 2011).

2.3.5 Comparing SFA & DEA - why DEA?

SFA and DEA, have been further compared against each other to determine the method most suited to pavement maintenance. SFA can inherently differentiate statistical noise from the efficiency/ inefficiency scores, whereas DEA is unable to explicitly account for noise. However, DEA's inherent variable weighting system would automatically present each DMU in 'the best possible light' by prioritising the variables in which it 'performs best'. Thus, if a DMU, i.e., an RCA, is presented as inefficient relative to other RCAs, it would be truly inefficient (Ozbek, 2007). Additionally, it has been previously mentioned that DEA, unlike SFA, does not require pre-formulated assumptions or variations to carry out its analyses. This further reduces chances or subjective error in efficiency comparisons and is the key point of DEA's superiority over SFA, along with its non-parametric form. Hence, it was determined that DEA would be most suitable for pavement maintenance benchmarking. (Shivaramu et al., 2022b; Cooper et al., 2011)

Table 2.4: Comparison of benchmarking techniques (Shivaramu et al., 2022b)

Selection criteria	**Benchmarking Techniques**					
	Partial Efficiency Measure	**Total Factor Efficiency Measure**	**Balanced Scorecard**	**Regression Analysis**	**Stochastic Frontier Analysis (SFA)**	**Data Envelopment Analysis (DEA)**
Ability to handle multiple inputs or outputs	Produces multiple ratios	A single composite measure is calculated	Produces multiple ratios	Incorporated in the analysis to a degree	Incorporated in the analysis, produces a single composite measure	Incorporated in the analysis, produces a single composite measure
Choice of weights	N/A	Subjective assignment of weights	Subjective assignment of weights	Incorporated in the analysis	Weights are optimised as part of the analysis	Weights are optimised as part of the analysis
Benchmark produced	Best performers for each ratio	Best performers for a single ratio	Best performers for each ratio with interdependent perspectives	Hypothetical average performer	Frontier of best performers	Frontier of best performers
Method for dealing with unique network characteristics	Peer groups	Peer groups	Peer groups	Incorporated in the analysis, although peer groups could also be incorporated	Incorporated in the analysis	Incorporated in the analysis, although peer groups could also be incorporated
Complexity of the technique	Relatively simple	Some complexity added through definition of weights	Relatively simple	Complex, given that a full functional relationship has to be defined	Complex functional form and maximum likelihood estimation	Complex linear programming technique
Usefulness of outputs	Difficult to draw a definitive conclusion from multiple ratios	Single ratio, hence, conclusions easily drawn	Lacks comparison metrics and difficult to draw a definitive conclusion from multiple ratios	Benchmarking against average not as useful as comparisons to best performers	Efficiency benchmarking; statistical inference	Comparisons to best performers, efficiency score and peer DMUs identified

2.3.6 Limitations of DEA

Limitations of DEA have also been identified across the literature. Primarily, total flexibility with DEA's automatic variable weighting is detrimental to understanding the realistic extent of a DMU's potential inefficiency. For example, an RCA may be extremely efficient with regards to maintaining a good pavement surface and its associated variable would gain a high weighting, but the RCA may be inefficient in maintaining pavement strength and thus, this associated variable would gain a low weighting. DEA would rank such an RCA more towards the efficient frontier irrespective of inferior performance in one or more variables. However, it is stated that imposing appropriate weight constraints based upon sound judgement and practicality can resolve this issue. Another key limitation is that having too many influencing variables within the DEA model could cause most DMUs to shift towards the efficient frontier. Dubbed the 'curse of dimensionality', the greater the number of variables, the lesser the level of discrimination between them. This aspect could be especially detrimental when analysing a small sample size of DMUs. In particular, DEA does not accept DMUs if they have incomplete variable data, and this may reduce the amount of DMUs available in the dataset for analysis. Understandably, only the variables with greatest impact on performance would be included in the analyses. (Rouse et al., 1997; Shivaramu et al., 2022b; Cook et al., 1994)

2.3.7 How and why DEA has been previously used

Previous studies, such as Cook et al. (1994), de la Garza et al. (2009), Rouse et al. (1997), Rouse and Chiu (2009), and Shivaramu et al. (2022a, b), have utilised DEA to develop benchmarking frameworks for pavement maintenance performance. A discussion follows regarding DEA's utilisation in these studies as well as the inclusion of environmental variables.

(i) Cook et al. (1994):

Cook et al. (1994) have explored the application of DEA for measuring the efficiency of highway maintenance patrols in Ontario, Canada. The 244 highway maintenance patrols in Ontario are each responsible for maintaining a particular region of the territory and carrying out numerous maintenance activities. Data from 62 patrols was used in this study. The study emphasises that DEA's capability to incorporate numerous variables, as discussed previously, is a great asset in such an application. Numerous input and output variables were used in the study's model and have been further discussed in the subsequent section. Notably, an environmental input variable, i.e., Climatic factor (CLF), has been incorporated wherein a climate 'subfactor' has been developed by collating snowfall, rainfall and temperature data captured within Ontario. Thus, each patrol's region has an individual subfactor which the study used to explain the impact of climatic conditions upon patrol pavement maintenance efficiency.

(ii) de la Garza et al. (2009):

de la Garza et al. (2009) utilised DEA to benchmark the performance of highway maintenance operations across eight counties in Virginia from 2003 to 2007. Multiple input and output variables were considered, as depicted in the subsequent section, including an aggregated climate variable, i.e., an 'environmental harshness factor' that reflected environmental challenges faced by DMUs (Counties) in Virginia. The authors believed themselves successful in developing a method that accurately represented the maintenance performance whilst realistically reflecting the observed pavement condition across the eight counties. Please refer to de la Garza et al. (2009) for further information on this model.

(iii) Rouse et al. (1997):

Rouse et al. (1997) also used DEA for performance measurement purposes regarding highway maintenance, but in a New Zealand context and with respect to the efficiency of Territorial Local Authorities (TLAs). They also developed the concepts of effectiveness, efficiency, and economy, to provide a holistic view of an organisation and its environment, as previously discussed. Multiple input and output variables were incorporated in their model, depicted in the subsequent section, and a single environmental variable, i.e., 'environmental difficulty' was incorporated into the model. This variable served to make DEA efficiency rankings more realistic by adjusting the TLAs' performances with regards to their environmental challenges, vehicle kilometres travelled (VKT) and the ratio of urban and rural highways (%UR). The variable also accounts for geological and climatic conditions, such as soil quality, pavement gradient, land contours, temperature, freeze/thaw cycles, etc., that create challenges for TLAs to undertake maintenance activities. The study further states that environmental factors can be major cost and process drivers and thus, their inclusion into a performance measurement framework would be crucial. However, the authors agreed that this single environmental variable used in their study was not specific enough to adjust the efficiency rankings of TLAs to be as realistic as they expected.

(iv) Rouse and Chiu (2009):

Building upon findings in Rouse et al. (1997), this study uses DEA to further evaluate the performance of the 73 TLAs in New Zealand from a life cycle perspective, considering their efficiency, effectiveness, and economy. The study suggested that a TLA would perform best when the total expenditure budget, i.e., the monetary input, comprised an appropriate proportion of rehabilitation, resealing, and routine maintenance activities, as per the needs and challenges of each TLA. Thus, this would ensure that pavement asset life was extended for as long as possible. Notably, the study used the 'environmental difficulty' variable in this study, as in Rouse et al. (1997), but also established numerous input and output variables that would best evaluate either economy, effectiveness, or efficiency.

(v) Shivaramu et al. (2022a, b):

These successive studies are the latest to apply DEA in developing a benchmarking framework for pavement maintenance efficiency with respect to New Zealand's RCAs. Benchmarking models have been progressively developed throughout both studies and have incorporated learnings from literature. A key contrast with previous studies has been the incorporation of multiple distinct environmental variables. Uncontrollable environmental factors such as climate, geology, and subgrade type have not been explicitly considered in other studies mentioned above. Thus, variables have been developed that cater to climate/geology and subgrade type individually. Further variable information is presented in the subsequent section.

It has been noted that climate and subgrade type greatly influence pavement performance, with wetter regions experiencing faster pavement deterioration. Moisture in pavement layers can lead to numerous defects such as cracking, aggregate stripping, and other surface deformations. Given New Zealand's heavy rainfall, young moisture sensitive soils, and the type of bound and unbound granular pavement layers used, it is a significant challenge for agencies to maintain and operate road networks (Mia et al., 2017). Thus, an advanced DEA model should explicitly consider individual environmental variables to better reflect challenges faced by RCAs. The subsequent section details variables used in the DEA models in studies discussed above, as well as evaluating the merits of variables included or excluded within in them.

2.4 Variables included in DEA models

Tables 2.5 to 2.9 show variables that have been included in previously mentioned studies to show the range of factors that have been included in previous DEA models pertaining to pavement management.

Table 2.5: Variables used in a DEA model by **Cook et al. (1994)**

Variables	Description
Maintenance expenditure (MEX) - Input	Total expenditures linked directly to each patrol, including work done by sub-contractors.
Capital Expenditure (CEX) - Input	Total expenditure for improving existing highway infrastructure, including resurfacing, structural repairs, etc.

Climatic Factor (CLF) - Input	Aggregated factor to inform patrol performance in each region, comprising four subfactors, i.e., snowfall, major and minor temperature cycles, and rainfall.
Assignment (region) size factor (ASF) - Output	Extent of workload under each highway maintenance patrol.
Average traffic served (ATS) - Output	Incorporates the road length and AADT under a patrol's territory, to gauge benefit of patrols to users.
Rating change factor (RCF) - Output	A gauge of actual pavement conditions observed as compared to expected conditions over a specific period.
Accident prevention factor (APF) - Output	Indicates the extent of work required by each patrol for accident mitigation, as part of maintenance activities.

Table 2.6: Variables used in a DEA model by **de la Garza et al. (2009)**

Variables	Description
Maintenance expenditure - Input	Total costs of sub-contracting and self-performed work for routine maintenance.
Total Area Served (TAS) - Input	Amount of road-surface maintained by each DMU (county).
Traffic (AADT) - Input	Annual Average Daily Traffic (AADT) data used to inform impacts of traffic on pavement deterioration and maintenance performance.
Load (ESAL - Equivalent Single Axle Load) - Input	Measure of vehicle forces exerted on pavement causing degradation over time.
Environmental Harshness Factor (EHF) - Contextual Environmental	Aggregated factor indicating environmental conditions under which each DMU (county) operates.
International Roughness Index (IRI) - Output	Indicator of overall pavement smoothness.
Critical Condition Index (CCI) - Output	Indicator of pavement damage due to traffic loading and climate related issues.

Table 2.7: Variables used in a DEA model by **Rouse et al. (1997)**

Variables	Description
Total Expenditure (TE) - Input	Total expenditure on reseals, rehabilitation, and general maintenance, including sub-contractor costs.
Environmental Difficulty (ED) - Contextual Environmental	Aggregated assessment of environmental difficulty faced by each TLA.

General maintenance - Output	Comprising reported expenditure on sealed highways and an index of highway surface defects, measured in $/m of general maintenance needed to repair surface defects.
Roughness - Output	Combined measures of urban and rural highway roughness.
Level of Service (LOS) - Output	Measured by annual vehicle kilometres travelled.
Reseal and Rehabilitation Kilometres - Output	Kilometres of highway resealed and rehabilitated.

Table 2.8: Variables used in a DEA model by **Rouse and Chiu (2009)**

Variables	Description
Total Expenditure (TE) - Input	Total costs of routine maintenance, resealing, and rehabilitation work.
Environmental Difficulty (ED) - Contextual Environmental	A gauge of how each TLA's climatic and geological factors affect their maintenance difficulty.
Surface Condition Index (SCI) - Output	Indicates the level of surface defects within a TLA's territory, the lower the better.
Smooth Travel Exposure (STE) - Output	A measure of the proportion of vehicles travelling on roads meeting or exceeding a targeted pavement smoothness level.
Urban/Rural Split (%U/R) - Contextual	Percentage of urban and rural roads' split in a territory.
Vehicle Kilometres Travelled (VKT) - Contextual	A measure of the traffic and level of service in a territory.
Reseal and Rehabilitation Kilometres - Output	Kilometres resealed or rehabilitated across a territory.
Routine Maintenance Expenditure (RM) - Output	Expenditure for routine maintenance including isolated and low-severity pavement defects.

Shivaramu et al. (2022b) first developed a 'contextual' model that included one input variable, two output variables and two contextual variables. A subsequent 'environmental' model developed in Shivaramu et al. (2022a) added two distinct contextual environmental variables to account for the impacts of varying climatic and geological impacts on RCA performance. All these variables have been described in Table 2.9. Please refer to cited literature for further information about how these variables were established.

Table 2.9: Variables included in the DEA model by **Shivaramu et al. (2022a)**

Variables	Description
Maintenance Expenditure per lane kilometre - Input	Road maintenance costs in each RCA, normalised per kilometre of lane length.

Surface Condition Index (SCI) - Output	85th percentile SCI - a weighted index depicting surface defects.
Pavement Integrity Index (PII) - Output	85th percentile - Combined measure of functional failure and pavement distortion.
Vehicle Kilometres Travelled (VKT) - Contextual	Vehicle kilometres travelled per lane kilometre (VKT/km).
Percentage Urban/Rural roads (%UR) - Contextual	Percentage of urban and rural roads' split in an RCA.
New Zealand Drought Index (NZDI) - Contextual Environmental	Illustrates critical parameters such as rainfall, soil moisture, soil drainage, and temperature across RCAs to inform climate type.
Soil Risk factor (SRF) - Contextual Environmental	Shrink-swell behaviour of soils given the specific soil mineralogy and susceptibility to moisture, to inform the subgrade type and underlying pavement strength.

Table 2.10 summarises which aspects of pavement or highway maintenance are included in a study's variables, e.g., relating to expenditure, area served, traffic/loading, etc.

Table 2.10: Summary of variables included in evaluated studies

Variable Inclusions	**Study**				
	Cook et al. (1994)	de la Garza et al. (2009)	Rouse et al. (1997)	Rouse and Chiu (2009)	Shivaramu et al. (2022a)
Expenditure	*	*	*	*	*
Region size/Area served	*	*			
Traffic (AADT)	*	*			
Vehicle Kilometres (VKT)			*	*	*
Vehicle Load		*			
Pavement Condition	*	*	*	*	*
Road Safety	*				
Maintenance Conducted, e.g., kilometres resealed or rehabilitated			*	*	
Aggregated Environmental Factor	*	*	*	*	
Individual Environmental Factors					*

A discussion follows regarding variables used within models developed by studies evaluated above.

2.4.1 Input variables

Table 2.11: Different input variables used within DEA models across the five studies

Total Expenditure (TE)	Maintenance expenditure (MEX)	Climatic Factor (CLF)	Traffic (AADT)
Capital Expenditure (CEX)	Maintenance Expenditure per Lane Kilometre ($/km)	Total Area Served (TAS)	Load (ESAL - Equivalent Single Axle Load)

Expenditure related variables are the most common input variables across all studies. As described in the tables above, most of these expenditure variables cover the entire costs of road maintenance, including any work performed by sub-contractors. Understandably, this type of variable is a crucial input into any DEA model as the amount of money that a territorial authority can spend on the maintenance of their road network will directly influence the magnitude and quality of maintenance undertaken. As discussed in Section 2.3, efficiency gains would be made if the territorial authorities are able to extract maximum maintenance performance from their limited budgets. Notably, all studies except Shivaramu et al. (2022a, b) have utilised aggregated measures of expenditure across the entire extents of a land authority's territory. Shivaramu et al. (2022a, b) have incorporated a more specific variable of expenditure measurement across RCAs, i.e., maintenance expenditure per lane kilometre ($/km). This provides more uniformity when comparing expenditure capability across RCAs. Interestingly, Rouse and Chiu (2009) have included an output expenditure variable, RM, as described in Table 2.8 above. From an output perspective, this variable is dependent upon the territory size and the number of defects observed, thus dictating the money a TLA will allocate to their remediation.

de la Garza et al. (2009) have uniquely included a territorial size related variable within their inputs, i.e., Total Area Served (TAS), when the only other study using such a variable (Cook et al., 1994) has included it as an output. The TAS variable (de la Garza et al., 2009) includes the amount of road surface maintained by each DMU, thereby influencing the resulting pavement condition across their territories, considering their available maintenance budgets. Whereas the Assignment (region) size factor (ASF) output variable used by Cook et al. (1994) depicts the extent of maintenance work that each Highway Patrol can carry out across their territory, with respect to the available budget and climatic conditions. Thus, two perspectives exist when using a territorial size related variable.

The CLF, an environmental variable, has been used as an input by Cook et al. (1994), while all other studies have used environmental variables as contextual variables, i.e., uncontrollable factors influencing difficulty faced during maintenance. The CLF variable aggregates climatic information from four other subfactors as described in Table 2.4, to yield an overall uncontrollable factor that informs climatic difficulty affecting maintenance performance. Further discussion on climatic variables follows.

Traffic, measured using AADT, is another variable that has been uniquely used as an input by de la Garza et al. (2009). They use it in their model to inform the impacts of traffic on pavement deterioration and resultant maintenance effort required. The amount of traffic present will affect the performance of maintenance crews due to lane closures and scheduling issues. Thus, the study has determined that Traffic was an uncontrollable input as it also captured operational conditions throughout maintenance. However, Cook et al. (1994) have used ATS as an output variable, measuring the overall benefit from maintenance to road users (AADT) within a patrol's territory.

de la Garza et al. (2009) have also uniquely used the input variable of 'Load' (ESAL - Equivalent Single Axle Load), which as per Table 2.6, measures damaging forces exerted on the pavement by vehicles. Data regarding pavement forces exerted by different types of vehicles was collected and then converted to a 'Load' factor corresponding to traffic distribution upon a particular road. The study considered this to be an uncontrollable input variable. Depending upon available data in NZ, this would be a useful variable to consider including in a model as it would help inform the level of damage experienced by roads in each territory with respect to the types of vehicles trafficking it, particularly heavy commercial vehicles (HCVs).

2.4.2 Output Variables

Table 2.12: Different output variables used within DEA models across the five studies

SCI	Rating change factor (RCF)	General maintenance	IRI	Assignment (region) size factor (ASF)	Average traffic served (ATS)	Accident prevention factor (APF)
PII	Critical Condition Index (CCI)	Roughness	Smooth Travel Exposure (STE)	Reseal and Rehabilitation Kilometres	Level of Service (LOS)	Routine Maintenance Expenditure

Different variables that provide information about pavement condition and defects, i.e., SCI, PII, RCF, CCI, General Maintenance, Roughness, and STE, have been used throughout all studies. Notably, Shivaramu et al. (2022a, b) have utilised SCI as one of their pavement condition variables, also used in Rouse and Chiu (2009). SCI is a weighted index of pavement surface defects and age of surfacing, with a range from 100 (perfect condition) to 0 (worst condition). Shivaramu et al. (2022a, b) have used the 85^{th} percentile SCI values, unlike Rouse and Chiu (2009), as these values would "provide a better representation of relatively imperfect road sections", thus giving "better insight into pavement sections that require more expenditure in terms of maintenance, renewals and operations". Similarly, 85^{th} percentile values have also been used for the output variable PII. It has only been used by Shivaramu et al. (2022a, b) and is a combined measure of functional failure and pavement distortion in sealed road surfaces, ranging from 100 (perfect integrity) to 0 (very bad). It should be noted that SCI and PII are performance indices used by the NZTA based upon direct data from RCAs to depict pavement and surfacing condition across the territories. Thus, it is prudent to incorporate these factors into a performance monitoring framework. As described in Table 2.5, the RCF variable used by Cook et al. (1994) measures the actual change in Pavement Condition Rating (PCR) across road sections relative to an expected 'standard' change in PCR, considering the pavement age and climatic conditions. PCR data from patrols is used in this variable, and the SCI and PII variables reflect similar information for NZ. As described in Tables 2.6 to 2.8, General maintenance and Roughness (Rouse et al., 1997), IRI (de la Garza et al., 2009), and STE (Rouse and Chiu, 2009) are other individual surface defect and roughness related variables that use available data to inform the quality and quantity of pavement maintenance across respective territories. For future studies in a New Zealand context, it may be better to use available data that incorporates these and also other factors in the reporting, such as in the SCI and PII variables, to give a more accurate and robust depiction of pavement condition.

Reseal and Rehabilitation Kilometres (Rouse et al., 1997; Rouse and Chiu, 2009) across a territory are insightful in depicting the extent of maintenance carried out across a territory, however, not all studies have utilised this variable, as shown in Table 2.10. This would likely be due to the usage of other variables such as VKT or pavement condition variables that indirectly depict the level of maintenance being carried out.

LOS, as described in Table 2.7, has been used by Rouse et al. (1997) to reflect utilisation of highway capacity. However, the study states that a direct measure of highway capacity usage was unavailable, and hence a substitute measure of VKT was used. It should be noted that the other two studies incorporating a VKT variable, as per Table 2.10, have included it as a contextual variable due to its uncontrollable nature.

Lastly, APF, used by Cook et al. (1994), is the only variable regarding road safety across all five evaluated studies. Accident prevention should be a goal of pavement maintenance and network management, and direct data reflecting the number of incidents across road sections within RCAs would be available through New Zealand's Ministry of Transport. A specific road safety related variable should be considered for development in future work.

A note about the recently developed Pavement Health Index (PHI) condition variable

The Pavement Health Index (PHI) is a recently developed composite index-based variable that includes information regarding roughness, rutting, cracking. It was originally developed for Auckland Transport (AT) but was later adopted into the Waka Kotahi National Long-Term Programme (NLTP) analysis and is a more refined successor of the Pavement Integrity Index (PII) variable. Required data for developing every asset or territory's PHI is readily available, and generated values are easily understood on a scale of 0 (poor) to 100 (perfect). Moreover, territorial authorities such as RCAs are being encouraged to pursue robust data collection procedures to drive widespread adoption of this useful performance measure (IDS, 2021b). Thus, for a current DEA benchmarking model, PHI would be a strong output variable to use instead of PII.

2.4.3 Contextual Variables

Table 2.13: Different contextual variables used within DEA models across the five studies

VKT	NZDI	Environmental Difficulty (ED)
%UR	SRF	Environmental Harshness Factor (EHF)

VKT, as used in Rouse and Chiu (2009), and Shivaramu et al. (2022a, b), is an uncontrollable contextual variable reflecting traffic volume and the level of service of the road network within a territory. It is known that increased traffic loading increases the rate of pavement deterioration and thus, it's important to include this factor in a model. The Traffic and ATS variables discussed previously, used as inputs, also captured similar information in their studies. However, VKT also captures the distance travelled by traffic, thus, making it a more robust variable. Rouse and Chiu (2009) have also used VKT as one of their contextual environmental variables, along with %UR and ED, as they justified that these were uncontrollable environmental factors unique to each territory. Whereas, Shivaramu et al. (2022a & b) have included VKT and %UR as one of their non-environmental contextual variables, as other variables that directly deal with climatic and geological factors have been added to their model, i.e., NZDI and SRF.

%UR, used by Rouse and Chiu (2009) and Shivaramu et al. (2022a, b), describes the ratio of urban to rural roads within each territory and is an important variable to include as unit costs of fixing an urban road are significantly higher than a rural road (Henning et al., 2022). Urban roads also experience a higher volume of heavy commercial traffic compared to rural roads. Thus, this is an important variable, for which data is readily available. Rouse and Chiu (2009) have demarcated roads with a speed limit of 70 km/h and above as rural roads, and roads of lower speed limits as urban roads, whereas Shivaramu et al. (2022a, b) have used the percentage split of urban and rural roads given in NZTA's data for each RCA.

All evaluated studies have utilised at least one environmental factor to address the impacts of varying climatic and geological conditions upon pavement management. However, all except Shivaramu et al. (2022a) have utilised only one aggregated variable that compiles information from multiple 'subfactors' to provide an overall weighted factor. Moreover, as discussed, Cook et al. (1994) have uniquely placed their CLF variable in the inputs, and not as a contextual variable like the rest of the studies. The ED variable has been used by both Rouse et al. (1997), and Rouse and Chiu (2009) and is evaluated as a ranking from 1 (high difficulty) to 9 (low difficulty). The variable utilises collected geological and climatic factors for each territory to inform the level of road maintenance difficulty. The EHF variable, used by de la Garza et al. (2009), similarly indicates the environmental conditions under which each DMU operates, with data collated from other subfactors.

However, Rouse et al. (1997) agree that using an aggregated variable is “too coarse a measure” to obtain a realistic impact on DMU efficiency ratings. Shivaramu et al. (2022a) also agree that a single variable cannot successfully portray information relating to all the environmental factors impacting RCA performance. Thus, the most descriptive environmental factors were developed from available data to account for variabilities in soil subgrade type (SRF) and climatic conditions (NZDI). Descriptions of SRF and NZDI are given in Table 2.9 and suggest that these are robust variables that would be ideal for future inclusion into DEA models.

2.4.4 DEA variable weighting restrictions

Previous research demonstrates that allowing DEA complete flexibility for assigning variable weights in a regular unbounded DEA model results in unjustifiably high performance ratings for some DMUs. Variables received unreasonably high or low weightings without any uniformity as DEA tried to present DMUs in the ‘best possible light’ (Ozbek, 2007; Thanassoulis and Allen, 1998; Cooper et al., 2011).

It is stated across the literature that an unbounded DEA model would not satisfactorily account for realistic operational and environmental conditions. Such a model would also not be readily accepted in industry, where some influencing variables are effectively ignored, such as in an RCA’s performance rating. Thus, there is consensus amongst the literature that imposing some form of weighting restriction would contribute towards more realistic and justifiable DEA performance ratings to better support benchmarking comparisons and drive efficiency improvements (Dyson and Thanassoulis, 1988; Cook et al., 1994; Shivaramu et al., 2022a, b).

However, no clear-cut procedure exists to set ‘correct’ weighting limits on chosen variables that would yield ‘accurate’ performance ratings, as there would likely be unique nuances and challenges to be considered in each benchmarking scenario. Thus, sound judgement, industry guidance, and the relative importance of the selected variables must be considered, as the level of restriction can significantly influence final outcomes. Moreover, DEA’s characteristic trait of flexibility in variable weight application must still be respected to an extent, such that there is still reasonable weight optimisation freedom within acceptable bounds (Dyson and Thanassoulis, 1988; Cook et al., 1994.; Bjørndal et al., 2008; Ennen and Batool, 2018).

