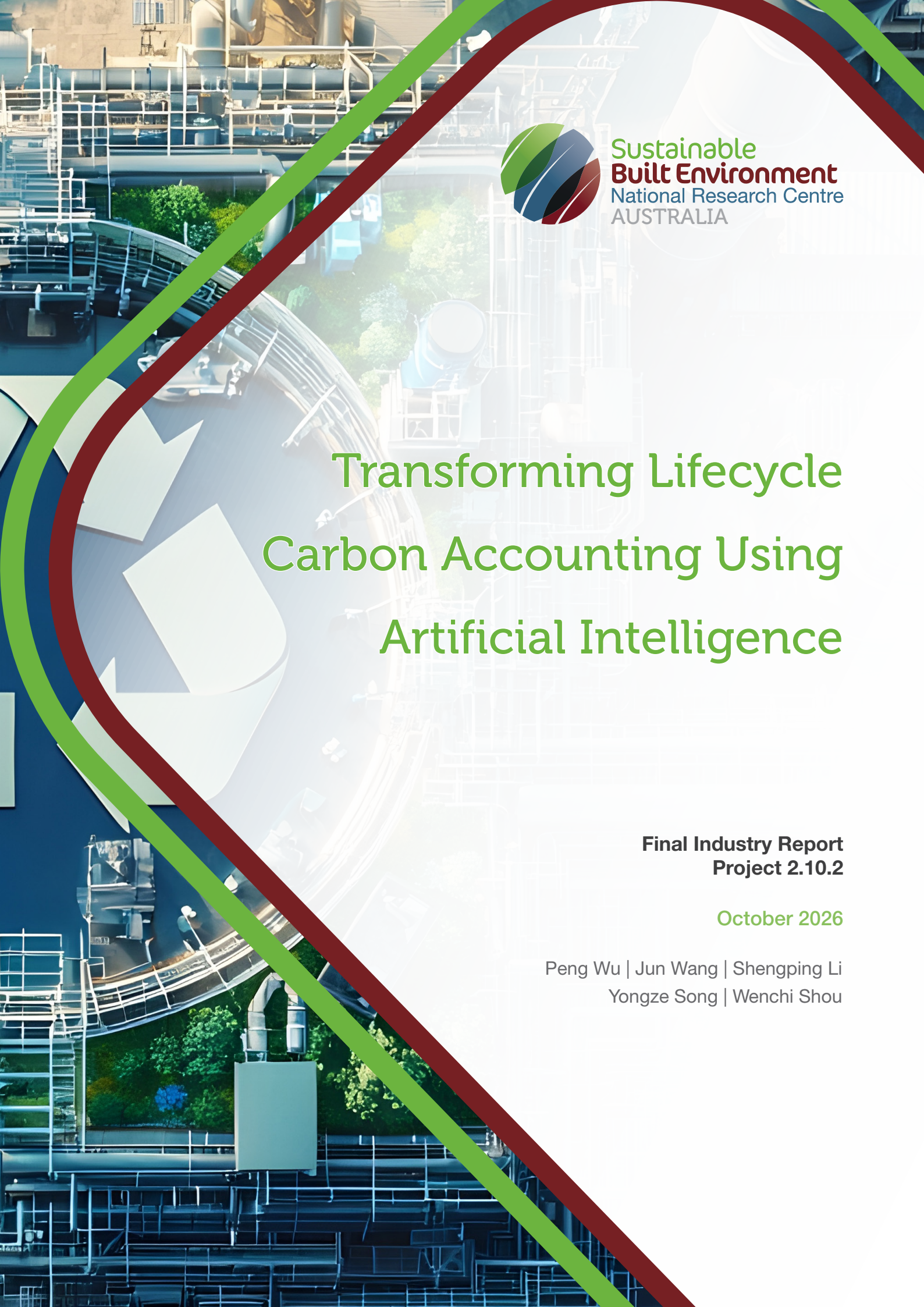

Sustainable Built Environment National Research Centre AUSTRALIA

Transforming Lifecycle Carbon Accounting Using Artificial Intelligence

Final Industry Report
Project 2.10.2

October 2026

Peng Wu | Jun Wang | Shengping Li
Yongze Song | Wenchi Shou

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Project Team

Project Leader

Peng Wu	Curtin University

Project Steering Group Chair

Andrew Curthoys	Australasian BIM Advisory Board

Research Team

Jun Wang	Western Sydney University
Wenchi Shou	Western Sydney University
Yongze Song	Curtin University
Shengping Li	Curtin University

Project Steering Group

Kelvin Grace	ATCO Australia
Storm Taylor	ATCO Australia
Carl Barrett	BGC Australia
Keith Hampson	SBEnrc Australia
Will Hackney	SBEnrc Australia
Lindsay Kyle	SBEnrc Australia
Ammar Mohammed	Main Roads Western Australia
Qindong Li	Main Roads Western Australia
Lalinda Karunaratne	Main Roads Western Australia
Victor Mantilla	Sunshine Coast Council
Rolf Engel	Sunshine Coast Council
Stephanie Zhang	WA Department of Transport
Andy Boyle	WA Department of Communities
Ricky Bester	WA Department of Communities
Lilly Sinclair-Jones	WA Department of Communities
Alexandra Meek	WA Department of Housing and Works
Rainie Zhang	WA Department of Housing and Works
John Clifton	DevelopmentWA
David Kelly	Transport for NSW
Greg Paul	Transport for NSW
Megan Ward	Infrastructure for NSW
Glenn Egan	Infrastructure for NSW
Cara McNicol	Queensland Department of Environment, Science and Innovation
Sylvia Pierce	Queensland Department of Environment, Science and Innovation
Craig Ingram	Queensland Department of Housing, Local Government, Planning and Public Works
Cameron Marshall	Queensland Department of Housing, Local Government, Planning and Public Works
Grant Smith	Queensland Department of Housing, Local Government, Planning and Public Works
Susan Ellison	Queensland Department of Housing, Local Government, Planning and Public Works
Mohamad Fajajo	Department of Defence
Dominique Holani	Australasian Procurement and Construction Council
Teresa Scott	Australasian Procurement and Construction Council
Indumathi V	Engineers Australia
Brenton Reynolds	URBIS