Thus, literature deems it important to set weight restrictions in accordance with existing technology, information, and guidance from decision makers, as these factors will influence the extent of restriction placed on a particular performance indicator and resulting DMU efficiency. Cook et al. (1994), and Wong and Beasley (1990) suggest general guidelines and questions for consideration when developing any weight restrictions.

Cook et al. (1994) suggest the following general guidelines:

1. Assigning a variable a higher or lower range of weighting should be determined by the role the associated activity plays in the performance of a DMU.
2. A narrow or tight weighting range should be set for a factor where there is certainty about the importance of that factor, such as for expenditure related variables. Conversely, contextual or environmental variables may require a broader restriction range due to a potential lack of accurate, unambiguous data, and since the full extent of climatic influences may not be understood.

Wong and Beasley (1990) suggest considering the following questions:

(a) Could the importance of an output variable *'i'* in evaluating DMUs be as low (or as high) as '*z%*'?
(b) Should the importance of an output variable *'i'* in evaluating DMUs be allowed to be as low (or as high) as *'z%'*?

Most other studies also refer to guidance given in relevant literature, as well as asking questions to industry, academia, and decision makers themselves to help assign weight restrictions. It should be noted that different RCAs may associate a higher value to a particular output or input based upon their individual challenges and resources available. Thus, weighting restrictions may not be able to fully cater to DMUs on extremes of performance ranges, i.e., very high or low performers within a particular variable. Additional measures may be taken to scale and normalise performance data across DMUs to encourage more sound benchmarking comparisons.

2.5 Summary

Effective asset management is a cornerstone of robust decision-making, long-term economy, and asset performance. The value of having robust data has been demonstrated through numerous case studies and is related to all elements of asset management, such that improvements in data quality can directly yield significantly better financial and maintenance outcomes. Performance benchmarking is widely used across industries and supports more robust asset management decisions through comparisons against an entity's well-performing peers and identifying potential areas for improvement. Statistical performance benchmarking techniques are prevalent, and the most popular amongst them is DEA, which can consider a

DMU's performance efficiency in comparison to peers across different influencing variables. DEA has been previously studied within RCA network maintenance performance contexts and does not require manual input regarding the importance or 'weighting' of different performance variables.

Various studies have been discussed that utilise different input, output, and contextual variables within DEA models. Expenditure related variables were common inputs as they could be the sole controllable factors for DMUs that influence maintenance performance. Output variables commonly included pavement condition variables such as SCI, PII, General Maintenance, Roughness, etc. PHI is a more robust, recently developed successor to PII, and it is being widely adopted since it is an easily understood aggregated index-based measure of rutting, roughness and cracking information. Contextual variables were beyond a DMU's control and commonly included traffic loading, e.g., VKT or AADT, and environmental variables, e.g., SRF or NZDI. The merits of including particular variables in a DEA model have also been evaluated regarding relevance for New Zealand, any potentially better options, and the scope of this study.

Crucially, DEA's inherent flexibility to allocate unrealistic variable weights in order to present DMUs with the highest possible efficiency score has been identified across literature as a significant limitation to the robustness and acceptability of its performance ratings within industry. To this end, numerous studies support the application of variable weighting restriction within DEA to obtain more realistic performance evaluations. However, there are no concrete guidelines as to the 'correct' level of restriction for variables within a particular benchmarking scenario. Studies agree that restrictions should be set on chosen variables based on sound judgement regarding the relative importance of variables and advice from industry specialists, whilst still allowing a measure of weighting flexibility to DEA.

Thus, to contribute towards advancing the maintenance performance benchmarking of New Zealand's RCAs, this study will seek to develop a DEA model with updated variables that most dominantly explain performance variations across RCAs and develop sound weighting restrictions to support more realistic comparisons of efficiency. Additionally, it would be prudent to assess the applicability of DEA benchmarking outcomes in conjunction with current performance assessments to evaluate the level of alignment across different measures. This study seeks to develop a sound basis for maintenance performance comparisons and guide future refinements in realistic DEA benchmarking models.

Chapter 3 - Methodology

This chapter describes the DEA analysis procedure, how efficiency scores are assigned to DMUs, variable selection and preparation for DEA analysis, and the process of applying weight-control to chosen variables. The applicability of DEA results in conjunction with presently used performance indicators is also discussed, such that more holistic RCA performance assessments may be conducted. Figure 3.1 depicts the study's methodology framework for a more visual summary of objectives, research questions and associated analysis procedures.

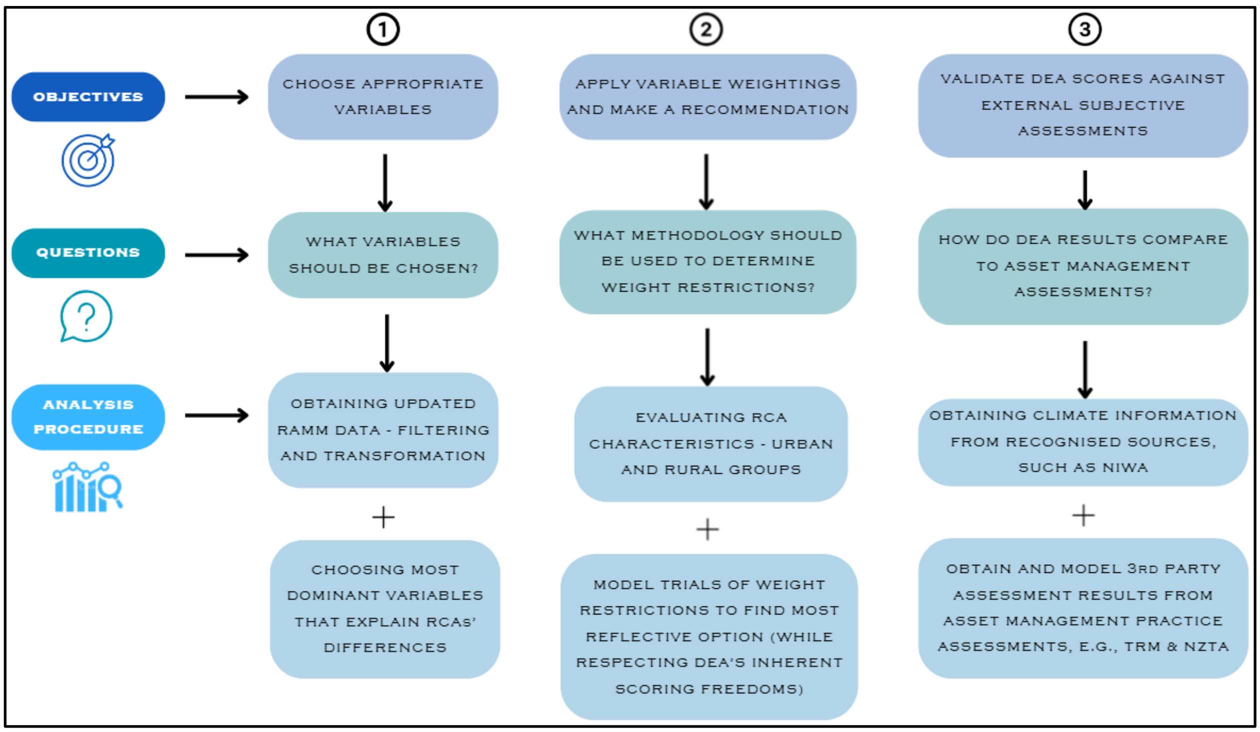


Figure 3.1: Methodology framework

3.1 The DEA technique and selected settings

The analysis software used in this study is identical to that used in Shivaramu et al. (2022a, b). Since this study aims to expand upon their work, it was critical to maintain analysis consistency. The following sub-sections describe how DEA assigns efficiency scores to a DMU, and which DEA optimisation settings were set for the study.

3.1.1 How DEA assigns efficiency scores

The efficiency of a DMU, in this case an RCA, depends on its ability to produce specific outputs using available inputs in comparison to other units (its peers) within the dataset. For each DMU, the weighted sum of outputs divided by the weighted sum of inputs yields an efficiency score. As an example, for a DMU 'n' with two outputs, y_1 and y_2, and three inputs x_1, x_2, and x_3, this relationship may be expressed mathematically as;

$$E_n = \frac{a_{n1}y_1 + a_{n2}y_2}{b_{n1}x_1 + b_{n2}x_2 + b_{n3}x_3} \qquad \text{Equation 3.1}$$

Where,

- E_n refers to the efficiency score for a DMU 'n'.
- $a_{n1,\ 2,\ 3}$ and $b_{n1,\ 2,\ 3}$ refer to the individual weightings given to a DMU's output and input variables, respectively.

The ratio of weighted outputs to weighted inputs will be less than or equal to 1. When a DMU's ratio lies on the DEA frontier (highest output for given input), it is relatively efficient amongst its peers. Optimum weightings (in percentages from 0-100%) are automatically assigned by the technique to yield the highest possible efficiency score with the given combination of inputs and outputs.

As discussed in the literature review, DEA's automatic weighting procedure under no restriction will give higher weighting to variables in which a DMU performs well or demonstrates economy, while giving lower weightings to variables where a DMU performs poorly. However, lower or upper limits on the possible weightings of particular variables may be set in the software to observe efficiency scores amongst DMUs within these new constraints. With manual weighting constraints applied, DMUs that were previously efficient under no constraints may become inefficient, and previously inefficient DMUs may become efficient.

3.1.2 DEA analysis settings

Some crucial DEA optimisation settings were applied through the software to ensure that this study's results appropriately develop upon previous work done by Shivaramu et al. (2022a, b). These are described below:

1. **Output oriented model -** DEA models may be input-oriented or output-oriented. Input-oriented models focus on reducing inputs whilst keeping outputs constant. Conversely, output-oriented

models seek to maximise outputs with constant input levels. This study focuses on how well RCAs perform network maintenance given their specific budgets and challenges, i.e., the magnitude of outputs produced using set inputs. Thus, this analysis will be output-oriented.

2. **Variable Returns to Scale (VRS) -** Two primary types of DEA models exist: Constant Returns to Scale (CRS) and Variable Returns to Scale (VRS). In this study, there is significant variation in the size of DMUs and their individual challenges related to their available resources. Dyson et al. (2001) state that the VRS specification has been developed to account for such high variation, producing a non-linear relationship between inputs and outputs and allowing the efficiency frontier to respond to constant, increasing and decreasing returns to scale. Thus, this study will utilise a VRS model.

3.2 Selected input and output variables

This study aims to expand upon previous research done to utilise the DEA method to benchmark RCA network maintenance and management efficiency. As such, those variables that most dominantly express differences across RCAs have been chosen from the available data. Some of these variables are similar to those used in Shivaramu et al. (2022a) but have been used with updated data for the years 2021/2022. The data was taken from the national Road Assessment and Maintenance Management (RAMM) database. This study's variables include:

Controllable Input:

1. **Expenditure** – combines pavement maintenance costs and surfacing maintenance costs recorded every three years (corresponding to three-yearly maintenance budgeting cycles).

Uncontrollable Inputs (Contextual Variables):

1. **Percentage of Urban Roads (%UR) –** this is the percentage of urban roads compared to rural roads in an RCA.
2. **Vehicle Kilometres Travelled per Kilometre (VKT/km) –** (in millions) this records the total VKT across an RCA, per lane kilometre.

Output:

1. **Pavement Health Index (PHI)** – this combines rutting, cracking and roughness information into one variable.

The key difference between the analysis done by Shivaramu et al. (2022a) and this study is that less input and output variables have been utilised due to the limited scope of this study and the initial aims of developing a sound methodology for applying variable weighting restrictions, whilst understanding the dynamics of DEA. Additionally, PHI is a recently developed condition variable (IDS, 2021b) which has been utilised in this study. More variables, such as environmental contextual variables, may be added to the analysis once the final procedure has been developed but is outside the scope of this study. Moreover, the rule of thumb proposed by Cooper et al. (2011) has been followed, where the number of DMUs must be greater than three times the sum of input and output variables. Bowlin (1998) suggests that this will "ensure sufficient degrees of freedom for a meaningful analysis".

3.3 Data for analysis

3.3.1 Data Sourcing

The list of all RCAs and their associated data was sourced from a clone of the Insight Tool SQL Backend database created by Company-X, which was then imported into Python to create a web-based reporting dashboard, as mentioned in IDS (2023). The database maintained by Company-X contains all core RAMM information dumped by councils at the end of each year, the latest being 2022. All reported data is in its raw form, i.e., no lane averaging or aggregated treatment lengths. All road network lengths across RCAs have been included except for those that are unsealed or are bridges (IDS, 2023).

3.3.2 Data Preparation

Steps were taken to ensure the raw data was suitable for analysis in the software. These are described below:

1. RCAs that had missing variable information were removed from the dataset as DEA will not run a model with missing information.
2. Variables mentioned previously were transformed to get them into the correct scale as the software will not handle data that is too far apart in scale. 0-100 is a practical scaling range given the scale of some variables, such as VKT and expenditure values in millions, compared to PHI and %UR values that are percentages within a range of 0-100%.

The scaling and orientating procedure for each variable is given below.

i) Expenditure (Controllable Input)

- All raw expenditure data mentioned previously was combined to create 'Combined Costs'.

- Combined costs were then divided by total network lane kilometres, to give 'Combined cost ($/km)'
- 'Combined cost ($/km)' was then scaled between 0-100:

$$\frac{Cost - Cost_{min}}{Cost_{max} - Cost_{min}} * 100 \qquad \text{Equation 3.2}$$

Where,

- Cost - Combined Cost in $/km for an RCA
- $Cost_{min}$ - the minimum identified Combined Cost ($/km) value across all RCAs
- $Cost_{max}$ - the Maximum identified Combined Cost ($/km) value across all RCAs

- Multiplying by 100 ensures all values are in a range of 0-100, giving **"0-100 Cost ($/km)"**.
- Higher values suggest higher maintenance budgets in RCAs, which should ideally yield better pavement outcomes, i.e., higher PHI values.

ii) Percentage of Urban Roads (%UR) (Contextual Input):

Higher %UR values suggest more maintenance expenditure as urban roads are significantly costlier to maintain, even though there is a much greater proportion of rural roads (Henning et al., 2022). Thus, values will be inverted because the DEA software understands that a smaller value means greater hardship. Those RCAs with smallest inverted values are expected to gain more weighting for the %UR variable.

- All values are already in a scale of 0-100.
- Every RCA's value is then subtracted from 100 to give **'INV %UR'**, where 'INV' indicates an inverted value**.**

iii) VKT - in millions (Contextual Input):

Higher values suggest more maintenance challenges due to greater traffic loading. There is a huge gap between the largest VKT value (RCA 80) and all other VKT values. To avoid results being skewed and unrealistic, the raw VKT data was first normalised by being divided by the total network lane kilometres recorded for each RCA, giving 'VKT/km'.

- VKT/km is then scaled between a range of 0-100, across all RCAs:

$$\frac{VKT - VKT_{min}}{VKT_{max} - VKT_{min}} * 100 \qquad \text{Equation 3.3}$$

Where;

VKT - individual VKT/km for an RCA

VKT_{min} - the minimum identified VKT/km value across all RCAs

VKT_{max} - the maximum identified VKT/km value across all RCAs

- Multiplying by 100 gets all values to a range of 0-100, giving 'VKT/km - 0-100'.
- 'VKT/km - 0-100' values have been inverted by subtracting them from 100 to give **'INV VKT/km - 0-100'** as the software understands that a smaller value means greater hardship.

iv) Weighted Average PHI (Output):

These values are already in a scale from 0-100, and higher values indicate better pavement condition in territories, thus, PHI values were not inverted.

The VKT/km values were used to split the available RCAs into either a 'High-Traffic (HT)' group or a 'Low-Traffic (LT)' group. Higher concentrations of traffic loading over an RCA's territory would suggest a more urbanised territory, or a territory that may have more rural areas but with some areas experiencing high traffic loads. This separation of RCAs was done to further understand DEA's 'moving-parts' when restrictions were applied and individually study the performance of RCAs with similar characteristics. As such, those RCAs with VKT/km values greater than or equal to 0.5 were grouped as HT RCAs, and the rest as LT RCAs. This demarcation also allowed the HT group to include all 'city-council' RCAs as well as those 'district-council' RCAs known to have regions of relatively high urbanisation and traffic within their territories. HT RCAs and the associated transformed data have been shown in Table 3.1 in order of descending VKT/km, with the list of all LT RCAs and transformed data given in Chapter 4.

Table 3.1: High-Traffic (HT) RCAs and their associated data

RCA No.	Road Council	Abbreviation	City/ District	0-100 Cost ($/km)	INV %UR	VKT/km	INV VKT/km (0-100)	PHI
11	Hamilton City Council	HCC	City	9.61	6.70	1.63	0.01	72.70
80	Auckland Transport	AT	City	7.83	30.85	1.63	0.35	70.90
15	Tauranga City Council	TCC	City	100.00	6.07	1.59	2.84	73.66
76	Christchurch City Council	CCC	City	16.14	19.55	1.49	9.48	62.81
24	Hutt City Council	HCC	City	1.05	6.29	1.41	14.49	69.85
37	Wellington City Council	WCC	City	8.26	8.39	1.30	21.58	68.30
31	Porirua City Council	PCC	City	18.50	16.63	1.23	26.25	65.94
30	Nelson City Council	NCC	City	26.11	6.00	1.19	29.22	69.62

68	Queenstown-Lakes District Council	QLDC	District	5.84	44.03	0.83	52.79	67.27
61	Dunedin City Council	DCC	City	20.33	35.99	0.64	65.11	62.01
25	Kapiti Coast District Council	KCDC	District	19.94	38.83	0.61	67.44	74.38
40	Hastings District Council	HDC	District	0.57	74.59	0.59	68.81	73.11
7	Taupo District Council	TDC	District	6.76	66.29	0.52	73.47	67.53
19	Waipa District Council	WDC	District	2.28	79.06	0.51	73.65	72.36

Initially, this study focuses on determining the efficiency rankings for the HT RCA group with weighting restrictions applied on one or more input variables. HT RCAs are considered first due to challenges with higher traffic loading, urbanisation, and associated budget challenges, especially due to the higher maintenance and renewal costs of urban roads which may be more expensive than rural roads by more than $10,000 per kilometre (Henning et al., 2022). LT RCAs also face challenges related to traffic loading and urbanisation but to a lesser extent than HT RCAs. However, financial issues would likely affect both types of RCAs similarly, such that better budget management, accurate performance reporting, and appropriate funding would lead to better maintenance outcomes. Thus, weighting restrictions developed for HT RCAs may also be suited to LT RCAs depending upon which variable's weighting is controlled. To summarise this section, Figure 3.2 shows the procedure for obtaining and transforming DEA data for subsequent analysis.

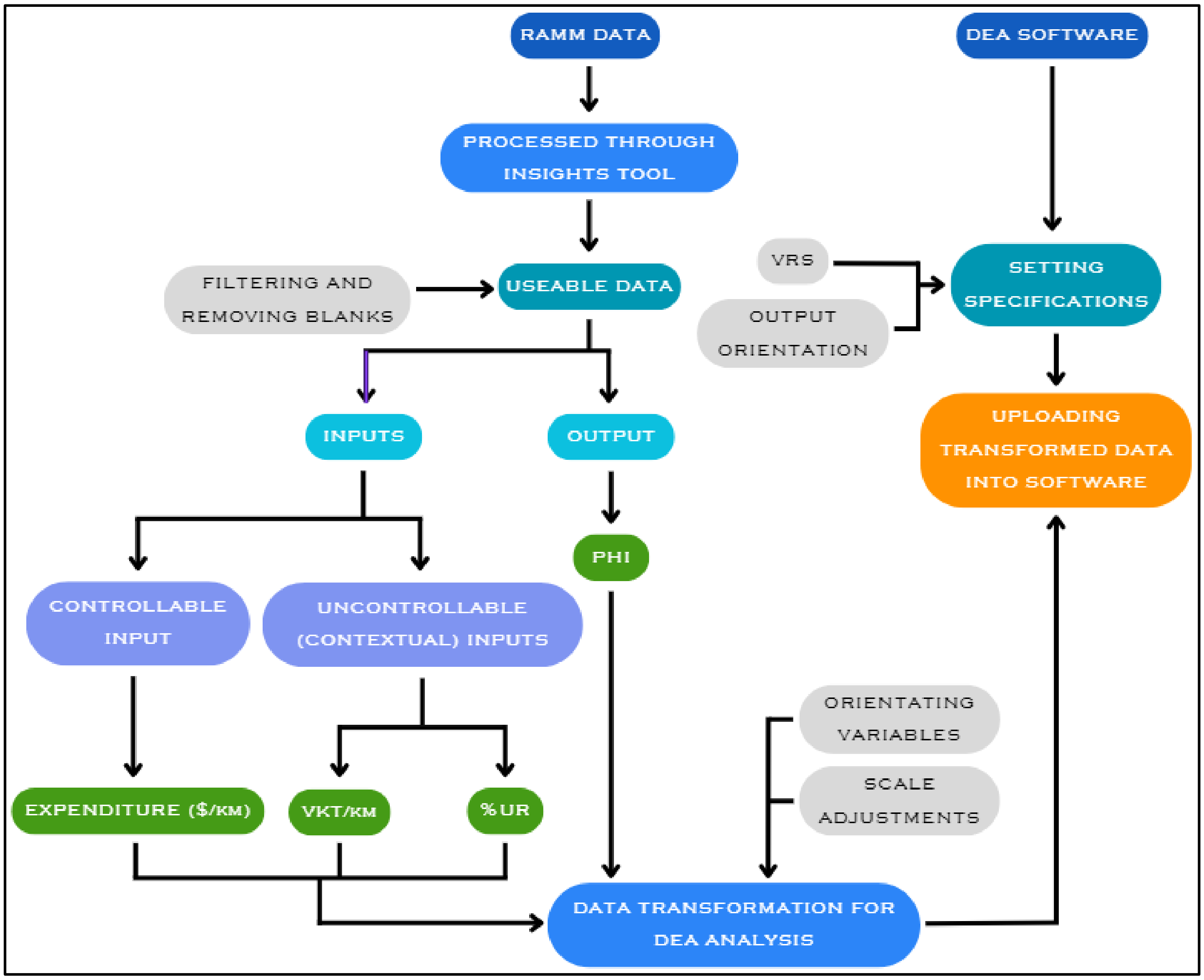


Figure 3.2: Obtaining and transforming data for DEA analysis

3.4 Development of the process to apply weight control

In the DEA software, weight restrictions can be applied on variables from both the minimum and maximum end, i.e., restrictions may be 'a minimum 30% weighting for variable-x', and 'a maximum 60% weighting for variable-y'. Knowing the extent of restrictions to be applied and on how many variables depends greatly on engineering judgement. To aid this judgement, two different weight-restriction configurations had been trialled on the variables prior to developing a final configuration. In all trials, it was understood that as PHI was the sole output variable, it would have 100% overall weighting in the efficiency score.

Studied literature states that those familiar with subject-matter should seek consensus on appropriate restrictions for a variable. This will be done in future research as a workshop with industry specialists to seek guidance on which variables, if any, should be assigned weighting restrictions and why. However, such an exercise hasn't been conducted for this study, as it was necessary to first understand the dynamics of DEA when weight restrictions were applied with a handful of variables, and to generate different scenarios of restrictions with varying outcomes. Such an exercise has not been conducted within a New Zealand road network maintenance context, and the outcomes from different scenarios would later assist in gaining consensus among specialists for determining sound variable restrictions.

3.4.1 Trial 1 - Applying both minimum and maximum weight restrictions

The first trial applied a maximum and minimum weighting restriction on individual input variables across a range of restraints, and neither of the remaining variables were restrained. This process of applying restraints to one variable while the other two were kept unconstrained was repeated until all three input variables had been cycled through. The range of weighting restrictions (as well as no restraints) tested is given in Table 3.2 below. For every weight combination, the weighting was recorded for the two unconstrained variables when one variable was controlled. The smallest minimum restriction applied was 20%, as a variable's restriction setting lower than this would likely produce insignificant impact within the overall efficiency score, as compared to the two other variables.

Table 3.2: Combinations of weight restrictions tested in Trial 1 for every variable

Minimum weighting (%)	**Maximum weighting (%)**
0	100
20	90
30	80
40	70
50	60
40	50
30	40
20	30
20	35

3.4.2 Trial 2 - Applying either minimum or maximum weight restrictions

The second trial involved applying weight control from only one end on each input variable, i.e., a minimum or maximum limit. This was done to promote some freedom in DEA's weights assigned to a DMU's variables. One variable was tested across a range of restraints at a time. VKT/km and %UR were controlled from a maximum end, i.e., maximum weightings of 70%, 60% or 50%, while expenditure was controlled from a minimum end, i.e., minimum weightings of 50%, 40% or 30%. These weightings were set with the primary focus of not being too high or low so that other unconstrained variables could also be given reasonable weightings if they contributed towards a better overall efficiency score. %UR and VKT/km were controlled from a maximum end as these factors are outside RCAs' control, and setting a maximum upper limit would enable DEA to limit the variable weighting that could be given to RCAs with higher values in these variables. Conversely, Expenditure is the only thing RCAs can control and should be included relatively significantly in the weighting mix. Without restrictions, most RCAs tended to ignore or give insignificant weighting to expenditure as they demonstrated poor expenditure economy within DEA or greater hardships were faced with %UR and VKT/km.

3.4.3 Final Configuration - Applying only minimum expenditure restrictions

For the final configuration, it was decided that all efficient and inefficient RCAs would be considered in output analyses to gauge applicability of the weighting restrictions. Additionally, it would be most useful to have restrictions applied on the expenditure variable from the ‘minimum-end’, as that is the only controllable factor for RCAs. This would achieve a guaranteed minimum expenditure weighting and ensure efficiency scores sufficiently reflect whether an RCA performs well or poorly, mainly in terms of budget management and value-for-money. Hence, the other two input variables would be left to DEA to adjust autonomously to yield highest possible efficiency scores. The final model’s weight-restrictions for expenditure ranged from 0% (unconstrained), and then from a minimum of 30% to 60% weighting, in increments of 10%. The 30% and 60% expenditure weightings may cause the other two input variables to be overrepresented or underrepresented respectively. However, they were included to see the trend of scores across a spectrum of restrictions and guide a recommended weight restriction for the entire dataset, i.e., both HT and LT RCAs. Additionally, it would be advantageous to have a recommended weight restriction where distorted variable distributions could be avoided, alongside the primary aim being a guaranteed inclusion of expenditure within RCAs’ scoring mixes. If it was shown that restricting expenditure was successful on HT RCAs, known to have challenging traffic loading, urbanisation, and much greater maintenance costs, then it is likely that restricting expenditure would also be applicable on LT RCAs given their challenges with maintenance budgets. Outcomes from the final configuration have been discussed in detail within Chapter 4.

3.5 Evaluating DEA results in conjunction with subjective council performance assessments

The DEA model’s results will be completely data-based and objective. On one hand this is advantageous, as performance assessments will be completely devoid of subjectivity. However, assessing RCA performance by considering these results in conjunction with presently used performance assessments will support the applicability of this DEA technique within the transport and asset management sector.

Specifically, current performance assessments considered in this study are the Asset Management Plan (AMP) report assessment scores given to RCAs by Waka Kotahi (NZTA) and Te Ringa Maimoa (TRM), formerly the Road Efficiency Group (REG). The TRM and NZTA scores are derived from subjective reporting assessments based on each organisation's specific assessment criteria. RCAs achieve higher scores if their AMPs align with as many assessment criteria as possible, however a high score in one organisation's assessment does not guarantee a high score in the other. The TRM assesses AMPs against elements of the "Te Ringa Maimoa Pillars of Success", including, "Systems, Evidence, Communicating, Decision Making, Service Delivery and Improvement Plan". Whereas the NZTA assesses AMPs against elements of the five-case model for a Programme Business Case including, "Strategic Case, Programme Case, Commercial Case (procurement context) and Management Case (delivery and performance)" (TRM, 2022a). High scores across both types of assessments indicate significant alignment across both sets of evaluation criteria, but such an RCA's DEA efficiency ranking may or may not reflect this high performance due to a completely different objective evaluation lens.

Considering the given RCA performance data and any alignment or misalignment between subjective and objective evaluation tools would provide holistic insight into potential gaps in RCA reporting or performance. Such an amalgamated assessment would aid in identifying challenges faced by RCAs and how they may attain higher performance outcomes.

The next chapter, Chapter 4, discusses results obtained from the final configuration when applied to both HT and LT RCAs, suggests recommended weightings for expenditure, and evaluates the applicability of DEA alongside different assessment measures described above.

Chapter 4 - Results and Discussion

This chapter presents results obtained from the final DEA model tested on HT RCAs and then on LT RCAs and evaluates the behaviour of efficiency scores and variable weightings along a range of expenditure weight restrictions. An overall recommendation on the suggested expenditure weighting range for both RCA groups (HT and LT) has been provided with justification. Subsequently, RCAs exhibiting notable performance have been discussed further, and their efficiency score details have been considered alongside currently used subjective performance assessment scores.

4.1 Interpreting results for RCAs

The software presented overall efficiency scores and individual results of variable weightings for all selected RCAs, across all weighting restrictions. Figure 4.1 shows the overall efficiency scores of unconstrained HT RCAs, as well as the minimum efficiency score for this run which is 83.5% for RCA 61, i.e., Dunedin City Council (DCC). Green ticks and circles represent the RCAs with 100% efficiency scores, i.e., they are efficient under these weight restriction settings. Yellow circles represent moderately inefficient RCAs, having efficiency scores between 90% and 100%. Red circles represent inefficient RCAs, with 90% or lower efficiency scores.

Units	Comparison 1		
Unit name	Score	Efficient	Condition
24	100.0%	✓	
11	100.0%	✓	
15	100.0%	✓	
25	100.0%	✓	
30	100.0%	✓	
40	100.0%	✓	
80	100.0%	✓	
19	98.8%		
37	94.4%		
68	92.1%		
7	91.9%		
31	90.0%		
76	86.1%		
61	83.5%		
14 units	Min: 83.52		

Figure 4.1: Efficiency scores (%) for HT RCAs without weight restrictions

Figure 4.2 shows an example of individual variable 'unit' details for an RCA. These unit details show variable weightings that comprise an RCA's efficiency score. Unconstrained details for RCA 40 - Hastings District Council (HDC) have been shown and it was efficient as per Figure 4.1.

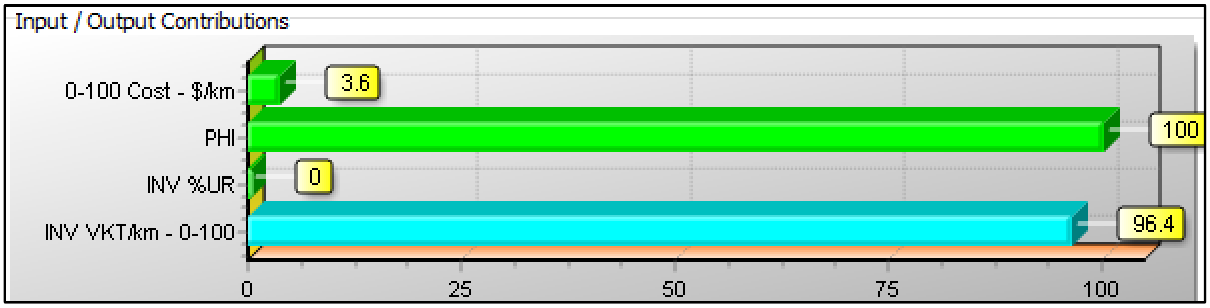


Figure 4.2: Unit details for RCA 40 (HDC) under no weight restrictions

These unit details are interpreted by considering the variable orientations described in Chapter 3. To reiterate, VKT/km and %UR values were inverted so that DEA would understand that a lower value suggested hardship or challenging conditions for these variables and could weight these variables appropriately. The higher the actual value, e.g., for traffic loading (VKT/km), the lower the inverted value would be. The lower the actual value the higher the inverted value would be, suggesting lesser hardship or challenges faced by an RCA for that factor. However, Expenditure, i.e., *'0-100 Cost - $/km',* and PHI were not inverted as higher or lower values for these variables directly reflect better or worse conditions within an RCA, respectively. Inverted VKT/km is represented by *'INV VKT/km - 0-100'*, and inverted %UR is represented by *'INV %UR'*. Considering actual RCA conditions supports the interpretation by evaluating whether these scores align with industry knowledge and practice.

Reviewing the example of RCA 40 above, DEA gave 3.6% weighting to Expenditure, 96.4% weighting to VKT/km, and has ignored the factor of %UR. As mentioned in Section 3.4, if an RCA is deemed efficient, then it is likely that numerous variable weight combinations would yield 100% efficiency. One such combination has been presented by the software for RCA 40. Input data for RCA 40 from Table 4.1 shows it had the smallest expenditure ($/km) amongst all HT RCAs, third smallest VKT/km value, second smallest %UR, and one of the higher PHI (output) values across HT RCAs. Thus, the data and DEA scoring suggest that all these factors contributed to achieving a high PHI and that this RCA is efficient.

4.2 Trial 1 DEA outcomes

As per the methodology, the first trial applied weight restrictions from both the minimum and maximum limits on each variable individually. A sample output graph from this trial has been shown in Figure 4.3.

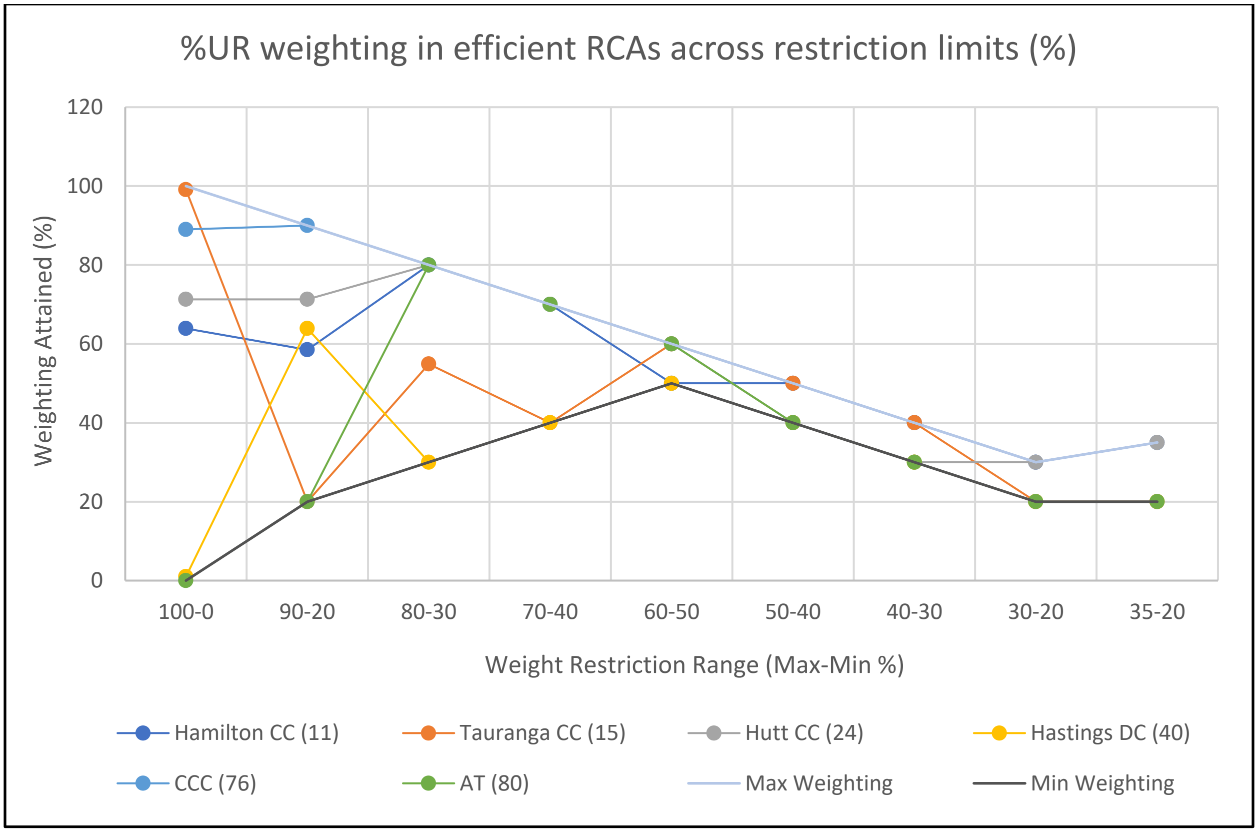


Figure 4.3: %UR weighting in Efficient RCAs across varying Restriction Settings - Trial 1

The variable weighting outputs from this first trial's configuration showed that there was no set sequence in how they reacted to restrictions. It was expected that DMUs displaying comparative economy and a lean value within the controlled variable would have weighting assigned towards the 'maximum' limit of the restraints, and those facing less hardship would have variable weighting towards the 'minimum' limit. However, output graphs from every variable's weight control showed that weighting assigned to a DMU had no set pattern and often fluctuated between the maximum and minimum end of the restrictions until convergence of weighting scores was observed in the last five highly restrictive restraint combinations. One of the pillars of DEA is that it has autonomy in assigning weights to a DMU's variables. Thus, it was decided that double-ended weight control, as in this trial, was against DEA's core principles and was ineffective in understanding the extent to which weight-control should be applied.

Figure 4.3 depicts an example of progressively converging weights assigned to one of three input variables, in this case, %UR. Highly fluctuating weighting is seen across all RCAs and does not yield any insight into whether any scoring trend exists across efficient RCAs. Additionally, the other two unconstrained variables display even more erratic and unpredictable weighting behaviours across all RCAs, as depicted by an example graph in Figure 4.4, showing the expenditure variable's behaviour across the range of restrictions while %UR was being controlled - refer to Figure 4.3.

The other unconstrained variable in this example, i.e., VKT/km also displayed the same unpredictable weighting behaviour. In fact, within this model configuration, each set of constrained and unconstrained variables gave similar results that did not help understand whether there was any trend to assigning higher or lower weighting to a particular RCA. Thus, it was concluded that such double-ended weight control would not be suitable moving forward, and more specificity would be required as to the limits of restriction for each variable, or, if only certain variables should be controlled.

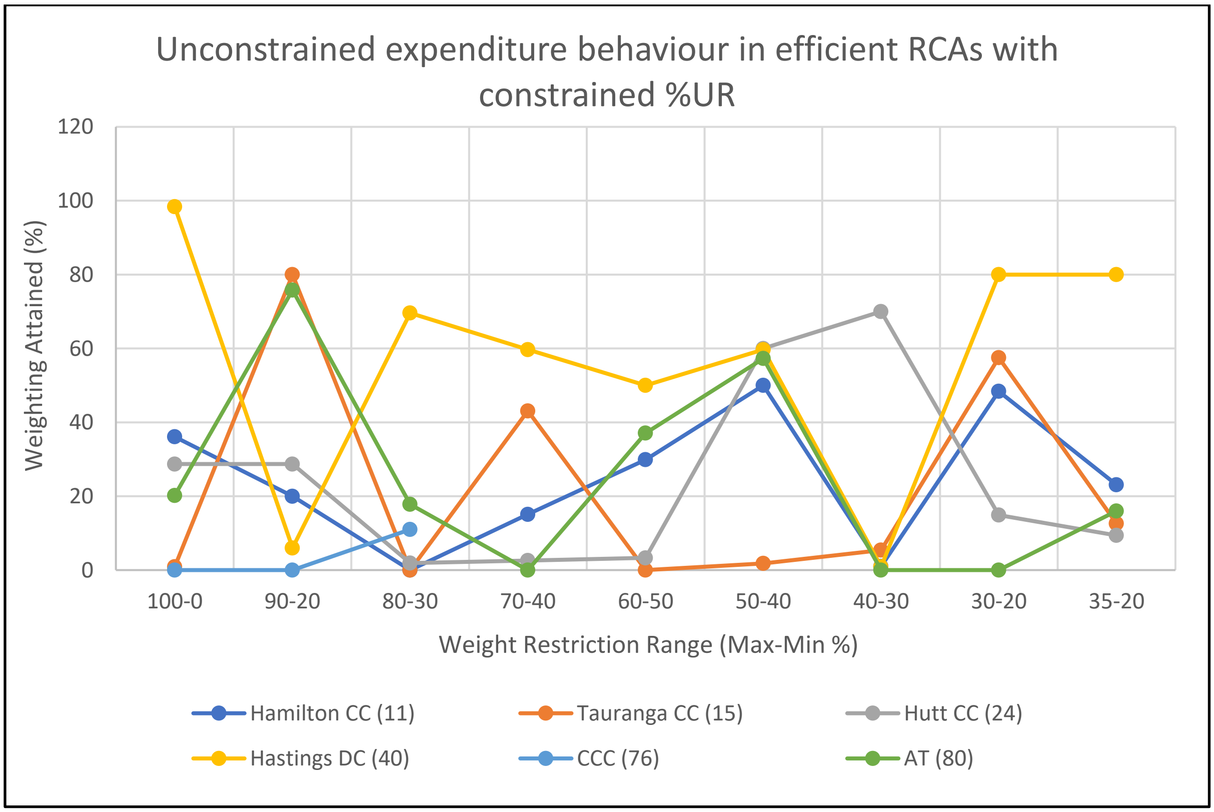


Figure 4.4: Unconstrained expenditure weighting behaviour under constrained %UR - Trial 1

4.3 Trial 2 DEA outcomes

This second trial controlled each input variable from either a minimum or maximum end. Specifically, VKT/km and %UR were controlled from the maximum limit, and expenditure was controlled from the minimum limit. As in the first model, variable weighting behaviour was evaluated across efficient RCAs. This model's outputs also gave no insight as to any tangible trend for assigning higher or lower weightings to certain RCAs. As an example, this can be seen through Figures 4.5 and 4.6, which respectively show the fluctuating constrained %UR behaviour and the corresponding unconstrained VKT/km behaviour. Behaviour for the constrained and unconstrained expenditure variable was similarly unpredictable, but figures of this are not included for brevity.

Overall, weight restrictions were applied to curb DEA's tendency to only give higher weightings to variables that highlighted good DMU performance and neglect variables that suggest inefficiency. As in the first trial, this second trial's outputs also showed that efficient DMUs' weighting mixes suggested no clear trend when expenditure, VKT/km or %UR were controlled. This clearly indicated that if DEA deems a DMU efficient, there are likely numerous variable weighting distribution combinations across a range of restrictions that would allow that DMU to be efficient. Consequently, the DEA software autonomously decides which combination to present, which may not be in accordance with expected practical weighting distributions.

Additionally, this model proved that evaluating both efficient and inefficient RCAs is crucial to making well-rounded judgements on overall efficiency rankings and whether DEA was weighting variables in accordance with practical expectations. The outcome of Trial 2 resulted in the decision, moving forward, to structure the final configuration based on constraining only one variable (expenditure), and only specifying the minimum weighting to ensure that expenditure remains an essential consideration of efficiency rankings.

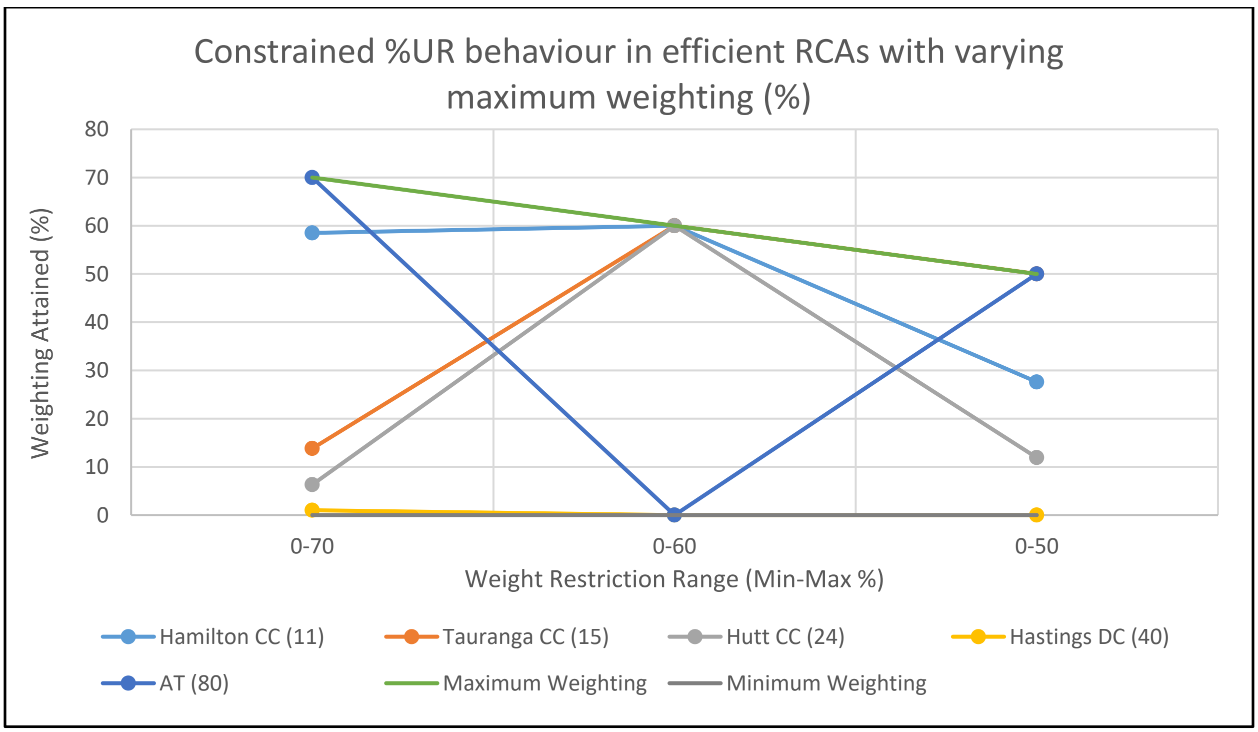


Figure 4.5: Constrained %UR in efficient RCAs with varying maximum weighting - Trial 2

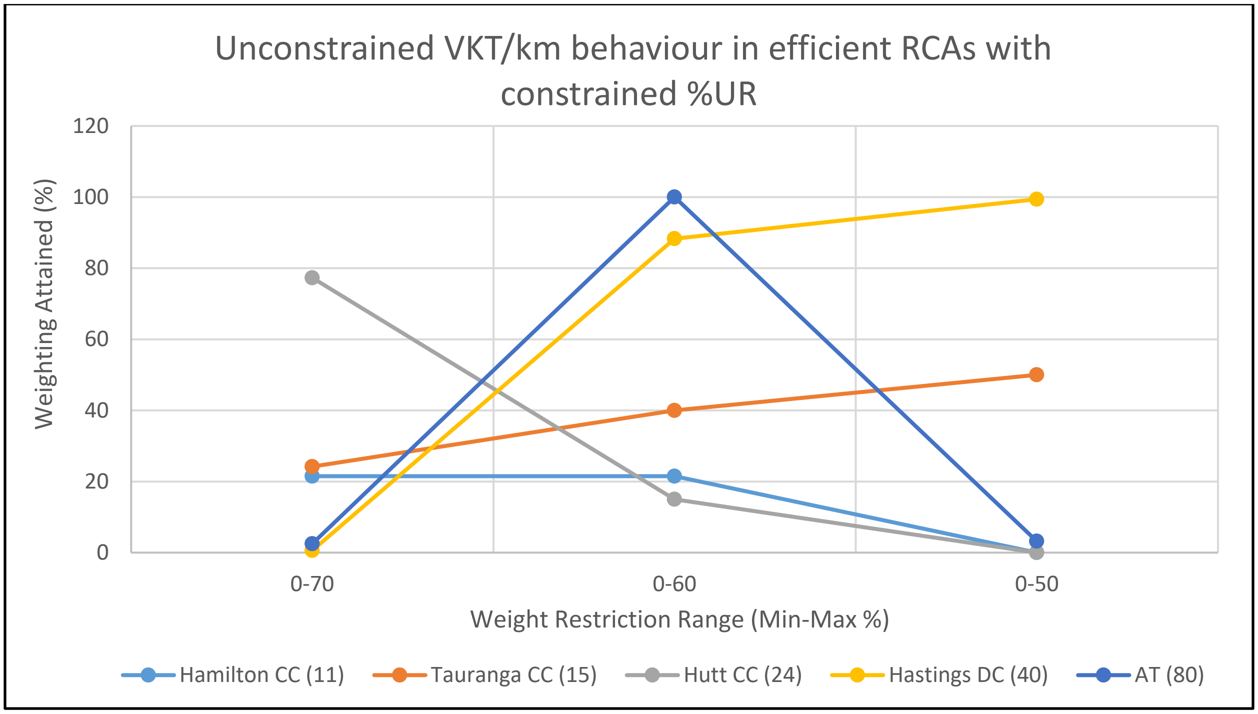


Figure 4.6: Unconstrained VKT/km behaviour in efficient RCAs with constrained %UR - Trial 2

4.4 Final Configuration - Outcomes from expenditure weight control on HT RCAs

This section presents various graphs that show the efficiency performance of HT RCAs within the final model configuration, where only expenditure is controlled from the minimum limit and both inefficient and efficient RCAs' weighting behaviour is evaluated. Weighting changes in the three input variables across the restriction settings and more detailed discussions about the performance of notable RCAs are also included.

4.4.1 Efficiency score performance

Figure 4.7 is a box and whisker plot depicting the distribution of efficiency scores across varying minimum expenditure weight restrictions. It is noticeable from the plot that efficiency score data is highly negatively-skewed, indicating that at least 75% of HT RCAs score above 91% across all weight restrictions, i.e., most RCAs are either moderately inefficient or efficient. The mean score remains around 95% (moderately inefficient) across all restrictions. An overall trend of slightly decreasing efficiency scores is also observed through the change in minimum score, lower quartile, mean, and median score values as the minimum expenditure restrictions are progressively increased. This is to be expected.

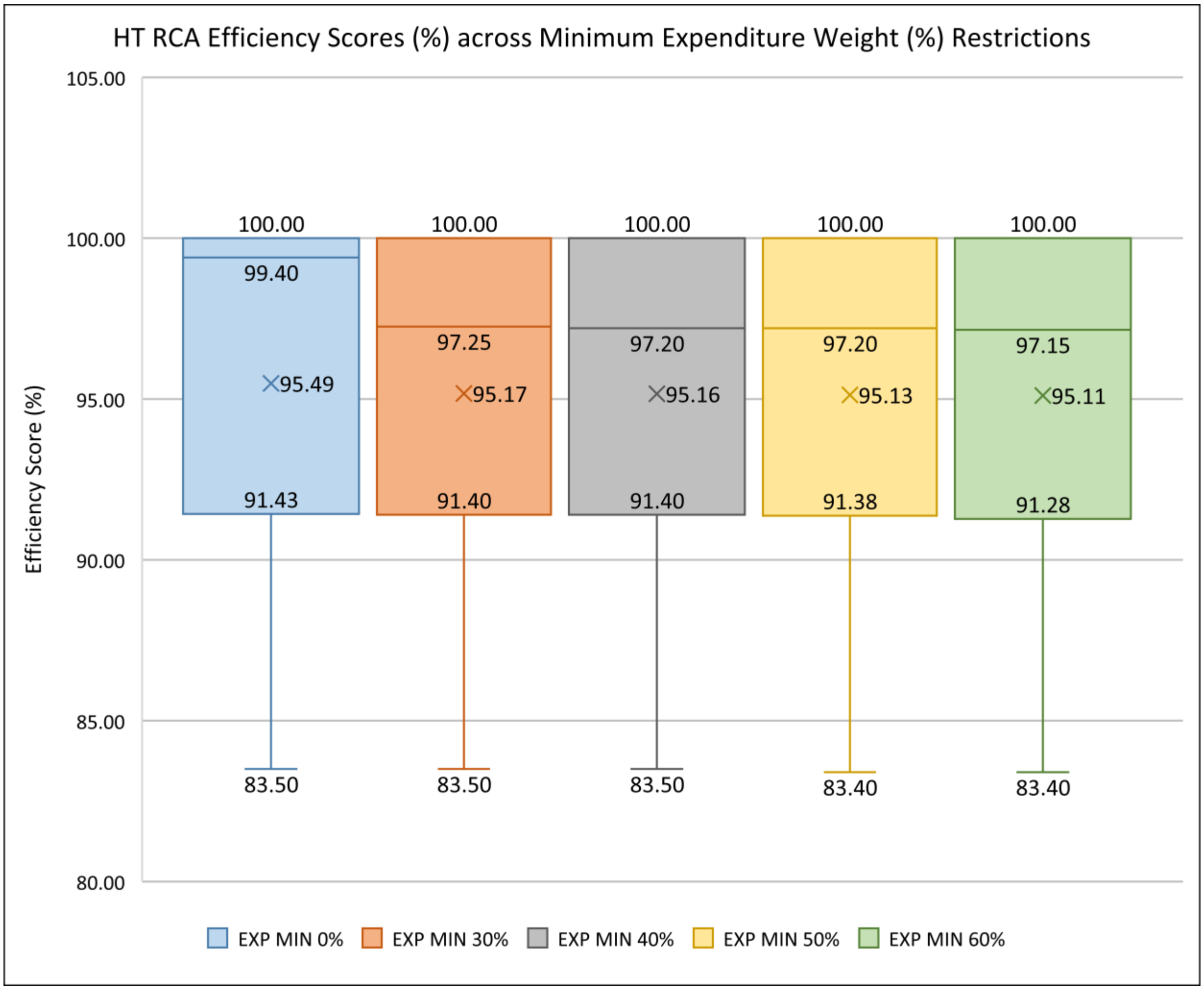


Figure 4.7: Box and whisker plot showing distribution of HT RCAs' efficiency scores across expenditure weighting (%) restrictions

Figure 4.8 is a histogram depicting the efficiency scores achieved by all HT RCAs across the tested expenditure weight restrictions range. It is evident from the histogram that there is not much fluctuation in efficiency scores across the varying expenditure weight restrictions. When no restrictions were applied, seven out of fourteen HT RCAs were efficient, they were;

- RCA 11 - Hamilton City Council (HCC)
- RCA 15 - Tauranga City Council (TCC)
- RCA 24 - Hutt City Council (HCC)
- RCA 25 - Kapiti Coast District Council (KCDC)
- RCA 30 - Nelson City Council (NCC)
- RCA 40 - Hastings District Council (HDC)
- RCA 80 - Auckland Transport (AT)

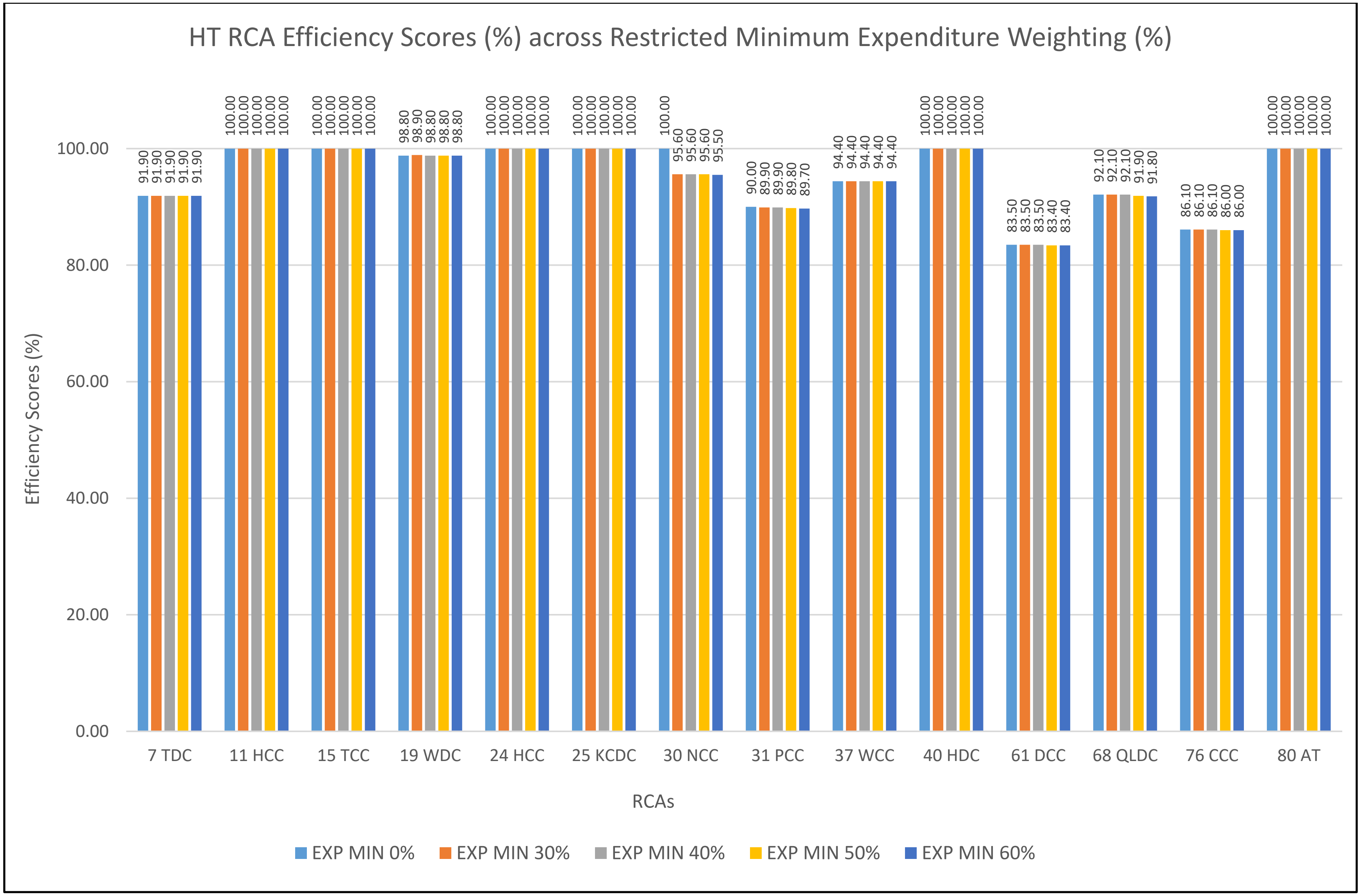


Figure 4.8: Efficiency scores for HT RCAs across varying minimum expenditure weight restrictions

All RCAs mentioned previously except RCA 30 (NCC) remained efficient throughout the range of tested restrictions. This shows that expenditure was an area of poor performance for RCA 30, becoming inefficient when DEA was forced to assign a minimum weighting of 30% or above to expenditure. The unit details in Figure 4.9 for RCA 30 under no weighting restrictions further show that 96.3% weighting had been given to %UR, no weighting was given to VKT/km, and only 3.7% weighting was given to expenditure. It is for this very reason that appropriate weighting restrictions must be applied to DEA to ensure a model gives meaningful inclusion to expenditure in the score. Throughout all subsequent expenditure restrictions, RCA 30 always had the minimum possible weighting for expenditure. Furthermore, data for RCA 30 shows that it has moderate VKT/km, highest %UR, and second highest expenditure ($/km) out of all HT RCAs but achieves only a moderate PHI output, suggesting significant inefficiency in expenditure management given the varibales considered in this study.

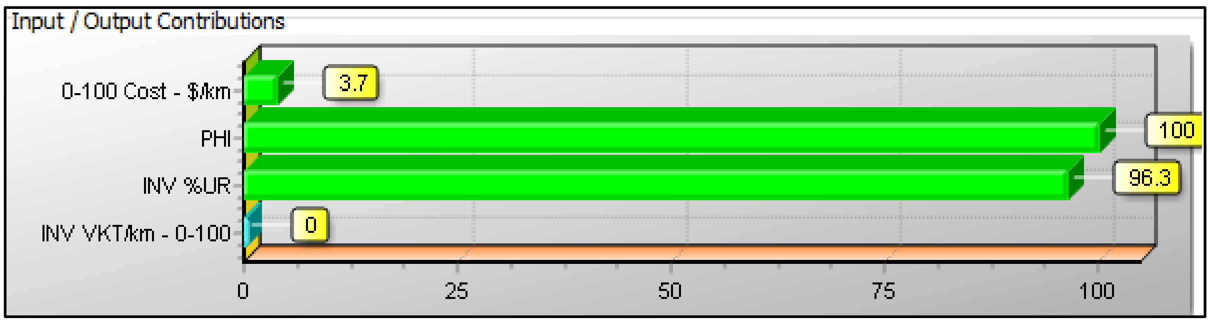


Figure 4.9: Unit details for RCA 30 (NCC) under no weight restrictions

4.4.2 Variable weighting changes

Changes in variable weightings must be observed for HT RCAs across all restrictions to ascertain the optimum level of restriction. The criteria for assessing the efficacy of a specific restriction level are stated below, given the considered variables in this study.

Primarily, each RCA must include expenditure performance within their efficiency score as it is the sole controllable factor.

Additionally, if feasible, DEA should be prevented from giving all or most of the input weighting to a single variable. Thus, the greater the equality of %UR and VKT/km variable distribution observed, the more effective a particular restriction setting will be.

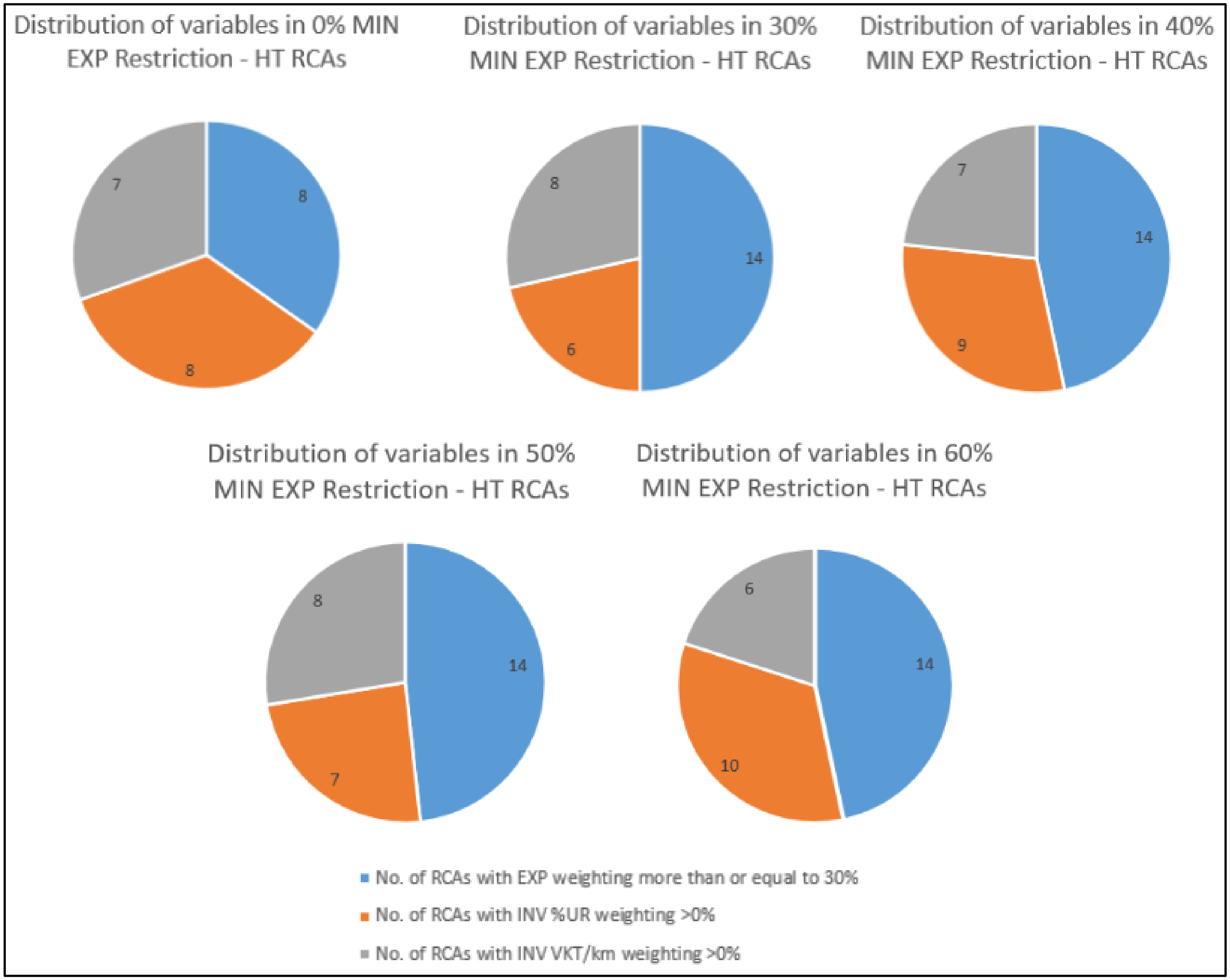


Figure 4.10: Distribution of variables across different expenditure restriction settings - HT RCAs

Under no restrictions, 5 out of 14 RCAs give minimal or no weighting to the expenditure variable, such as RCA 15, 25, 30, 40, and 61. Only RCA 61 is inefficient and remains so throughout all restrictions. Out of the remaining four, all except RCA 30 remain efficient across all restrictions. Overall Figure 4.10 shows that there are no guarantees of expenditure being considered within an RCA’s efficiency score under no restrictions. In subsequent restrictions ranging from 30% to 60%, all RCAs gave at least the minimum weighting to expenditure, including those that previously excluded or underrepresented it. However, efficient RCA 40 gave expenditure nearly 100% of the input weighting from the 30% restriction onwards - again, this can be explained by the multiple likely variable combinations available for an efficient DMU. Full details of each HT RCA’s efficiency score composition can be found in Items 1 to 5 of Appendix A.

It is evident from Figure 4.10 that within the range of 30% to 50% minimum expenditure restriction, there is the best overall distribution of VKT/km and %UR across HT RCAs, as well as having a guaranteed inclusion of expenditure. Some RCAs gave the majority or total input weighting to expenditure however, again, the primary objective is to ensure expenditure is considered in the score. Furthermore, within the restriction ranges of 30% to 50%, almost similar amounts of VKT/km and %UR variables were expressed across the HT RCA group. This expression wasn’t observed for the two variables at the 60% restriction level, where it was distorted towards %UR. Overall, a minimum expenditure restriction setting of 50% for the HT RCA group is recommended as it produces the most even distribution of %UR and VKT/km.

4.4.3 Review of some notable RCAs

This section evaluates the performance of some HT RCAs that achieved varying results due to notable differences or similarities, across the different weighting restrictions. Some RCAs with significant similarities in results are also discussed. RCA performance will be evaluated across factors such as performance data from Table 3.1, as well as Asset Management Plan (AMP) assessment scores from Te Ringa Maimoa (TRM) and Waka Kotahi (NZTA). This evaluation across multiple assessment criteria will provide deeper insight and triangulation for more holistic performance assessments.

Figure 4.11 shows the AMP assessment scores given to HT RCAs by TRM and NZTA. Additionally, each RCA’s dot has been colour coded to represent its efficiency rating as per DEA’s categorisation, within the recommended restriction setting of 50% for HT RCAs. Green dots represent efficient RCAs, amber dots represent moderately inefficient RCAs, and red dots represent inefficient RCAs. There are also four quadrants within the figure highlighting the alignment in scores achieved by different RCA performance assessments. These quadrants were segregated based on the average scores achieved in the TRM and NZTA AMP assessments. For HT RCAs, the TRM scores’ average was 2.30 out of 3.00, and the NZTA scores’ average was 1.90 out of 3.00. This indicates that on average, HT RCAs were better able to meet TRM's AMP scoring criteria as compared to NZTA.

Quadrant 1 (green) contains RCAs that have obtained high scores across both TRM and NZTA's AMP assessments. Quadrants 2 and 3 contain RCAs that achieved above-average scores in either the NZTA or TRM assessment, respectively. Lastly, Quadrant 4 contains RCAs that achieved below-average scores in both assessments. Incorporating the DEA efficiency categories would provide an objective measure of performance assessment in conjunction with the subjective TRM and NZTA assessments.

Overall, Figure 4.11 shows that most RCAs within the 50% expenditure restriction somewhat achieve alignment across all three evaluation types as to whether their performance is realistically rated. However, RCA 31 (Porirua City Council - PCC) categorised as inefficient by DEA lies in Quadrant 3, i.e., it gained the highest score out of all HT RCAs in TRM's assessment but is below average as per NZTA. PCC's data-based DEA score does not demonstrate efficient maintenance performance, aligning with the low AMP score from NZTA, while conversely attaining a high score from TRM. This indicates that misalignments in performance evaluation due to varying assessment criteria are likely to occur when totally subjective assessments are undertaken. It is for this reason that considering objective data-based performance (DEA) results in conjunction with subjective assessments will provide a holistic and more realistic view of RCA performance.

RCAs 76 (Christchurch City Council - CCC) and 61 (Dunedin City Council - DCC) are further examples of misalignments occurring between TRM, NZTA, and DEA evaluations. Neither of these two RCAs demonstrated efficiency in DEA, yet both TRM and NZTA assessments gave them high scores, placing CCC in Quadrant 1 and DCC on the borderline between Quadrants 1 and 2. This indicates that the AMPs for these councils significantly met both TRM and NZTA's assessment criteria, but this wasn't reflected in their objective performance data. These misalignments may occur due to a gap in performance data recording or excluded environmental variables within the current DEA model. Incorporating these factors would likely improve the efficiency score.

Conversely, RCA 11 (Hamilton City Council - HCC) is fully efficient as per DEA yet lies in Quadrant 4. This indicates that their AMP is not aligned with the TRM and NZTA assessment criteria, yet their actual performance data suggests high efficiency.

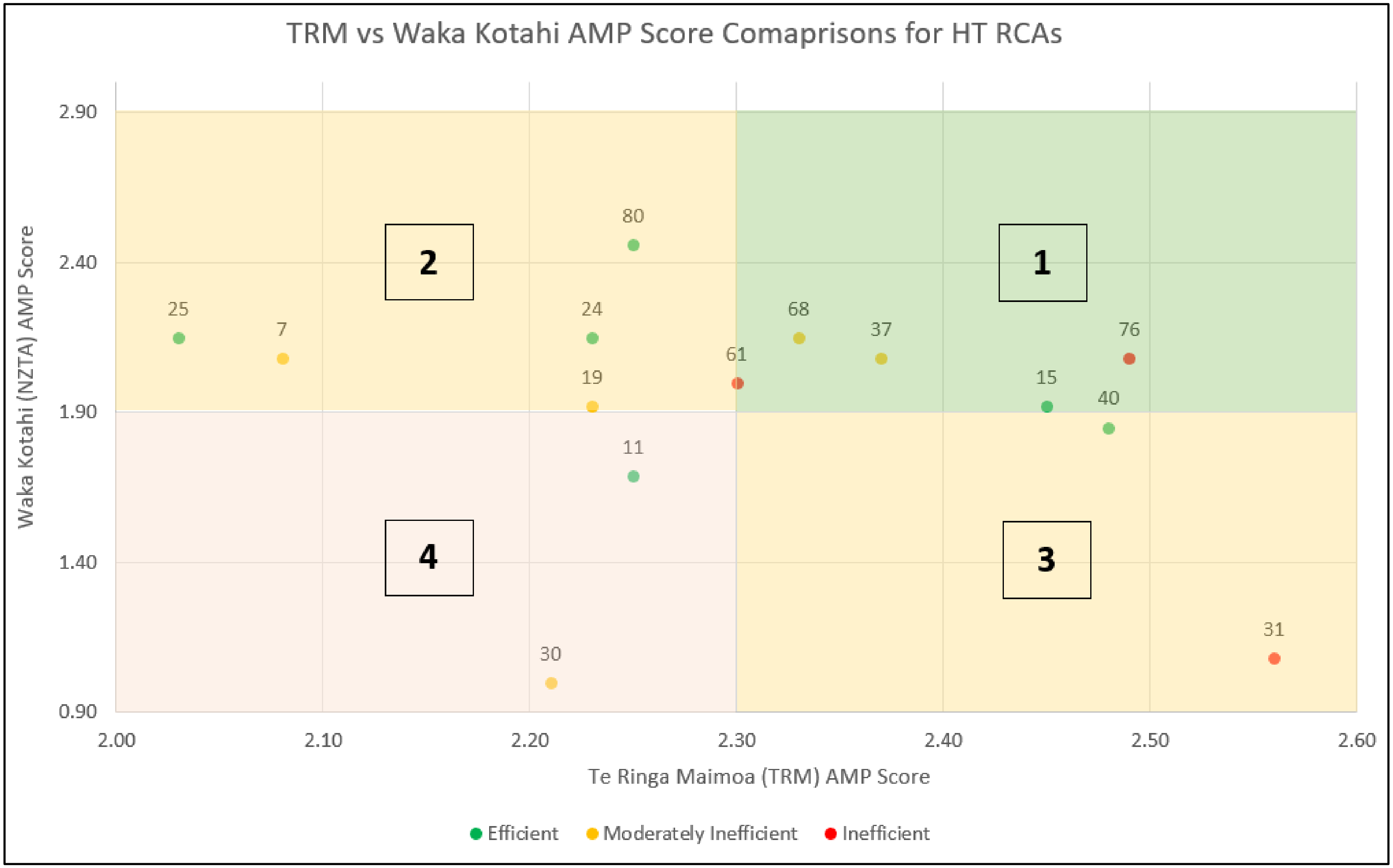


Figure 4.11: AMP Assessment Scores across HT RCAs from TRM and NZTA with DEA efficiency ratings

Table 4.1 summarises the counts of RCAs in each quadrant of Figure 4.11, with specific efficiency rankings by colour.

Table 4.1: Count of RCA DEA efficiency and subjective assessment alignments - HT RCAs

Quadrant \ Efficiency	Inefficient RED	Moderately Inefficient AMBER	Efficient GREEN
1	1	2	1
2	1	2	3
3	1	0	1
4	0	1	1

Note that RCA 61 (Inefficient) achieves a TRM assessment score of exactly 2.30, which is the mean for this group. Thus, RCA 61 has been counted within Quadrant 2. Interpretation notes and general observations regarding Figure 4.11 are given below.

Interpretation Notes:

- *Numbers*

  Each number next to a dot represents a specific district council.

- *Axes*

  - NZTA AMP scores assess the 'evidence' for each council's business plan through the specific assessment criteria, thus assessing practices such as data, analytics and field planning.
  - TRM AMP scores are an assessment of the AMP quality with respect to the specific assessment criteria.

- *Quadrants*

  - Green (1) - both NZTA AMP score and TRM AMP scores are high.
  - Red (4) - both NZTA AMP score and TRM AMP scores are low.
  - Amber (2) - NZTA AMP score high, but TRM AMP score is low (strong on-ground practice, AMP not that strong).
  - Amber (3) - NZTA AMP score low, but TRM AMP scores is high (strong AMP that does not reflect on-ground practice)

- *DEA Efficiency scores*

  - Efficient (Green dot), i.e., 100%

- 90% < Moderate (Amber dot) < 100%
- Inefficient (Red dot) < 90%

General observations:

- Two councils (11 and 30) in the Red quadrant (4) yielded an efficient and moderately inefficient outcome, respectively, as per DEA. Whereas all three inefficient councils were present in either Amber or Green quadrants.

- There were multiple completely or moderately inefficient councils in the Green quadrant (1). Only one efficient council (15) was present within this quadrant.

- Most efficient RCAs (4 out of 6) as well as 2 out of 3 inefficient RCAs were in Amber quadrants (2 and 3). Only 2 out 5 moderately inefficient RCAs were in Amber quadrants, representing alignment in DEA scores with weaker on-ground asset management practices or AMPs.

Further discussion on RCA performance scoring across the three assessment types follows, incorporating recorded data, known environmental conditions and their potential impacts on maintenance performance.

RCA 61 (Dunedin City Council - DCC) and RCA 68 (Queenstown-Lakes District Council - QLDC)

Both RCA 61 and 68 lie within the Otago region of the South Island, where exposed coastal territories such as RCA 61 are very windy. Otago also experiences frequent snowfall and frost, making network maintenance a challenge (Macara, 2015). RCA 68 (QLDC) is moderately inefficient, and a significant inland tourist destination. Both QLDC and DCC have moderate VKT/km values, but QLDC has higher VKT/km despite being a district council. RCA 61 (DCC) was observed to be the most inefficient out of all HT RCAs as it achieves the lowest PHI out of all HT RCAs but has much higher expenditure than RCA 68. A contributing factor to this could be DCC’s moderately higher %UR than QLDC which would require greater expenditure for maintaining urban roads. However, there is a vast difference between DCC’s and QLDC’s expenditure, as seen in Table 3.1, where DCC spent $20.33/km, which is nearly four times as much as QLDC’s expenditure of $5.33/km, within a scaling range of 0 - 100. Thus, the higher %UR factor within DCC is unlikely to be the sole reason behind their higher expenditure.

Additionally, DEA autonomously gave DCC’s expenditure variable an insignificant weighting of only 11.3% under no restrictions while QLDC’s expenditure variable had 40.8%, suggesting that DCC may experience poor budget management, as despite much smaller expenditure yet higher VKT/km, QLDC obtained a higher PHI. Under all subsequent restriction settings, both QLDC and DCC gave expenditure minimum weightings, with the remaining weighting given to %UR. Thus, despite similar challenges, DCC was presenting as less efficient than QLDC. When considered individually, both RCAs 61 and 68 achieved high scores from TRM and NZTA, which misaligns with the individual efficiency categorisation by DEA suggesting a gap in their performance data or another external influencing factor. However, the comparison of these RCAs' DEA rankings aligns with assessment outcomes from TRM and NZTA where DCC scores lower than QLDC in both evaluations, suggesting that this is a realistic representation of these RCAs' comparative performance.

RCA 11 (Hamilton City Council - HCC) and RCA 80 (Auckland Transport - AT)

Hamilton and Auckland are city council territories and are two of New Zealand's largest cities by area and population (TRM, 2022b, c). Both have relatively mild climates, but Hamilton being in Waikato, has colder winters. Both regions get plenty of rainfall and sunshine, with no snowfall. Frosts are more frequent in Hamilton. However, Auckland is known to have more severe weather events such as flooding and excessive rainfall (Chappell, 2013a, 2016). Overall, both territories face similar challenges related to environmental conditions and traffic loading due to their populations.

The HCC territory is smaller and has a much denser urban road network compared to AT's territory, which is much larger and encompasses rural regions as well, as depicted through their respective INV %UR values. Overall, they face highly similar performance challenges due to two of the greatest VKT/km loads across all RCAs, and as a result have very small expenditure ($/km) values. They achieve similar PHI values and are both efficient throughout all weighting restrictions, moreover both RCAs always received the majority of total variable weighting towards the expenditure variable, with the remainder mostly given to VKT/km. This suggests that their budget is well managed under the vast traffic loads and high urbanisation. When considered individually, AT lies in Quadrant 2, and its DEA performance aligns with its high score from NZTA, but it gains a below-average score from TRM. HCC gains the same TRM score as AT but also scores much lower than AT in the NZTA assessment which places it in Quadrant 4. Overall, the high data-based performance of both RCAs is not fully reflected by their positions in Figure 4.7, potentially due to gaps in reporting as per specific AMP assessment criteria.

RCA 15 (Tauranga City Council - TCC) and RCA 30 (Nelson City Council - NCC)

TCC and NCC are both very sunny coastal territories that experience mild climates and plentiful rainfall, with no snow and few frosts. They may experience dry spells and are not very windy (Chappell, 2013b, c). TCC is an efficient RCA and covers a smaller area than NCC which is moderately inefficient. NCC encompasses the entire Nelson region, yet both TCC and NCC have almost equal %UR values that are highest amongst HT RCAs. TCC has the third highest VKT/km loading while NCC has a much more moderate load. TCC and NCC also have the highest and second-highest expenditure ($/km), respectively, although NCC's value is much less than TCC when scaled across a range of 0-100 (see Table 3.1).

Since both TCC and NCC share the similar moderate climate, it is likely that TCC's higher PHI output due to a far greater expenditure, and high traffic load as well as high urbanisation, allow it to be efficient across all weighting restrictions. Comparatively, NCC is efficient under no restrictions but remains inefficient across all subsequent weighting restrictions, due to poor performance despite high expenditure, similar environmental conditions to TCC, and much less traffic loading. With respect to TRM and NZTA scoring, both RCAs' comparative positions and individual scores align with the observed DEA efficiency performance. RCA 30 lies in Quadrant 4, i.e., it has low scores from both TRM and NZTA, conversely, RCA 15 lies in Quadrant 1 with much higher scores from both assessments. The triangulated assessment of these RCAs suggests that there is unlikely to be a lack of performance reporting, and that these results are reflective of actual on-ground performance.

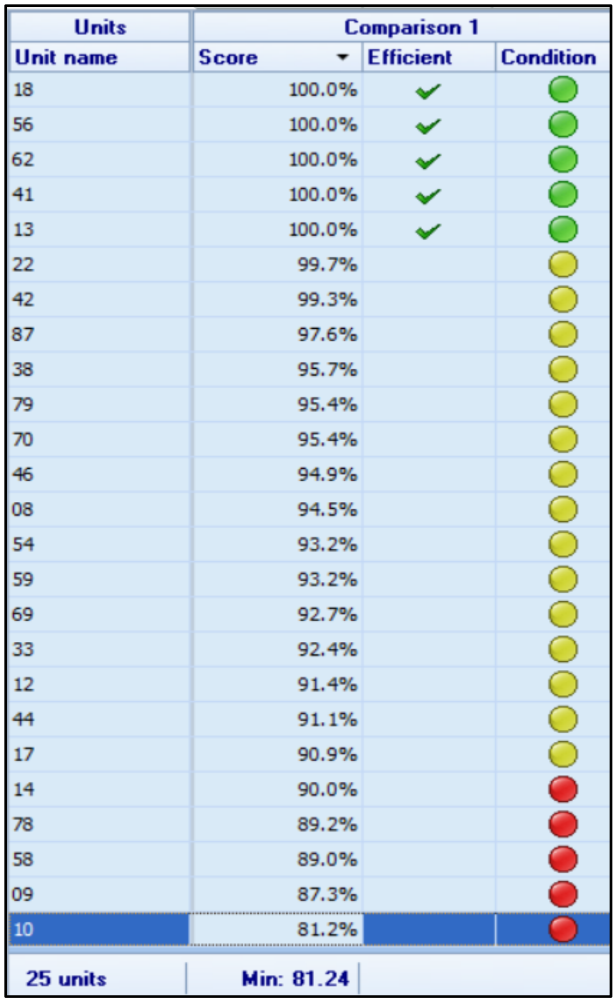
4.5 Outcomes from expenditure weight control on LT RCAs

The minimum expenditure weight restriction range of 30% to 50% gave the best overall distribution of all input variables within the HT RCAs' scoring mix. This enabled a more realistic assessment of their efficiency. It was stated in Chapter 3 that if expenditure restriction was successful upon HT RCAs, it may also be applicable to LT RCAs depending upon the controlled variable(s). All RCAs face expenditure-related challenges owing to environmental challenges and funding management. Thus, this section will present efficiency score results across LT RCAs by applying the same minimum expenditure restriction from the 30% to 50% range to evaluate this restriction range's efficacy upon all types of RCAs. As before, some notable LT RCAs displaying interesting performance across TRM, NZTA and DEA assessments will also be evaluated in conjunction. This would further support the applicability of results obtained from DEA.

Table 4.2 shows the names and input data for LT RCAs and normalised VKT/km values in descending order. Figure 4.12 shows the initial efficiency scores of LT RCAs without any weight restrictions. The minimum efficiency score under no restrictions is 81.2% for RCA 10, i.e., South Waikato District Council (SWDC).

Table 4.2: Low-Traffic (LT) RCAs and their associated data

RCA No.	Road Council	City/District	0-100 Cost ($/km)	INV %UR	VKT/km	INV VKT/km (0-100)	PHI
13	Western Bay of Plenty District Council	District	0.44	81.88	0.47	76.76	71.48
22	Waikato District Council	District	8.26	84.93	0.46	77.16	74.09
56	Whanganui District Council	District	12.30	59.91	0.45	77.77	78.63
44	New Plymouth District Council	District	14.16	70.85	0.43	79.04	71.94
87	Masterton District Council	District	5.79	78.13	0.43	79.40	74.56
8	Matamata-Piako District Council	District	5.66	86.11	0.40	81.14	73.34
79	Far North District Council	District	0.77	78.53	0.39	81.59	71.88
18	Thames-Coromandel District Council	District	3.79	38.80	0.37	82.76	69.54
33	Tasman District Council	District	1.77	78.55	0.37	82.95	71.13
78	Kaipara District Council	District	13.59	77.17	0.36	83.58	71.49
42	Manawatu District Council	District	0.53	87.98	0.32	86.64	78.55
70	Timaru District Council	District	1.36	75.54	0.30	87.66	76.62
9	Hauraki District Council	District	8.73	77.65	0.26	90.30	71.47
41	Horowhenua District Council	District	0.17	67.18	0.25	90.61	81.95
10	South Waikato District Council	District	1.37	76.72	0.24	91.42	66.58
59	Central Otago District Council	District	1.39	71.11	0.21	93.39	76.34
12	Opotiki District Council	District	0.87	76.61	0.19	94.61	74.88
62	Gore District Council	District	0.01	78.31	0.18	95.27	75.64
69	Southland District Council	District	1.84	89.67	0.15	97.38	76.00
17	Otorohanga District Council	District	4.02	94.24	0.14	97.97	74.46
58	Buller District Council	District	5.30	74.07	0.14	98.42	72.94
46	Rangitikei District Council	District	5.96	89.63	0.14	98.46	77.75
38	Central Hawke's Bay District Council	District	8.84	91.86	0.13	98.62	78.43
54	Tararua District Council	District	7.42	92.95	0.13	98.91	76.37
14	Waitomo District Council	District	5.89	89.55	0.11	100.00	73.74



Units	Comparison 1		
Unit name	Score	Efficient	Condition
18	100.0%	✓	
56	100.0%	✓	
62	100.0%	✓	
41	100.0%	✓	
13	100.0%	✓	
22	99.7%		
42	99.3%		
87	97.6%		
38	95.7%		
79	95.4%		
70	95.4%		
46	94.9%		
08	94.5%		
54	93.2%		
59	93.2%		
69	92.7%		
33	92.4%		
12	91.4%		
44	91.1%		
17	90.9%		
14	90.0%		
78	89.2%		
58	89.0%		
09	87.3%		
10	81.2%		
25 units	Min: 81.24		

Figure 4.12: Efficiency scores (%) for LT RCAs without weight restrictions

Figure 4.14 shows a line graph depicting overall efficiency score changes across LT RCAs under different weighting restrictions. When no restrictions were applied, five out of twenty-five LT RCAs were efficient, they were;

- RCA 13 - Western Bay of Plenty District Council (WBOP)
- RCA 18 - Thames-Coromandel District Council (TCDC)
- RCA 41 - Horowhenua District Council (HWDC)
- RCA 56 - Whanganui District Council (WGDC)
- RCA 62 - Gore District Council (GDC)

Across the range of tested restrictions, it was observed that only RCAs 41 and 62 remained consistently efficient. After 30% restriction, RCA 13 and RCA 56 became moderately inefficient. RCAs 18, 41 and 56 continued to be efficient at 40% restriction. However, RCA 18 became the second most ineffiecient when

DEA was forced to assign a minimum expenditure weighting of 50% or higher. The unit details in Figure 4.9 for RCA 18 under no weighting restrictions further show that 85.9% weighting had been given to VKT/km, 10.3% weighting to %UR, and a highly insignificant 3.8% weighting was given to expenditure.

Throughout all restrictions, RCA 18 always had the minimum possible weighting for expenditure. Data for RCA 18 in Table 4.2 shows that amongst LT RCAs, it has moderate VKT/km, highest %UR, moderately low expenditure ($/km), and achieves the second smallest PHI output. RCA 56 with the second highest %UR has significanlty higher expenditure compared to RCA 18, although data shows it has less than half of RCA 18's VKT/km and is able to achieve a much higher PHI.

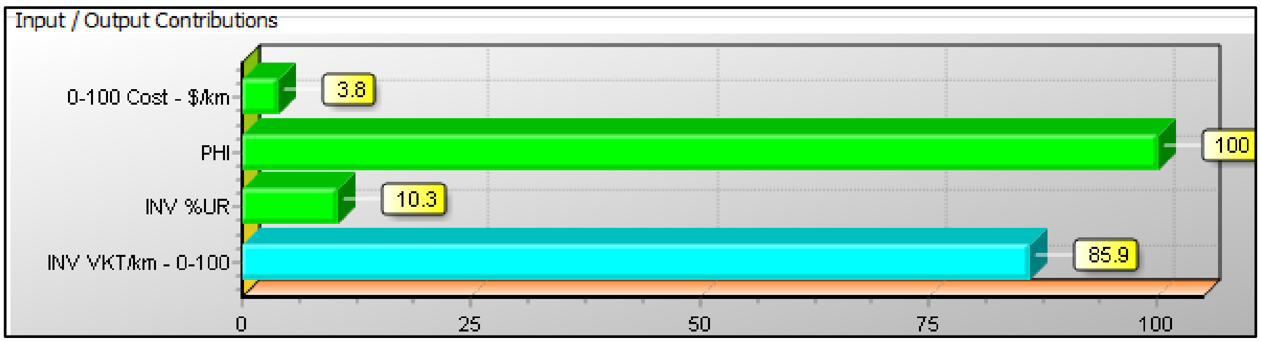


Figure 4.13: Unit details for RCA 18 (TCDC) under no weight restrictions

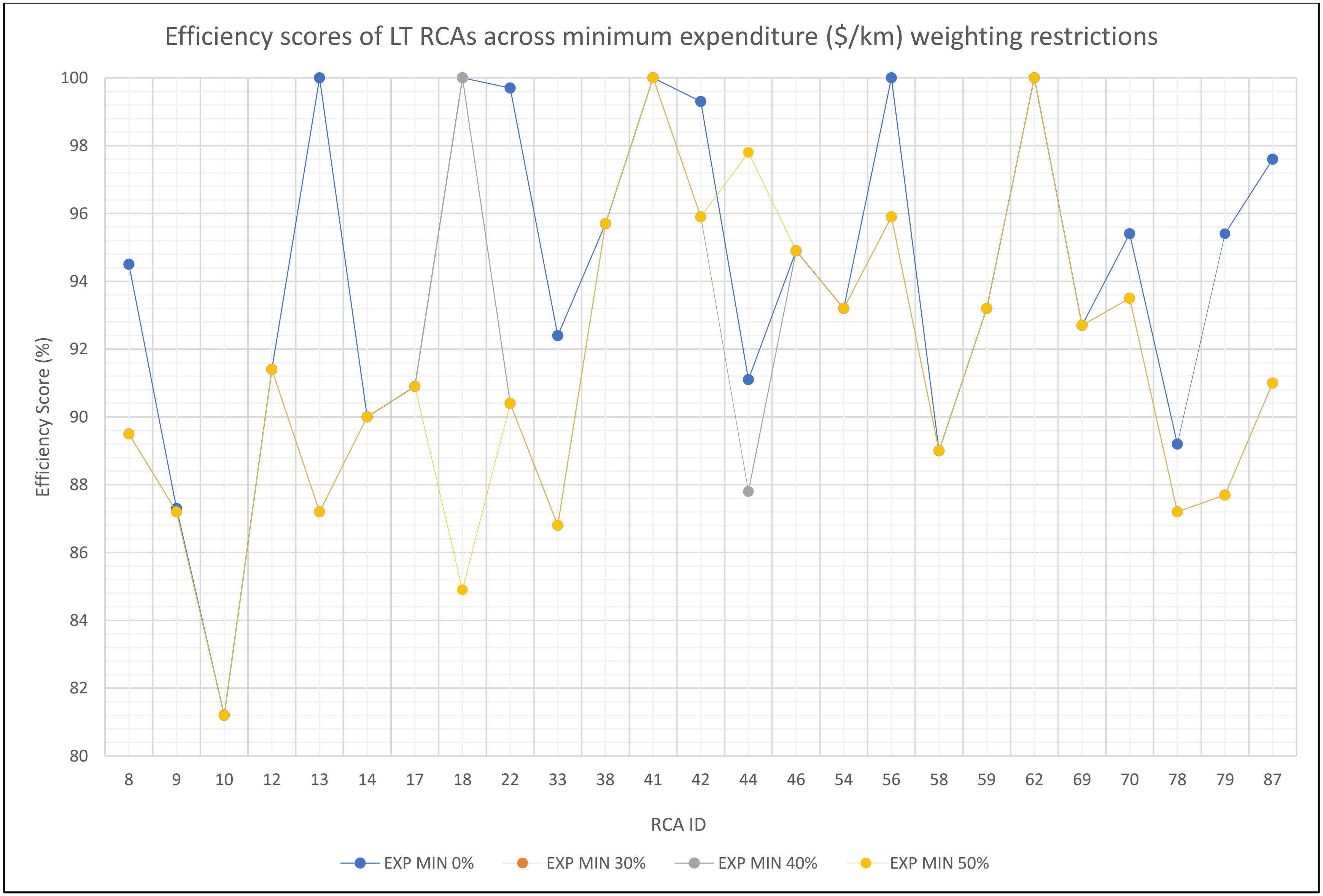


Figure 4.14: Efficiency scores of LT RCAs across the minimum expenditure ($/km) restriction ranges

4.5.1 Variable weighting changes

Pie charts in Figure 4.15 show efficiency score details for LT RCAs under no restrictions and minimum 30%, 40% and 50% restrictions upon the expenditure variable.

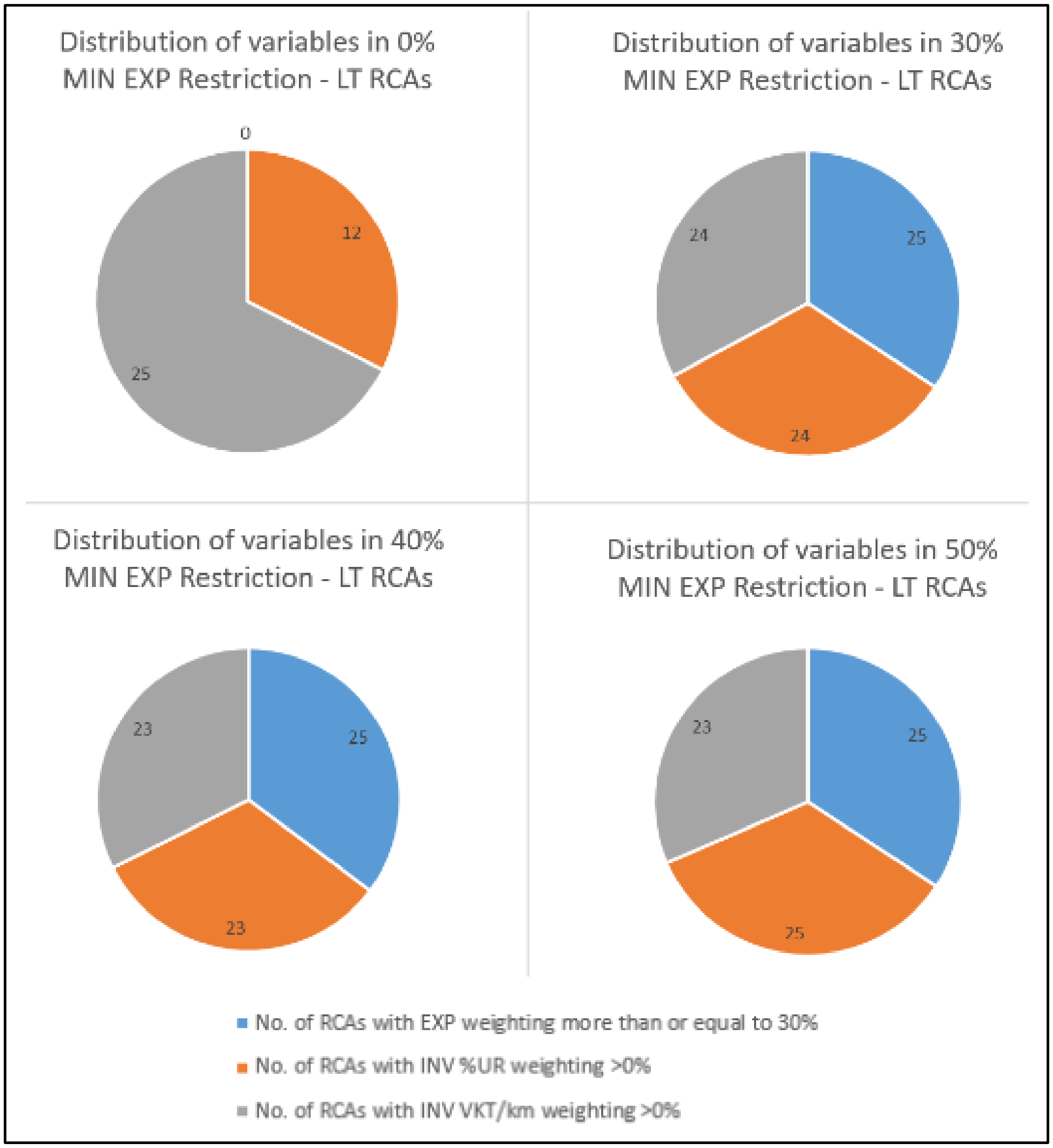


Figure 4.15: Distribution of variables across different expenditure restriction settings - LT RCAs

Under no restrictions, all LT RCAs gave insignificant or zero weighting to the expenditure variable, indicating that there are no guarantees of expenditure being considered within an RCA's efficiency score. From the 30% restriction onwards, RCAs that previously excluded or underrepresented expenditure always gave it the minimum possible weighting. However, efficient RCA 41 gave expenditure 100% of the input weighting at 40% restriction but gave minimum weighting in all other restrictions; as before, this is explained by the multiple likely variable combinations available for an efficient DMU. Full details of each LT RCA's efficiency score composition can be found in Items 6 to 9 of Appendix A.

It is evident that within the range of 30% to 50% minimum expenditure restriction, LT RCAs displayed a highly similar distribution of VKT/km and %UR and a guaranteed inclusion of expenditure. Except for RCA 41 under the 40% restriction, no RCAs gave insignificant or total input weighting to only a single variable. In fact, LT RCAs had a better distribution of all variables within the scoring mix than HT RCAs. Thus, this expenditure restriction model and particular restriction range of 30% to 50% is applicable across all RCA types for more realistic benchmarking assessments. Overall, an expenditure restriction of 30% is recommended for LT RCAs as the highest amount of VKT/km and %UR variables are expressed equally within this setting. This LT recommended restriction setting is laxer than the 50% recommended restriction upon HT RCAs.

4.5.2 Review of some notable RCAs

As for the HT group, RCA performance will be evaluated across factors such as performance data from Table 4.2, and AMP assessment scores from TRM and NZTA. This multi-faceted evaluation will provide deeper insight and triangulation for realistic performance assessments. Figure 4.16 shows the AMP assessment scores given to LT RCAs by TRM and NZTA. As before, the graph has been divided into four quadrants based upon the average TRM and NZTA scores, and each RCA's dot has been colour coded according to DEA's efficiency categorisation. The average TRM score for LT RCAs is 2.20 out of 3.00, and the average NZTA score is 2.07 out of 3.00. This indicates that on average, LT RCAs were better able to meet TRM's scoring criteria than NZTA, which is similar to the trend observed for HT RCAs.

Overall, the LT RCA group was less anomalous than the HT RCAs with regard to the alignment of their objective DEA categorisation and the two subjective assessments. This may be due to a larger number of RCAs within the LT group that enable a broader overview of performance. Mostly, an efficient or moderately inefficient RCA fell within Quadrants 1, 2 or 3, i.e., its DEA categorisation would align with at least one subjective assessment score.

However, five of the nine inefficient RCAs were present within Quadrant 1, namely RCAs 58 (Buller), 78 (Kaipara), 79 (Far North), 9 (Hauraki), and 44 (New Plymouth). This shows that these RCAs' AMPs scored well in both subjective assessments, which was not reflected in their objective data-based performance. Suppose more than half of the inefficient LT RCAs attain high scores across two out of three evaluation measures. In that case, it suggests that there may be a significant gap in performance data reporting, or another influencing variable not currently included in this DEA model. This observation is further reinforced by the presence of only one (RCA 18) out of three efficient RCAs within Quadrant 1, while the other two (RCAs 41 and 62) lie in Quadrants 2 and 3. Overall, all efficient RCAs are at least partially aligned across the three evaluation types, and the DEA results highlight a potential gap in AMP reporting that could allow these RCAs to attain higher subjective scores.

Further discussion on RCA performance scoring across the three assessment types follows, incorporating recorded data, known environmental conditions and their potential impacts on maintenance performance.

RCA 18 (Thames-Coromandel District Council - TCDC) and RCA 79 (Far North District Council - FNDC):

Thames-Coromandel and the Far North are both warm, humid, highly windy regions as they are exposed to the eastern and western coast of the North Island, respectively. Gales and sporadically heavy rainfall events are known to occur, often leading to slips and road closures. However, snowing does not occur, and frosts are infrequent in FNDC (Chappell, 2013d, 2016). In this study, FNDC has always remained an inefficient RCA with a moderately low PHI (71.88) amongst LT RCAs. TCDC has the second-lowest PHI (69.54) but is efficient under the 30% restriction, becoming highly inefficient upon the 50% expenditure restriction.

FNDC has a much larger area and population compared to TCDC, however, as per Table 4.2 its %UR is nearly 40% less. TCDC has slightly lower VKT/km than FNDC, but it spends \$3.79/km on maintenance expenditure compared to FNDC's comparatively marginal \$0.77/km, within a scaling range of 0 to 100. Given the similar level of environmental challenges faced, it is likely that TCDC's denser road network suggested by a higher %UR, is the main cause for such higher expenditure within a smaller and less populous territory, further enabling it to be efficient as per DEA. This also suggests that FNDC likely has insufficient budget allocation for network maintenance.

Additionally, while only RCA 18 is efficient, Figure 4.16 shows that both RCAs 18 and 79 have been included in Quadrant 1. RCA 18's better DEA ranking is reflected by its above average TRM and NZTA scores. However, RCA 79 attains significantly higher subjective scores, which are not reflected by its DEA performance. This follows the general trend of most of the reportedly inefficient RCAs being in Quadrant 1. In these cases, the data-based DEA evaluation has highlighted a potentially significant gap in data reporting or a missing variable in the model, contributing to lower objective performance scores.

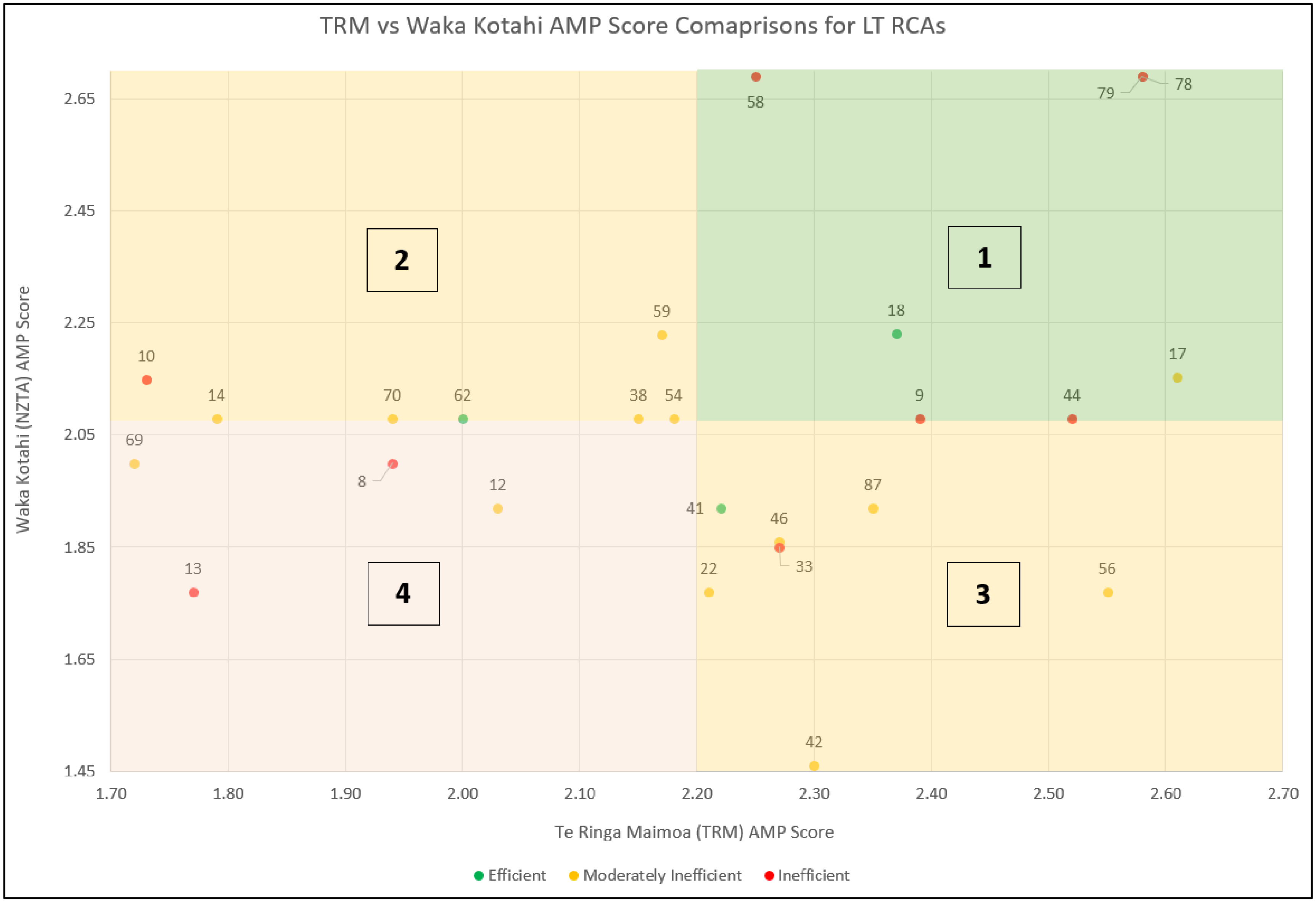


Figure 4.16: AMP Assessment Scores across LT RCAs from TRM and NZTA with DEA efficiency ratings

Table 4.3 summarises the counts of RCAs in each quadrant of Figure 4.16, with specific efficiency rankings by colour.

Table 4.3: Count of RCA DEA efficiency and subjective assessment alignments - LT RCAs

Efficiency / Quadrant	Inefficient RED	Moderately Inefficient AMBER	Efficient GREEN
1	5	1	1
2	1	5	1
3	1	5	1
4	2	2	0

Figure 4.16 is to be interpreted similarly to Figure 4.11. General observations are given below.

General observations:

- As expected, none of the councils in the Red quadrant (4) yielded an efficient outcome as per DEA.
- There were multiple completely or moderately inefficient councils in the Green quadrant (1), and most of the inefficient (red dot) councils were present within this quadrant. Only one efficient RCA (18) was present within this quadrant.
- The majority of RCAs (10 out of 14) in Amber quadrants (2 and 3) were also moderately inefficient with weaker on-ground asset management practices or AMPs. This represents alignment across different assessment measures.

RCA 9 (Hauraki District Council - HKDC) and RCA 41 (Horowhenua District Council - HWDC):

HKDC has a moderately larger area than HWDC, although the latter has a much larger population (TRM, 2022d, e) and higher %UR, indicating a denser road network. HKDC is next to the Thames-Coromandel District Council and borders the calm warm waters of the Firth of Thames and Bay of Plenty, while HWDC is a coastal RCA at the southern end of the Manawatu-Wanganui region along the more volatile Cook Strait (Tasman Sea). Both RCAs are sunny, receive plenty of rainfall and have few weather extremes (Chappell, 2013c, d). However, only HWDC is efficient throughout all restrictions and achieves the highest PHI across LT RCAs of 81.95, while HKDC has always been inefficient with the fourth lowest PHI of 71.47.

Given the RCAs have similar environmental conditions, it is clear from their recorded data in Table 4.1 why HWDC is more efficient than HKDC throughout all weight restrictions. Both RCAs experience nearly identical VKT/km, and HWDC spends only $0.17/km compared to $8.73/km by HKDC, which is the fifthlargest expenditure value across LT RCAs within a scaling range of 0 to 100. With its marginal spend, HWDC achieves the highest LT PHI despite nearly 10% higher %UR than HKDC, suggesting significant inefficiency in expenditure management within the latter.

When considering subjective and objective performance, a similar trend to RCAs 18 and 79 was observed, where efficient RCA 41 scored lower on both TRM and NZTA assessments than inefficient RCA 9. The latter is positioned just on the border between Quadrants 1 and 3, and RCA 41 is fully in Quadrant 3. Individually, both RCAs attained higher TRM scores, yet comparatively their overall positions in the graph do not reflect their data-based DEA performance. Again, this misalignment highlights the value of a third performance evaluation lens, suggesting that RCAs 41 and 9 may have gaps in AMP reporting and performance data reporting, respectively.

RCA 44 (New Plymouth District Council - NPDC) and RCA 56 (Whanganui District Council - WGDC):

NPDC and WGDC are coastal territories within the very windy, mountainous, and sunny Taranaki region which experiences evenly distributed rainfall, moderate temperatures, and rare hail at lower elevations although fog does occur in more inland areas (Chappell, 2014). Both RCAs are very similar in area although WGDC has roughly half the population of NPDC (TRM, 2022f, g). These factors indicate that both RCAs would likely experience similar environmental challenges within network maintenance and management, where the relatively moderate conditions would certainly support performance. However, while WGDC achieves the second highest LT PHI (78.63) with an expenditure of $12.30/km, NPDC achieves only a moderately low PHI (71.94) with the highest expenditure across LT RCAs of $14.16/km. WGDC achieves this result with nearly 11% higher %UR and a marginally lower VKT/km than NPDC.

Additionally, DEA has always given WGDC a much higher efficiency score than NPDC across all weighting restrictions, except for the last 50% restriction, where NPDC scores slightly higher due to greater emphasis on the expenditure variable. Overall, environmental conditions, recorded data, and DEA results suggest that NPDC has the potential to achieve a much higher PHI and efficiency score given its present expenditure. Conversely, NPDC may also become more efficient if there was a reduction in the maintenance budget but a sustained level of PHI output at its current figure.

However, Figure 4.16 shows that inefficient RCA 44 is positioned within Quadrant 1 on the border with Quadrant 3, whereas the more efficient RCA 56 is placed much lower in Quadrant 3. This highlights misalignment across objective and subjective performance measures. Individually RCA 56’s position reflects its moderately inefficient DEA ranking but achieves only a marginally better TRM score and much lower NZTA score than RCA 44, whose subjective scores do not reflect its poor DEA ranking. Overall, the subjective scores for RCA 56 likely reflect a realistic picture of the actual maintenance performance, but RCA 44 would likely need to demonstrate better on-ground performance to attain a higher objective score.

4.6 Expenditure weight control on all RCAs

Previous sections have suggested that the minimum expenditure weight restriction range of 30% to 50% is optimal for undertaking realistic benchmarking assessments across all types of RCAs, minimising the likelihood of any single variable being over or underrepresented. This section presents the efficiency score details when both HT and LT RCAs are assessed together under the optimal expenditure restriction range. A line chart is shown first (Figure 4.17), depicting the changes in efficiency score values across no restrictions and the tested restriction range. Subsequently, pie charts in Figure 4.18 clearly depict the applicability of the weighting restrictions through variable distributions across RCAs.

4.6.1 Efficiency score performance across recommended weight restriction range

As previously observed, there is an overall drop in efficiency scores across RCAs throughout increasing weighting restrictions, shown in Figure 4.17. The greatest total change is observed for RCAs 9 (HKDC), 18 (TCDC), 25 (KCDC), 30 (NCC), 40 (HDC), 61 (DCC), and 68 (QLDC). These councils were inefficient across all weighting restrictions except for NCC which was efficient only under no restrictions, for reasons previously discussed. Note that except for NCC, those RCAs deemed efficient initially under no restrictions, remained efficient across all restrictions. These efficient RCAs are:

- RCA 11 - Hamilton City Council
- RCA 15 - Tauranga City Council
- RCA 24 - Hutt City Council
- RCA 41 - Horowhenua District Council
- RCA 62 - Gore District Council
- RCA 80 - Auckland Transport

Of these efficient RCAs, only RCAs 11, 15, 24 and 80 were efficient within both the HT RCA comparison and across all RCAs. RCAs 41 and 62 were also the only ones to be consistently efficient across the LT RCA comparison and this combined comparison. However, RCAs were separated into HT and LT groups based upon their traffic loading (VKT/km) as a core step within this study's methodology to understand their varying performance under DEA restrictions. This also enabled more insight into DEA's dynamics with limited performance variables.

The subsequent section displays pie charts showing variable distributions across the restriction range; however, this is to show that overall, this is a highly appropriate restriction setting for more equitable variable consideration. Realistically, territories with similar data, performance, and ideally geographical characteristics should be placed in benchmarking clubs similar to the Waikato's Road Asset Technical Accord (RATA), for better understanding the relative differences in efficiency and, "achieving best practice road asset management" (REG, 2015). Moreover, any suggestions or learnings regarding performance and efficiency improvements would be more effective if they resulted from comparisons of RCAs with similar characteristics and challenges, rather than efficient yet highly dissimilar territories.

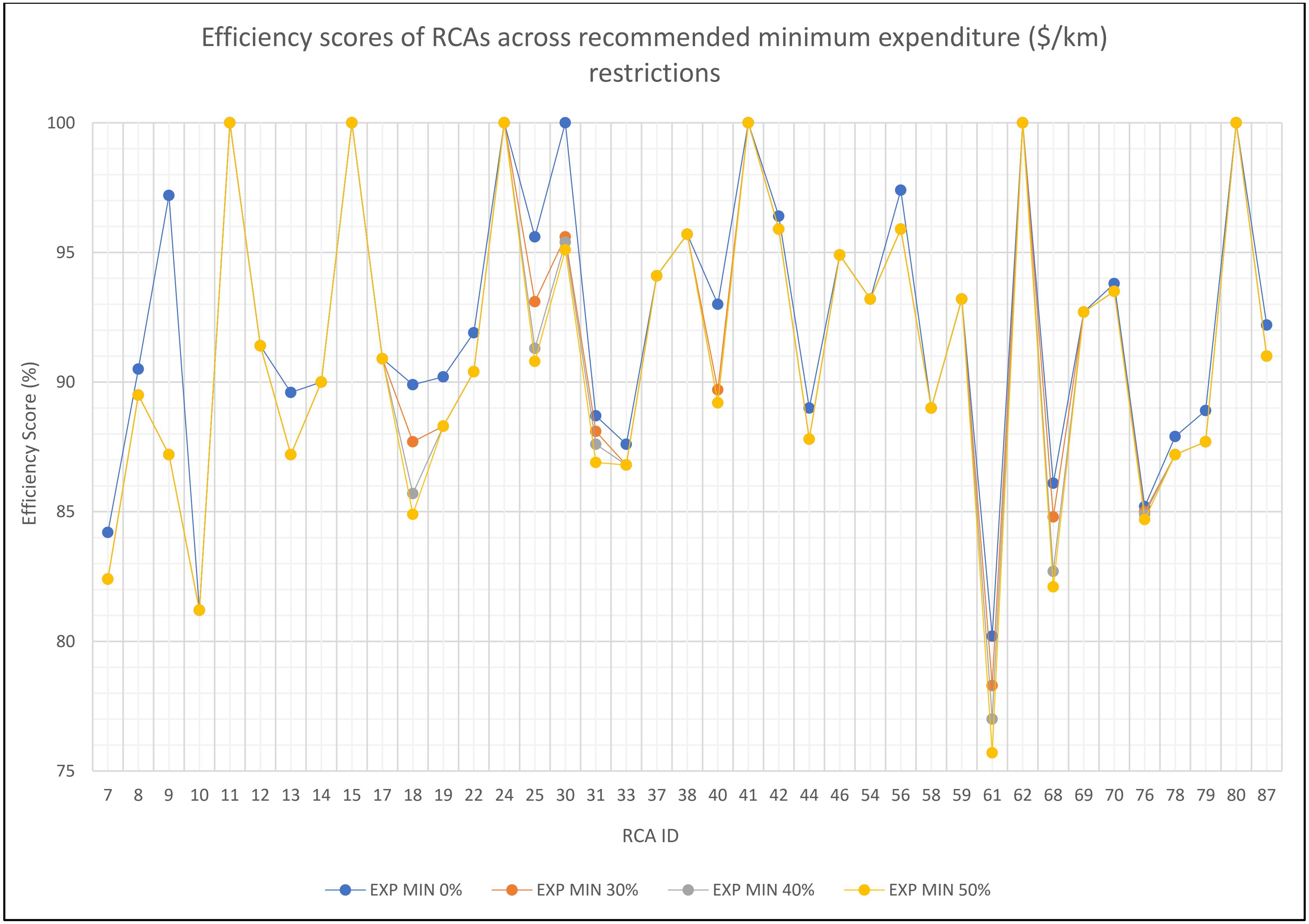


Figure 4.17: Efficiency scores of all RCAs across the recommended minimum expenditure ($/km) restriction ranges

4.6.2 Variable performance

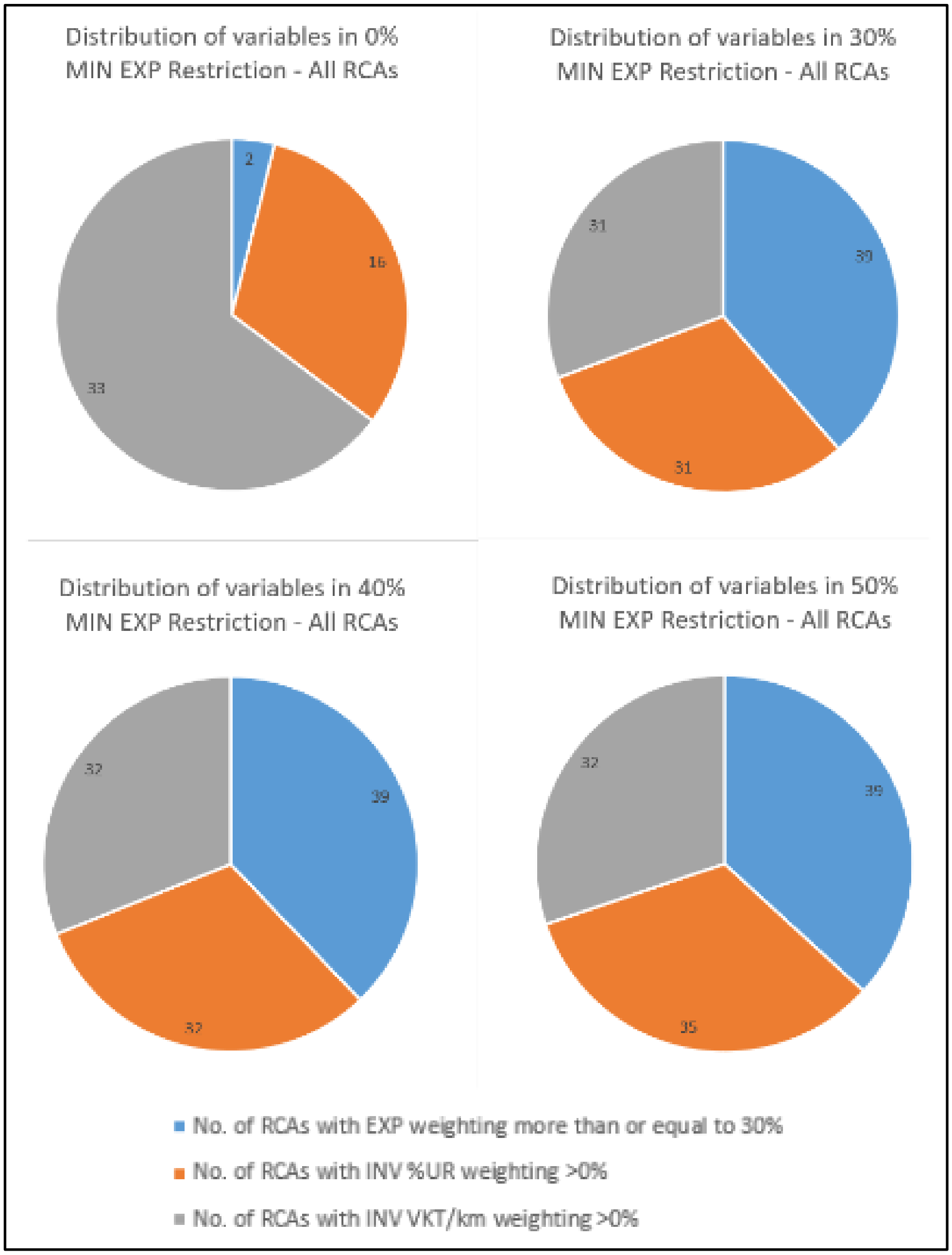


Figure 4.18: Distribution of variables across different expenditure restriction settings - All RCAs

As expected, under no restrictions most RCAs were either neglecting or insignificantly representing expenditure within their scoring mix. Upon applying the optimal weight restriction range to all RCAs, much more balanced variable distributions were observed, with no RCA giving all the weighting to any one variable except for efficient RCA 62 (Gore District). This demonstrates the applicability of this expenditure weight restriction range and indicates that this is a sound basis for realistic benchmarking assessments.

Moreover, for this combined RCA group, the ideal expenditure weight restriction appears to be 40% as it produces the greatest amount of equal VKT/km and %UR expression, refer to Figure 4.18. Full details of each RCA's efficiency score composition can be found in Items 10 to 13 of Appendix A.

However, as previously stated, there are variances between RCAs deemed as efficient within the singular HT or LT RCA assessments as compared to this combined model. It is suggested that similar territories be compared in individual models that are segregated based on a demonstrable difference in a critical factor such as VKT/km, as done in this study. Alternatively, %UR is another factor that may be used to segregate RCAs. Such segregation would likely yield more relevant learnings about areas for potential efficiency improvement for RCAs, as well as aid in better understanding DEA's scoring dynamics under restrictions.

Chapter 5 - Summary and Recommendations

This research contributes to advancing road network maintenance practices by improving the framework for effective performance benchmarking and offering insights into maintenance challenges through a holistic and triangulated evaluation of different assessment measures. This final chapter summarises the motivations for this research, the achievement of objectives, and the value and applicability of research findings. A final recommendation is given, along with the study's limitations and considerations for further model development.

5.1 Research motivations

New Zealand faces numerous challenges to achieving more sustainable transport, be it through direct emissions reductions or better management of ageing assets, such as its road networks. To align with the sustainability and climate change-related aims of the Government Policy Statement (GPS) on land transport, it is critical for entities such as RCAs to refine their road network maintenance and management practices to deliver strong outcomes with maximum efficiency. Performance benchmarking is a successful tool for achieving higher efficiency and identifying opportunities for improvement in comparison to one's high-performing peers.

Previous literature has proven that the statistical DEA technique is a popular and highly applicable technique for performance benchmarking within the transport and infrastructure asset management sector. Its main advantages are the capability to consider multiple variables that influence outputs and its inherent variable weighting system that automatically presents all DMUs with the highest possible efficiency score. However, it is well documented that such freedom in weighting variables, to the point of completely ignoring them within the overall efficiency score, often leads to exaggerated and unfaithful performance assessments for DMUs, in this case, RCAs. However, manual variable weight restrictions placed with sound justification can ensure that DEA considers all variables appropriately within the final score, such that DMUs would attain efficiency rankings that are more reflective of actual performance and operating conditions.

Thus, this study's focus was to develop a sound foundation for benchmarking RCAs' road network maintenance performance, which considered key variables and was more realistic by carefully applying weight restrictions. Additionally, this model needed to provide deeper insights into RCA performance in conjunction with currently used performance assessments. These focus areas would ensure that valuable, practical contributions could be made to improve the performance benchmarking initiative within the transport and infrastructure sector.

5.2 Achievement of research objectives

Three main objectives were set for this study to achieve strong outcomes related to the focus areas described above. The achievements and insights regarding each objective have been summarised below.

5.2.1 Choosing appropriate variables for testing weight control

The most updated performance data (from 2022) regarding RCA maintenance parameters was obtained from RAMM for accuracy. All RCAs with incomplete data were deleted as DEA does not accept missing values. Subsequently, four variables that most influenced maintenance performance and dominantly expressed differences across RCAs were chosen from the remaining data across 39 RCAs. There were three input variables, i.e., Vehicle Kilometres Travelled (millions) per lane kilometre (VKT/km), Percentage of Urban Roads (%UR), and Maintenance expenditure ($/km). All except expenditure were uncontrollable 'contextual' variables. The only output was a condition variable, i.e., Pavement Health Index (PHI). These variables were appropriately normalised, scaled to a range of 0-100, and orientated so that DEA could perform sound comparisons. Particularly, VKT/km and %UR had to be inverted, as lower inverted values would signify greater maintenance challenges to DEA. Expenditure ($/km) and PHI were left in their original forms as they directly corresponded to a greater budget and better pavement performance output, respectively.

Additional environmental contextual variables were not developed for this foundational model as it was crucial to first achieve an effective model from the readily available RAMM data. However, any future model development would benefit from including such variables as they would provide objective insights into environmental influence upon RCA efficiency.

5.2.2 Applying variable weightings and making recommendations

All RCAs were separated into an HT or LT RCA group based on their normalised VKT/km value. The HT group included all the city council RCAs and those district council RCAs with regions of high traffic loading, with the lowest cut-off being 0.5 VKT/km. All remaining RCAs were district councils that made up the LT RCA group. As mentioned, DEA can neglect or give insignificant weighting to poor-performing variables to yield the highest possible efficiency scores for RCAs, leading to unrealistic efficiency assessments. Under no weight restrictions, DEA most often ignored or insignificantly represented the expenditure variable within an RCA's scoring mix. This behaviour was detrimental to realistic assessments as the expenditure variable is the sole controllable factor for RCAs impacting performance efficiency in network maintenance. Thus, it was decided that weight restrictions would be applied only on expenditure and that DEA would be allowed to assign the remaining weighting to the two other input variables automatically.

After testing weight restrictions on the expenditure variable from both a minimum and maximum limit, it was found that the minimum restriction limit should be solely controlled. This would allow DEA to retain scoring flexibility to include VKT/km and %UR, yet also guarantee minimum expenditure expression within the final efficiency score. It was decided that a range of minimum expenditure weight restrictions from 30% to 60% would be applied first on HT RCAs to determine an optimal figure or range. HT RCAs were evaluated first as they experience the highest traffic loading, urbanisation, and also higher maintenance expenditure.

The most suitable range of restrictions on the expenditure variable appeared to be from 30% to 50%, and a specific restriction of 50% was recommended for the HT group. Overall, expenditure had a guaranteed expression in efficiency scores within this range, and the other two input variables, i.e., VKT/km and %UR, also had the most overall even distribution across HT RCAs. This range was then applied on the LT RCA group which also showed a robust distribution of all variables with the RCAs' scoring mixes. A specific restriction setting of 30% was recommended for the LT group as it resulted in equal VKT/km and %UR distribution. Note that LT RCAs had a laxer restriction recommendation that HT RCAs. The optimal 30% to 50% restriction range was also applied on all RCAs in a combined model, where the specific restriction setting was recommended at 40%. While equitable variable distribution like that in separate models was still observed, it is suggested that RCAs be segregated into 'benchmarking clubs', or 'peer-groups' based upon similarities in critical performance data or environmental conditions. This would allow more effective learnings to be obtained across similar RCAs regarding potential areas for performance and efficiency improvement.

5.2.3 Evaluating DEA scores against subjective performance assessments

The DEA results obtained throughout this study are a purely objective and data-based gauge of an RCA's performance efficiency in network maintenance. Various uncontrollable factors, such as climate change and challenging soil conditions also influence RCAs, and Shivaramu et al. (2022a) have developed variables for quantifying their impacts on RCA performance. Future research would benefit from incorporating these environmental variables in weight-controlled DEA analyses as these are RCAs' limiting factors and may not be reflected solely through recorded RAMM data. However, in this study, discussions that compared the performance of RCAs within regions of similar environmental challenges gave insight into potential causes for poorer or better DEA efficiency rankings due to chosen variables.

Additionally, considering TRM and NZTA scores for AMP assessments in conjunction with DEA efficiency scores presented unique observations regarding DEA's value and applicability with the transport sector. Both TRM and NZTA have individual criteria for scoring RCAs' AMP reports, and greater alignment with either set of criteria does not guarantee it in the other. However, as these are subjective assessments, bringing in an objective tool for performance measurement enabled triangulation of the evaluations that highlighted where alignments and misalignments occurred across them. Misalignments also highlighted potential gaps in both subjective and objective assessments that presented improvement opportunities. For example, there were more misalignments across the LT RCA group than the HT group. It was particularly interesting to note that the majority of LT RCAs deemed inefficient by DEA received very high TRM and NZTA assessment scores. A likely reason may be significant gaps in asset management reporting leading to this level of misaligned performance evaluations. Conversely, some RCAs such as 11 (Hamilton City) and 80 (AT) received 100% efficiency scores from DEA but lower subjective assessment scores from TRM and NZTA that did not reflect their apparently high on-ground performance. In this case, improving AMP reporting with greater alignment with specific criteria may yield better subjective scores.

Overall, incorporating numerous measures of performance assessment provided a new lens for more holistic, practical, and triangulated evaluations of RCA efficiency. Further DEA model development and robust data records would support greater accuracy for insights regarding RCA performance.

5.3 Recommendation

For a DEA efficiency benchmarking model comprising this study's chosen variables, the expenditure variable should be restricted to a minimum weighting between 30% and 50% for all evaluated RCAs. This will ensure fair and realistic efficiency benchmarking assessments without distorted variable distributions. Moreover, it would be beneficial to have RCAs with similar characteristics in individual clubs or peer groups to obtain effective learning regarding performance and efficiency improvements.

Additionally, objective performance assessments obtained through DEA should be evaluated in conjunction with currently used performance indicators, such as the subjective AMP evaluation scores by TRM and NZTA. Such varied performance evaluations will offer holistic, practical insight into factors influencing RCA efficiency and highlight potential areas for improvement, as observed through cases of aligning and misaligning performance assessments across the objective and subjective tools.

5.4 Limitations of this study

1. *Lack of environmental variables*

Only a few performance variables were chosen for this study to grasp the dynamics and behaviour of DEA when variable restrictions were applied. Additionally, the small group of RCAs with complete data meant that too many variables would diminish DEA's scoring discrimination. Thus, future research must be able to include a larger, robust dataset of RCAs with complete information to consider environmental variables.

2. *Data misalignments across different performance assessment measures*

Data misalignments have been observed across the three different performance assessment measures, namely, DEA, TRM AMP scores, and NZTA AMP scores. As discussed, likely reasons for this could be the lack of environmental variables considered in the current DEA model, or gaps in performance data or AMP reporting.

5.5 Considerations for further model development

This foundation model may be further developed for greater specificity to individual conditions across territories by adding more contextual (uncontrollable) or non-contextual (controllable) variables. Key considerations would then be:

1. *Scoring discrimination*

Different weight restrictions would be applied, or more variables may need to be controlled to maintain some scoring discrimination within DEA. For example, to include environmental variables in a DEA model, as in Shivaramu et al. (2022a), a greater dataset of RCAs with complete data would be required to maintain scoring discrimination.

2. *Available data*

A dataset of RCAs or Network Operating Contracts (NOCs) with more complete information encompassing as much of New Zealand as possible would provide a more refined and thorough tool for assessing asset management efficiency. Additionally, thorough data reporting would support more robust insights and realistic objective performance assessments. Hence, all territorial authorities should be encouraged to follow best practices in maintaining their records and data within the national RAMM database.

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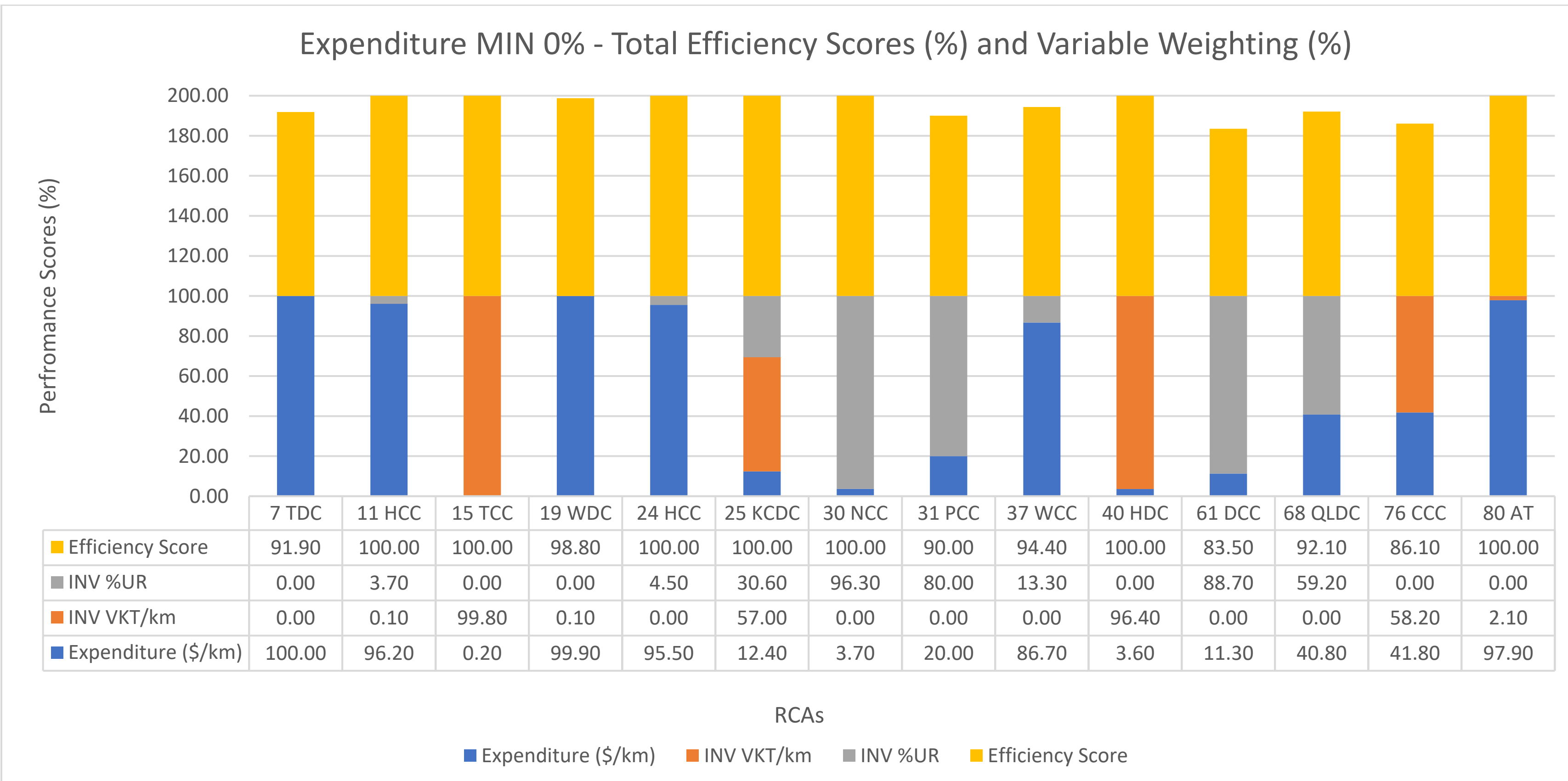
APPENDIX A - Efficiency score details for RCAs across restrictions

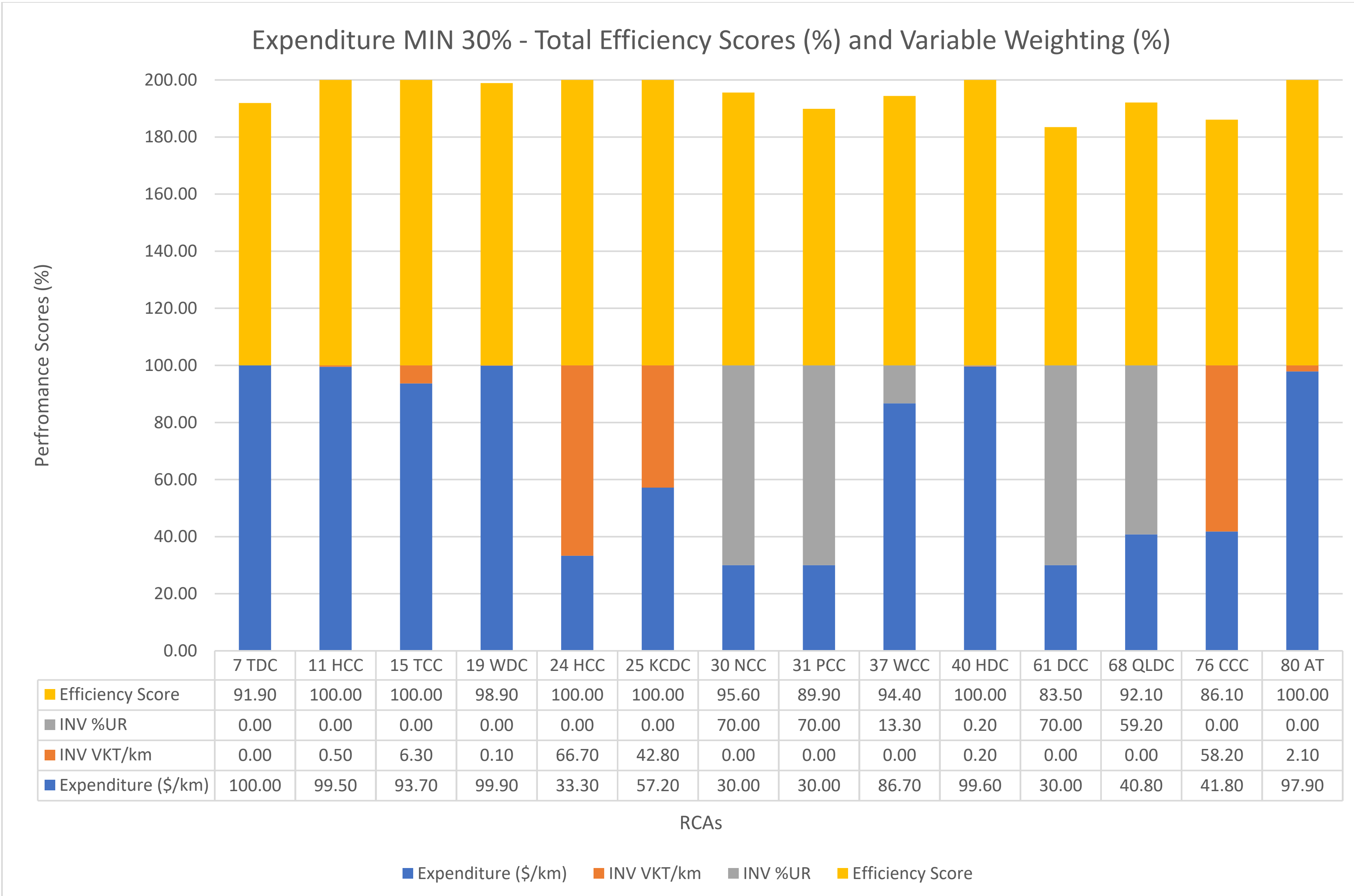
A.1 High-Traffic (HT) RCA score details

Note: These are stacked bar graphs, where overall efficiency scores lie between 100% and 200% on the y-axis; individual variable compositions lie between 0% and 100% on the y-axis. The table underneath each chart lists numerical quantities of weighting allocated to variables for each RCA to make up 100% of the efficiency scores.



	7 TDC	11 HCC	15 TCC	19 WDC	24 HCC	25 KCDC	30 NCC	31 PCC	37 WCC	40 HDC	61 DCC	68 QLDC	76 CCC	80 AT
Efficiency Score	91.90	100.00	100.00	98.80	100.00	100.00	100.00	90.00	94.40	100.00	83.50	92.10	86.10	100.00
INV %UR	0.00	3.70	0.00	0.00	4.50	30.60	96.30	80.00	13.30	0.00	88.70	59.20	0.00	0.00
INV VKT/km	0.00	0.10	99.80	0.10	0.00	57.00	0.00	0.00	0.00	96.40	0.00	0.00	58.20	2.10
Expenditure ($/km)	100.00	96.20	0.20	99.90	95.50	12.40	3.70	20.00	86.70	3.60	11.30	40.80	41.80	97.90

Item 1: Efficiency scores (%) and variable weighting (%) distribution under no expenditure restriction (Expenditure MIN 0%)



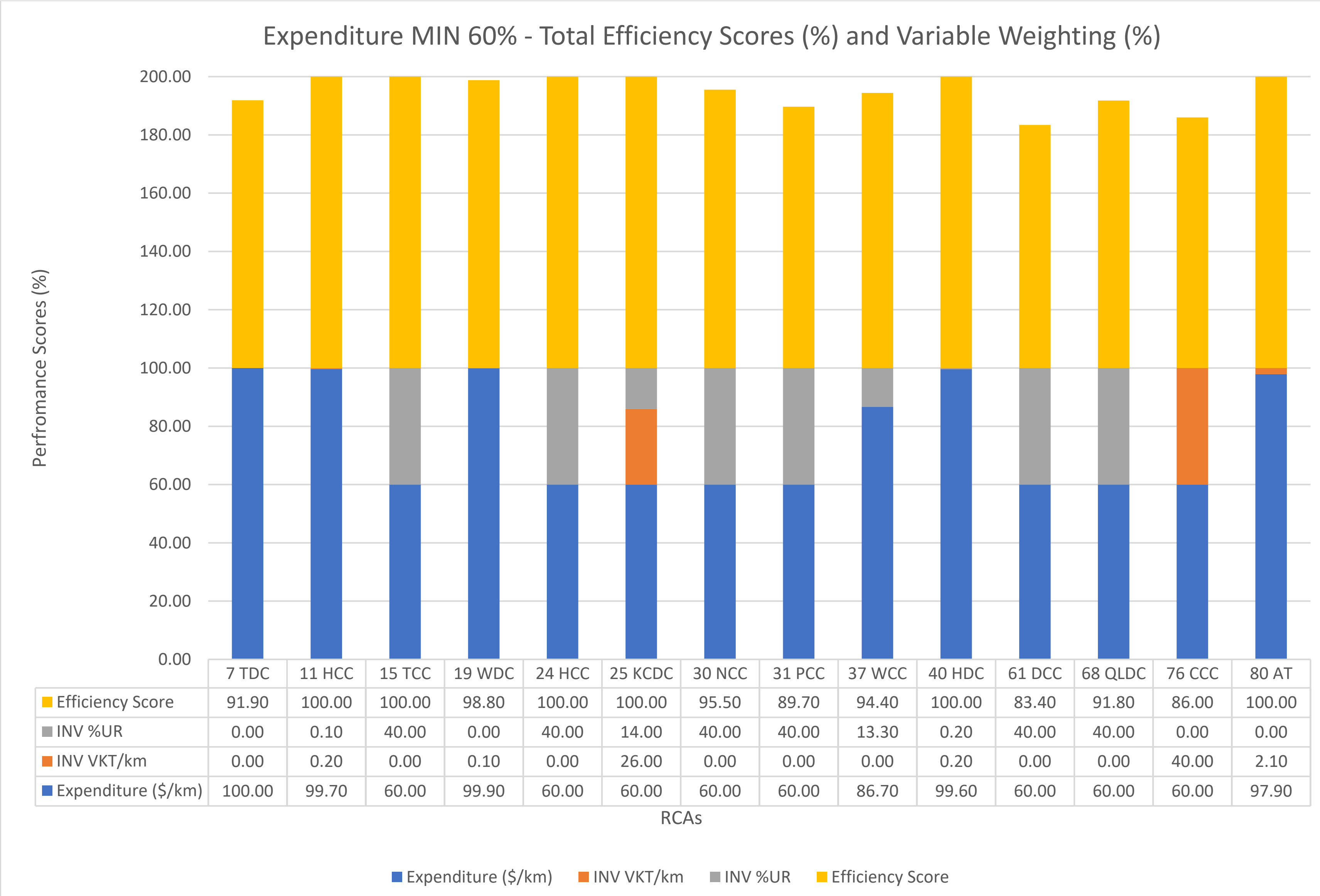
Item 2: Efficiency scores (%) and variable weighting (%) distribution under minimum 30% expenditure restriction (Expenditure MIN 30%)

	7 TDC	11 HCC	15 TCC	19 WDC	24 HCC	25 KCDC	30 NCC	31 PCC	37 WCC	40 HDC	61 DCC	68 QLDC	76 CCC	80 AT
Efficiency Score	91.90	100.00	100.00	98.80	100.00	100.00	95.60	89.90	94.40	100.00	83.50	92.10	86.10	100.00
INV %UR	0.00	0.10	60.00	0.00	16.60	0.00	60.00	60.00	13.30	0.20	60.00	59.20	0.00	0.00
INV VKT/km	0.00	0.20	0.00	0.10	43.40	60.00	0.00	0.00	0.00	0.20	0.00	0.00	58.20	2.10
Expenditure ($/km)	100.00	99.70	40.00	99.90	40.00	40.00	40.00	40.00	86.70	99.60	40.00	40.80	41.80	97.90

Item 3: Efficiency scores (%) and variable weighting (%) distribution under minimum 40% expenditure restriction (Expenditure MIN 40%)

	7 TDC	11 HCC	15 TCC	19 WDC	24 HCC	25 KCDC	30 NCC	31 PCC	37 WCC	40 HDC	61 DCC	68 QLDC	76 CCC	80 AT
Efficiency Score	91.90	100.00	100.00	98.80	100.00	100.00	95.60	89.80	94.40	100.00	83.40	91.90	86.00	100.00
INV %UR	0	0	0.00	0.00	0.00	17.50	50.00	50.00	13.30	0.20	50.00	50.00	0.00	0.00
INV VKT/km	0	0.5	50.00	0.10	50.00	32.50	0.00	0.00	0.00	0.20	0.00	0.00	50.00	2.10
Expenditure ($/km)	100	99.5	50.00	99.90	50.00	50.00	50.00	50.00	86.70	99.60	50.00	50.00	50.00	97.90

Item 4: Efficiency scores (%) and variable weighting (%) distribution under minimum 50% expenditure restriction (Expenditure MIN 50%)

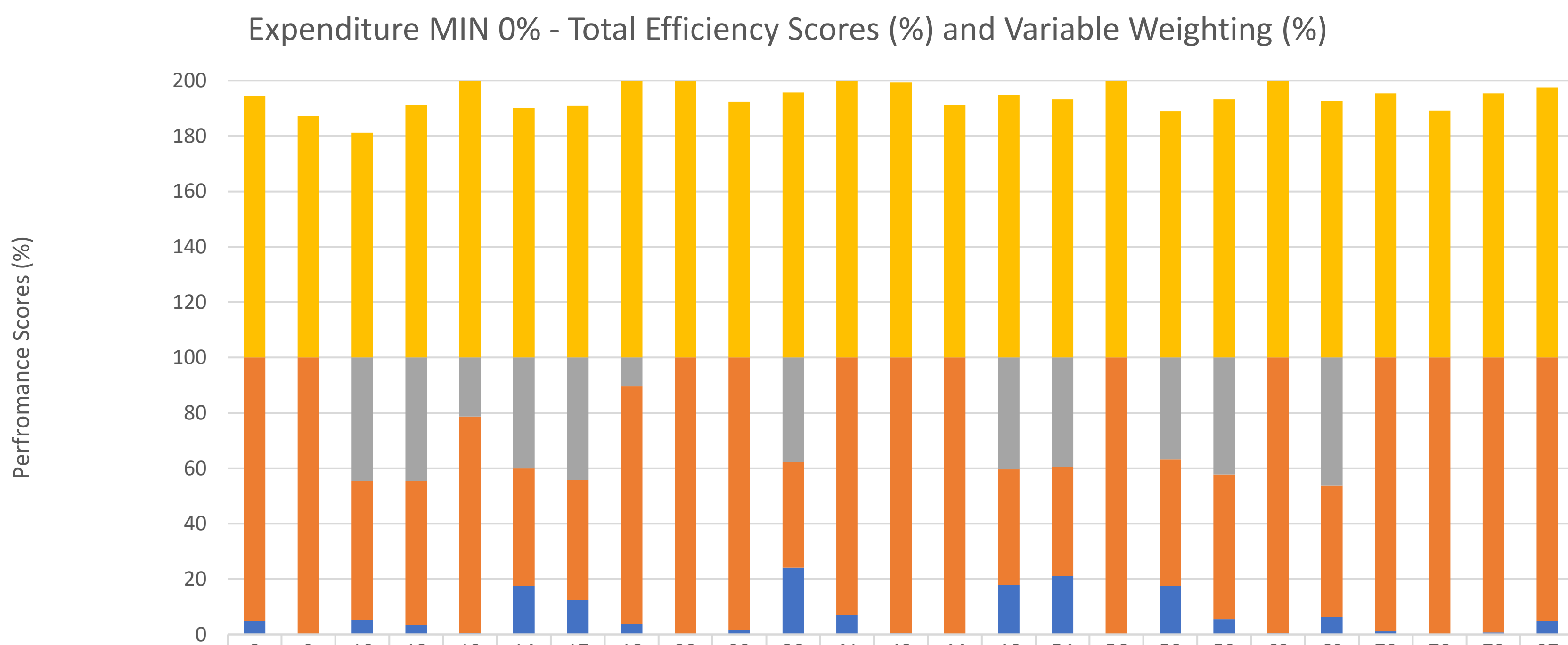


	7 TDC	11 HCC	15 TCC	19 WDC	24 HCC	25 KCDC	30 NCC	31 PCC	37 WCC	40 HDC	61 DCC	68 QLDC	76 CCC	80 AT
Efficiency Score	91.90	100.00	100.00	98.80	100.00	100.00	95.50	89.70	94.40	100.00	83.40	91.80	86.00	100.00
INV %UR	0.00	0.10	40.00	0.00	40.00	14.00	40.00	40.00	13.30	0.20	40.00	40.00	0.00	0.00
INV VKT/km	0.00	0.20	0.00	0.10	0.00	26.00	0.00	0.00	0.00	0.20	0.00	0.00	40.00	2.10
Expenditure ($/km)	100.00	99.70	60.00	99.90	60.00	60.00	60.00	60.00	86.70	99.60	60.00	60.00	60.00	97.90

Item 5: Efficiency scores (%) and variable weighting (%) distribution under minimum 60% expenditure restriction (Expenditure MIN 60%)

A.2 Low-Traffic (LT) RCA score details

Note: As in A.1, these are stacked bar graphs for LT RCAs and have the same presentation of score details.

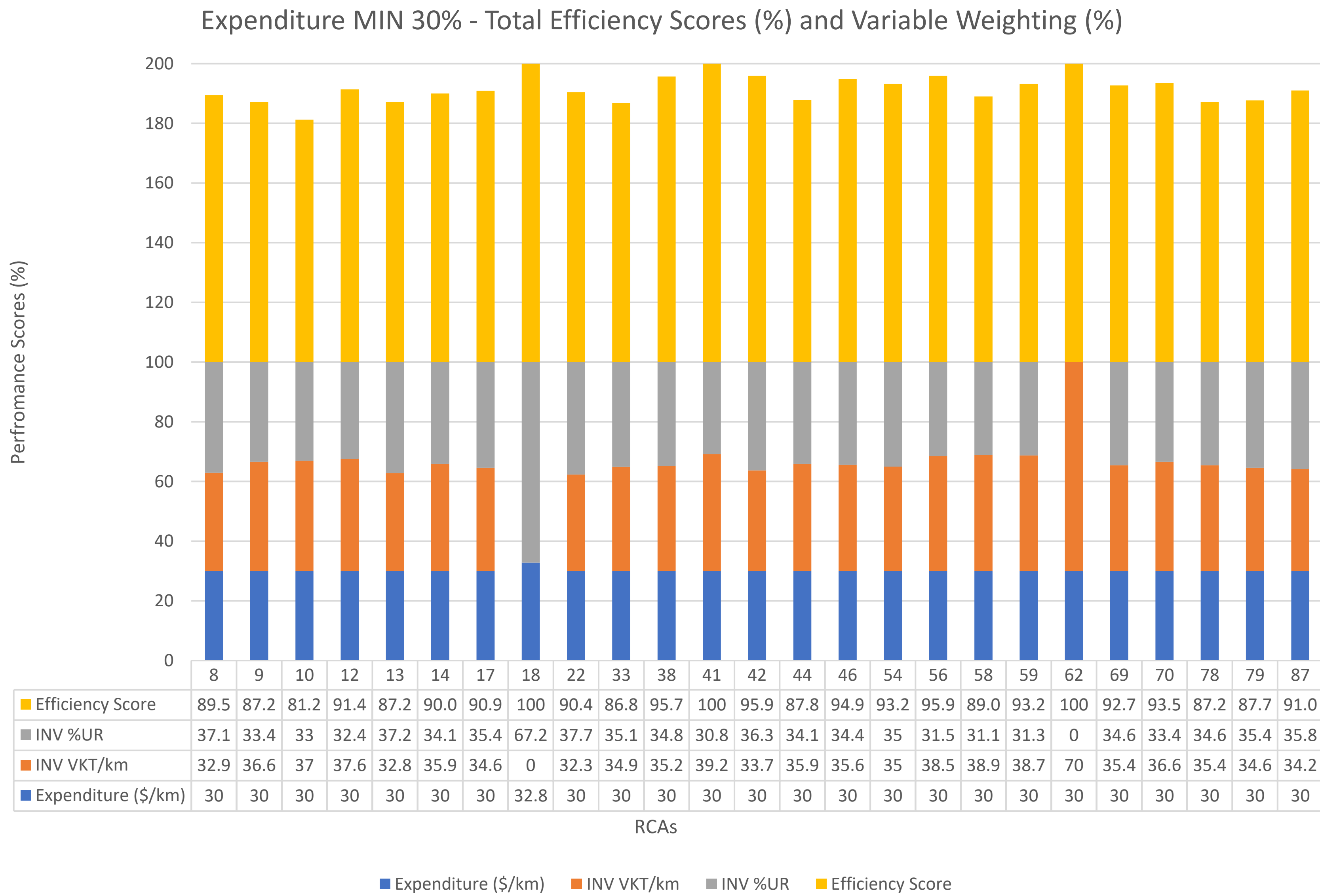


	8	9	10	12	13	14	17	18	22	33	38	41	42	44	46	54	56	58	59	62	69	70	78	79	87
Efficiency Score	94.5	87.3	81.2	91.4	100	90.0	90.9	100	99.7	92.4	95.7	100	99.3	91.1	94.9	93.2	100	89.0	93.2	100	92.7	95.4	89.2	95.4	97.6
INV %UR	0	0	44.6	44.6	21.3	40.1	44.2	10.3	0	0	37.7	0	0	0	40.4	39.5	0	36.7	42.2	0	46.3	0	0	0	0
INV VKT/km	95.3	100	50.1	52	78.2	42.3	43.3	85.9	100	98.5	38.2	93	99.6	100	41.8	39.5	100	45.8	52.3	99.6	47.4	98.9	100	99.3	95.1
Expenditure ($/km)	4.7	0	5.3	3.4	0.5	17.6	12.5	3.8	0	1.5	24.1	7	0.4	0	17.8	21	0	17.5	5.5	0.4	6.3	1.1	0	0.7	4.9

RCAs

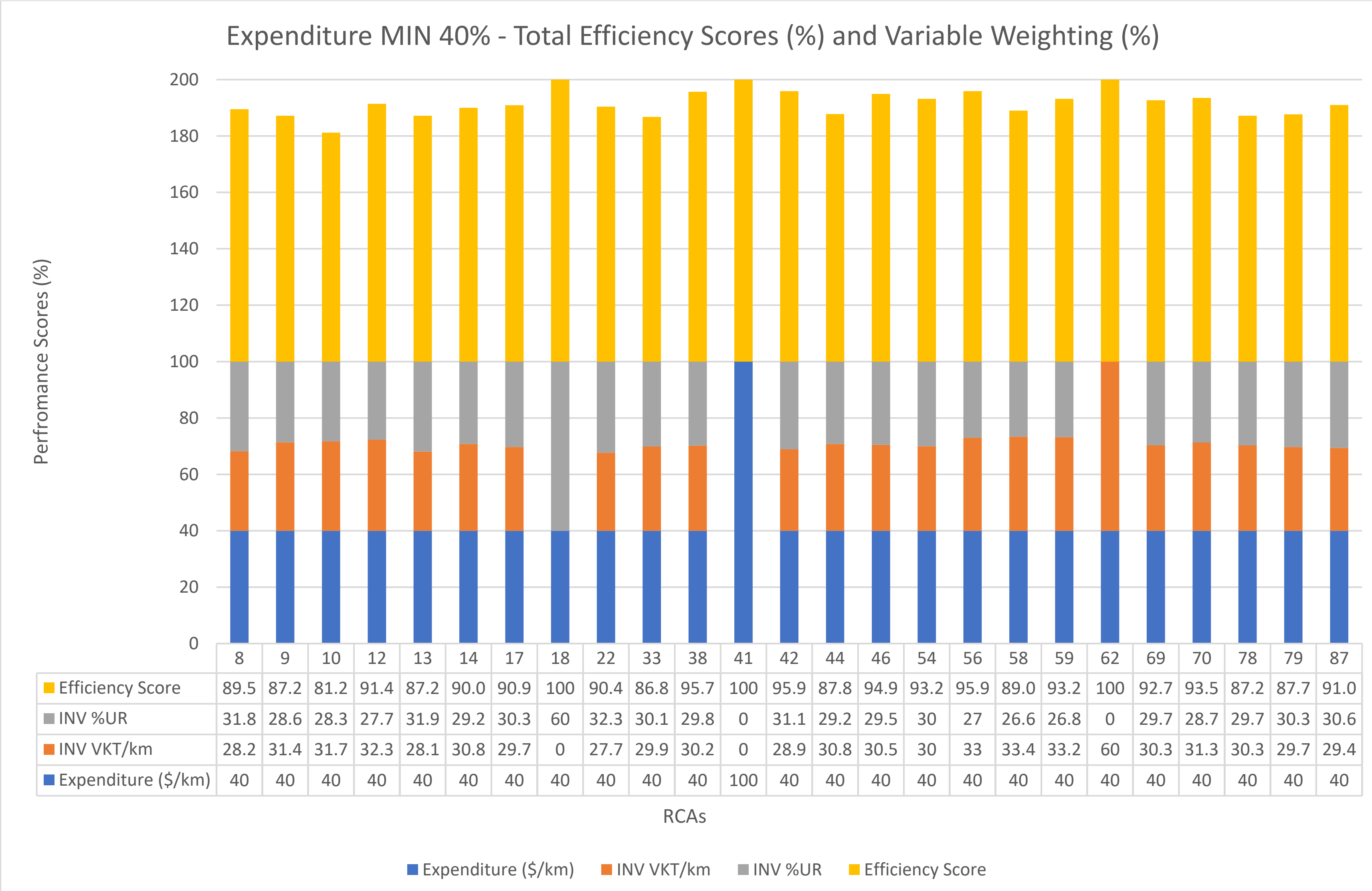
Expenditure ($/km) INV VKT/km INV %UR Efficiency Score

Item 6: Efficiency scores (%) and variable weighting (%) distribution under no expenditure restriction (Expenditure MIN 0%)



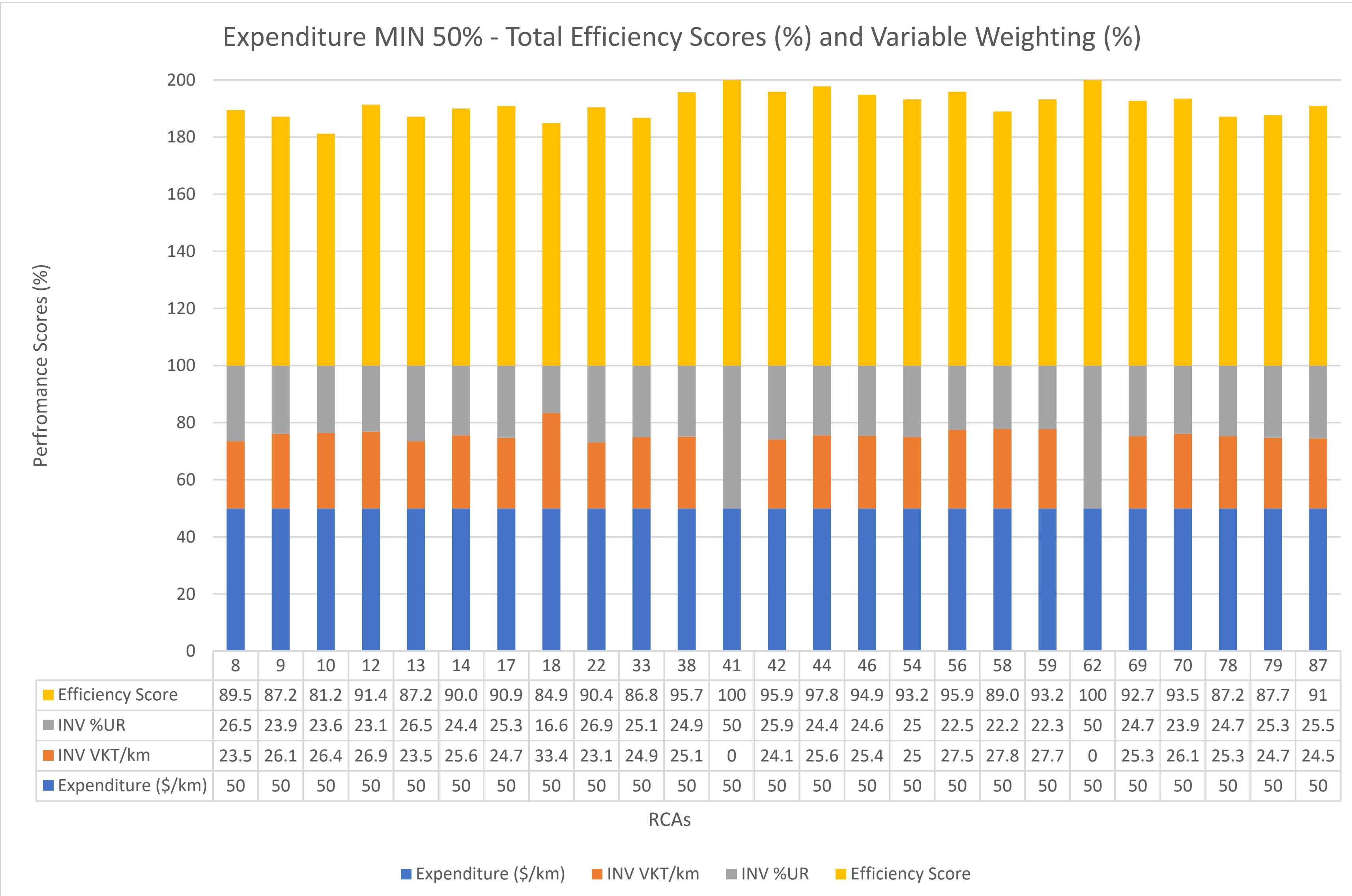
	8	9	10	12	13	14	17	18	22	33	38	41	42	44	46	54	56	58	59	62	69	70	78	79	87
Efficiency Score	89.5	87.2	81.2	91.4	87.2	90.0	90.9	100	90.4	86.8	95.7	100	95.9	87.8	94.9	93.2	95.9	89.0	93.2	100	92.7	93.5	87.2	87.7	91.0
INV %UR	37.1	33.4	33	32.4	37.2	34.1	35.4	67.2	37.7	35.1	34.8	30.8	36.3	34.1	34.4	35	31.5	31.1	31.3	0	34.6	33.4	34.6	35.4	35.8
INV VKT/km	32.9	36.6	37	37.6	32.8	35.9	34.6	0	32.3	34.9	35.2	39.2	33.7	35.9	35.6	35	38.5	38.9	38.7	70	35.4	36.6	35.4	34.6	34.2
Expenditure ($/km)	30	30	30	30	30	30	30	32.8	30	30	30	30	30	30	30	30	30	30	30	30	30	30	30	30	30

Item 7: Efficiency scores (%) and variable weighting (%) distribution under minimum 30% expenditure restriction (Expenditure MIN 30%)



	8	9	10	12	13	14	17	18	22	33	38	41	42	44	46	54	56	58	59	62	69	70	78	79	87
Efficiency Score	89.5	87.2	81.2	91.4	87.2	90.0	90.9	100	90.4	86.8	95.7	100	95.9	87.8	94.9	93.2	95.9	89.0	93.2	100	92.7	93.5	87.2	87.7	91.0
INV %UR	31.8	28.6	28.3	27.7	31.9	29.2	30.3	60	32.3	30.1	29.8	0	31.1	29.2	29.5	30	27	26.6	26.8	0	29.7	28.7	29.7	30.3	30.6
INV VKT/km	28.2	31.4	31.7	32.3	28.1	30.8	29.7	0	27.7	29.9	30.2	0	28.9	30.8	30.5	30	33	33.4	33.2	60	30.3	31.3	30.3	29.7	29.4
Expenditure ($/km)	40	40	40	40	40	40	40	40	40	40	40	100	40	40	40	40	40	40	40	40	40	40	40	40	40

Item 8: Efficiency scores (%) and variable weighting (%) distribution minimum 40% expenditure restriction (Expenditure MIN 40%)

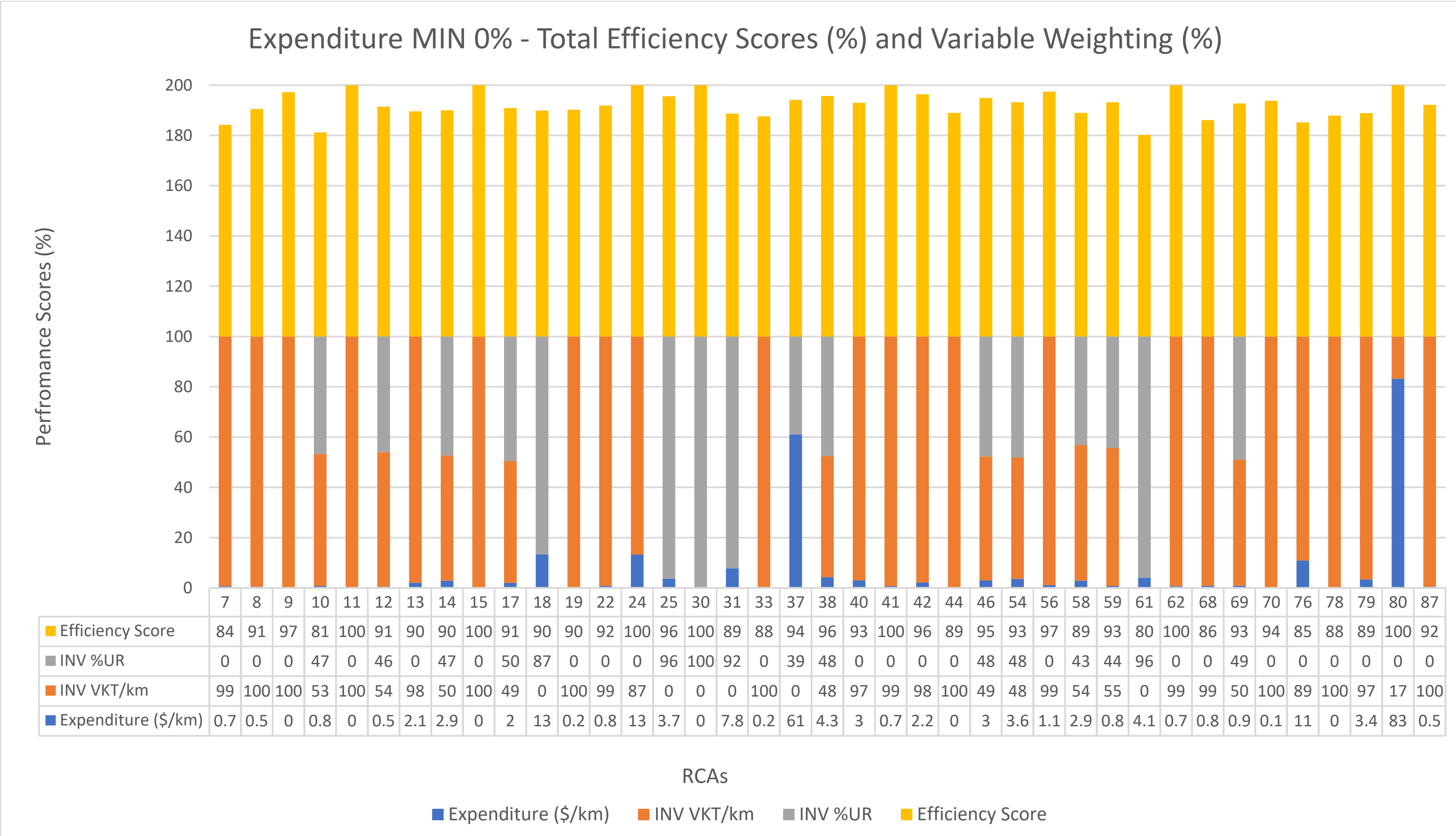


	8	9	10	12	13	14	17	18	22	33	38	41	42	44	46	54	56	58	59	62	69	70	78	79	87
Efficiency Score	89.5	87.2	81.2	91.4	87.2	90.0	90.9	84.9	90.4	86.8	95.7	100	95.9	97.8	94.9	93.2	95.9	89.0	93.2	100	92.7	93.5	87.2	87.7	91
INV %UR	26.5	23.9	23.6	23.1	26.5	24.4	25.3	16.6	26.9	25.1	24.9	50	25.9	24.4	24.6	25	22.5	22.2	22.3	50	24.7	23.9	24.7	25.3	25.5
INV VKT/km	23.5	26.1	26.4	26.9	23.5	25.6	24.7	33.4	23.1	24.9	25.1	0	24.1	25.6	25.4	25	27.5	27.8	27.7	0	25.3	26.1	25.3	24.7	24.5
Expenditure ($/km)	50	50	50	50	50	50	50	50	50	50	50	50	50	50	50	50	50	50	50	50	50	50	50	50	50

Item 9: Efficiency scores (%) and variable weighting (%) distribution under minimum 50% expenditure restriction (Expenditure MIN 50%)

A.3 Combined RCA score details

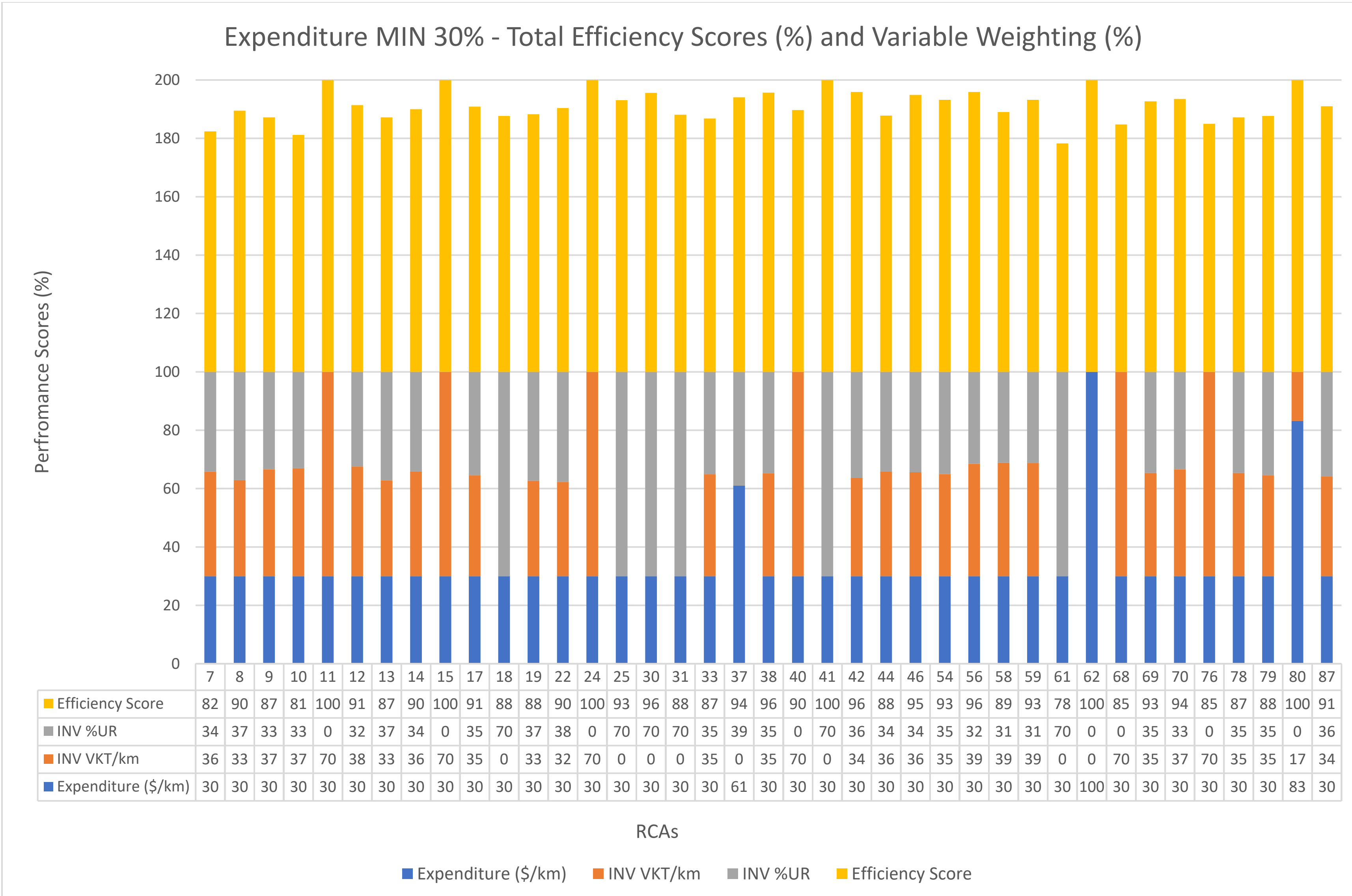
Note: As in A.1 and A.2, these are stacked bar graphs for all RCAs and have the same presentation of score details.



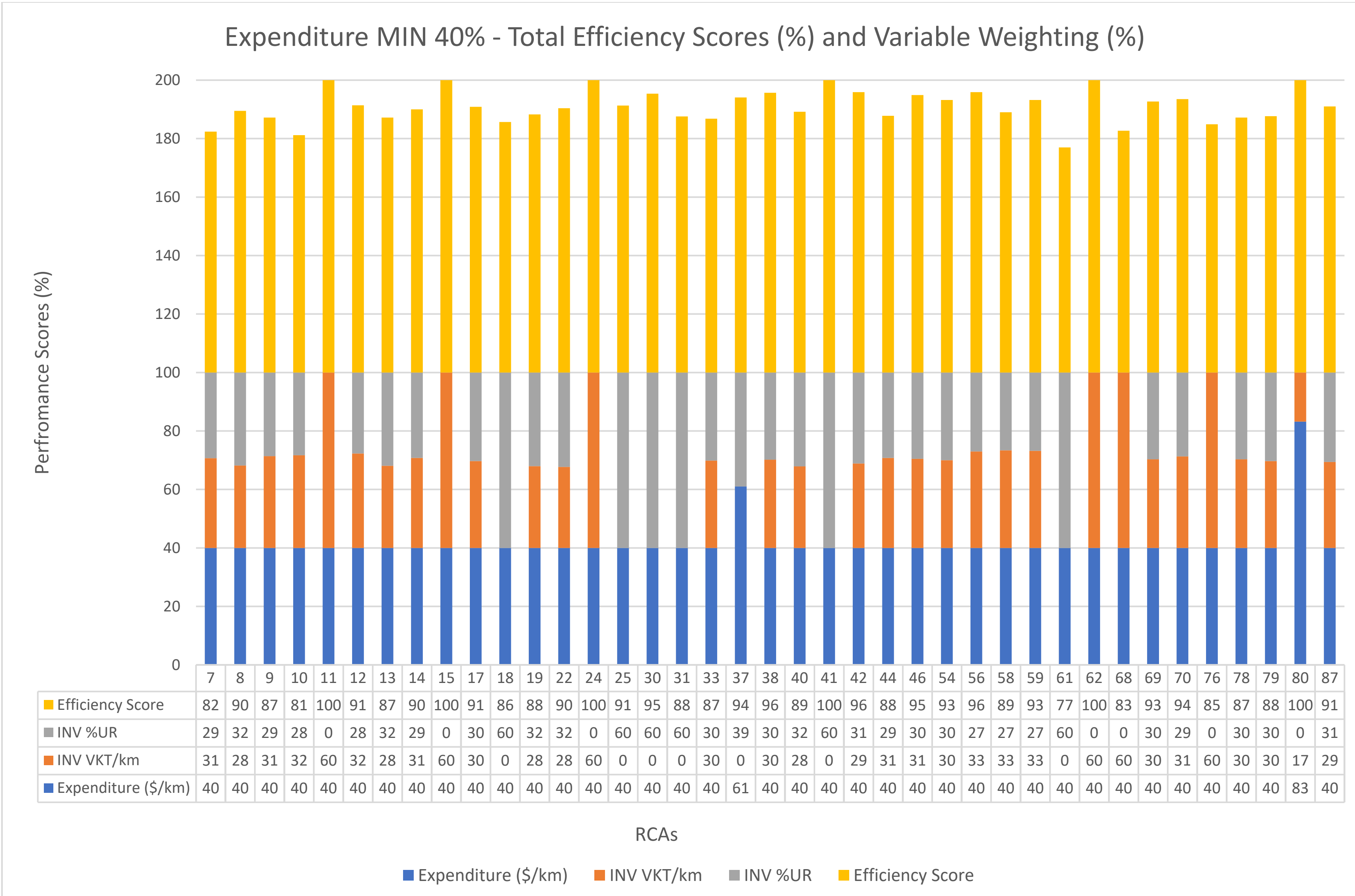
RCAs	7	8	9	10	11	12	13	14	15	17	18	19	22	24	25	30	31	33	37	38
Efficiency Score	84	91	97	81	100	91	90	90	100	91	90	90	92	100	96	100	89	88	94	96
INV %UR	0	0	0	47	0	46	0	47	0	50	87	0	0	0	96	100	92	0	39	48
INV VKT/km	99	100	100	53	100	54	98	50	100	49	0	100	99	87	0	0	0	100	0	48
Expenditure ($/km)	0.7	0.5	0	0.8	0	0.5	2.1	2.9	0	2	13	0.2	0.8	13	3.7	0	7.8	0.2	61	4.3

RCAs	40	41	42	44	46	54	56	58	59	61	62	68	69	70	76	78	79	80	87
Efficiency Score	93	100	96	89	95	93	97	89	93	80	100	86	93	94	85	88	89	100	92
INV %UR	0	0	0	0	48	48	0	43	44	96	0	0	49	0	0	0	0	0	0
INV VKT/km	97	99	98	100	49	48	99	54	55	0	99	99	50	100	89	100	97	17	100
Expenditure ($/km)	3	0.7	2.2	0	3	3.6	1.1	2.9	0.8	4.1	0.7	0.8	0.9	0.1	11	0	3.4	83	0.5

Item 10: Efficiency scores (%) and variable weighting (%) distribution under no expenditure restriction (Expenditure MIN 0%)

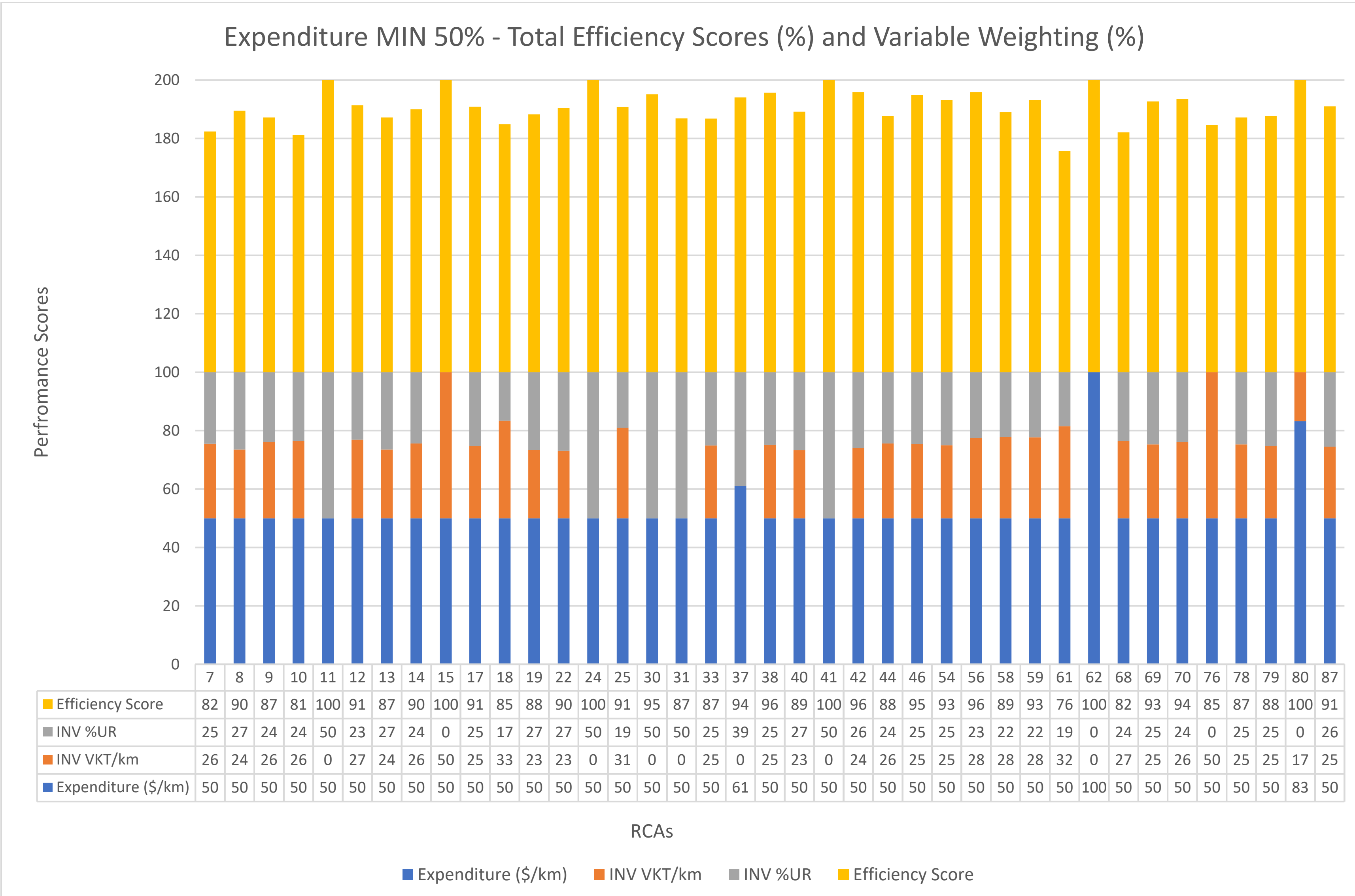


Item 11: Efficiency scores (%) and variable weighting (%) distribution under minimum 30% expenditure restriction (Expenditure MIN 30%)



	7	8	9	10	11	12	13	14	15	17	18	19	22	24	25	30	31	33	37	38	40	41	42	44	46	54	56	58	59	61	62	68	69	70	76	78	79	80	87
Efficiency Score	82	90	87	81	100	91	87	90	100	91	86	88	90	100	91	95	88	87	94	96	89	100	96	88	95	93	96	89	93	77	100	83	93	94	85	87	88	100	91
INV %UR	29	32	29	28	0	28	32	29	0	30	60	32	32	0	60	60	60	30	39	30	32	60	31	29	30	30	27	27	27	60	0	0	30	29	0	30	30	0	31
INV VKT/km	31	28	31	32	60	32	28	31	60	30	0	28	28	60	0	0	0	30	0	30	28	0	29	31	31	30	33	33	33	0	60	60	30	31	60	30	30	17	29
Expenditure ($/km)	40	40	40	40	40	40	40	40	40	40	40	40	40	40	40	40	40	40	61	40	40	40	40	40	40	40	40	40	40	40	40	40	40	40	40	40	40	83	40

Item 12: Efficiency scores (%) and variable weighting (%) distribution under minimum 40% expenditure restriction (Expenditure MIN 40%)



Item 13: Efficiency scores (%) and variable weighting (%) distribution under minimum 50% expenditure restriction (Expenditure MIN 50%)