SBEnrc Core Members

ATCO · ATLAS · BGC · Queensland Government · Sunshine Coast Council · NSW Government Transport for NSW · Western Australia · Curtin University · The University of Queensland · Western Sydney University · RMIT University

Preface

The Sustainable Built Environment National Research Centre (SBEnrc) Australia, the successor to the Cooperative Research Centre for Construction Innovation, remains committed to making a leading contribution to innovation across the Australian built environment industry after more than two decades of operation. We are dedicated to working collaboratively with industry and government to develop and apply practical research outcomes that improve industry practice and enhance our nation's competitiveness.

We encourage you to continue to draw on the results of our Centre's applied research to deliver tangible outcomes for your operations. By working together, we can transform our industry and communities through enhanced and sustainable business processes, environmental performance and productivity.



John V McCarthy AO
Governing Board Chair
Sustainable Built Environment
National Research Centre Australia
(February 2002–June 2026)



Professor Keith Hampson
Chief Executive Officer and
Governing Board Chair
Sustainable Built Environment
National Research Centre Australia
(CEO from July 2001– June 2026;
Chair from July 2026)



Will Hackney
Chief Executive Officer
Sustainable Built Environment
National Research Centre Australia
(From July 2026)

Table of Contents

Executive Summary 6

1.0 Case Study 1: Automating Construction Carbon Tracking Through AI-Powered Invoice Interpretation 7

1.1 Introduction 7

1.2 AI-Based Carbon Emissions Tracking from Invoices 7

1.3 Testing and Findings 9

1.4 Conclusions and Future Work 11

2.0 Case Study 2: Carbon Estimation and Tracking Using MetaBIM 12

2.1 Introduction 12

2.2 MetaBIM-Based Carbon Estimation 12

2.3 AI-Based Carbon Emissions Tracking from Invoices 17

2.4 Conclusions and Future Work 21

3.0 Case Study 3: Lifecycle Energy Assessment for Residential Buildings Using Remote Sensing and AI 22

3.1 Introduction 22

3.2 Case Study Objectives 22

3.3 Methods and Results 22

3.3.1 Building Data and Automated Residential Classification 23

3.3.2 Embodied, Operational and Lifecycle Energy Profiles 23

3.3.3 Embodied Energy Intensity of Residential Building Typologies 24

3.3.4 Operational Energy Intensity of Residential Building Typologies 25

3.3.5 Lifecycle Energy Intensity of Residential Building Typologies 26

3.3.6 Spatial Assessment and Suburb-Level Results 27

3.4. Conclusions and Future Work 28

4.0 Case Study 4: AI-Enabled Multi-Class Road Asset Detection and Automated Barrier Measurement Using LiDAR and Image Data 30

4.1 Introduction and Background 30

4.2 Motivation and Objectives 30

4.3 Methods 31

4.3.1 Point Cloud Data Labelling and Semantic Taxonomy 31

4.3.2 Data Structuring and AI Training Pipeline 32

4.3.3 AI Models and Geometry-Aware Learning 33

4.3.4 Model Performance and Deployment Readiness 34

4.3.5 AI Inference and Automated Dimension Measurement 36

4.4 Conclusions and Future Work 37

References 38

Table of Contents (cont'd)

List of Tables

Table 1. Model performance comparison

List of Figures

Figure 1. Processing raw invoices to extract carbon-related information

Figure 2. Reporting of calculated carbon by detailed material types

Figure 3. Reporting of calculated carbon by material categories

Figure 4. Create a project and upload the BIM model

Figure 5. Open the project and review object properties

Figure 6. Create a carbon-specific property set

Figure 7. Assign carbon properties to project objects and select material values from NABERS Embodied Carbon Database

Figure 8. Share the project with EasyCarbon

Figure 9. Automated carbon calculation (A1–A5) within EasyCarbon

Figure 10. Invoice upload and automatic classification

Figure 11. AI-based data extraction using agentic AI

Figure 12. Human-in-the-loop review and data verification

Figure 13. Carbon mapping and standardisation

Figure 14. Automated actual carbon calculation based on the uploaded invoices

Figure 15. Geographic Information System and AI-based bottom-up framework for lifecycle energy assessment

Figure 16. Embodied energy intensity for residential building typologies with material categories

Figure 17. Operational energy intensities by housing typologies with end-use categories

Figure 18. Lifecycle energy intensity for residential buildings by housing typologies

Figure 19. Case study of lifecycle energy of residential building stocks in Canning Vale, WA, at SA1 level

Figure 20. Point cloud data editing and annotation with CloudCompare

Figure 21. Automatic conversion of labelled point clouds

Figure 22. AI model training loss

Figure 23. Automated dimension measurement

Executive Summary

In the era of climate change awareness and sustainable development, accurate carbon accounting has become imperative for businesses and governments alike. However, traditional methods often fall short in providing the granularity necessary for informed decision-making. The tools that are available at the moment often require manual input of reported items, such as material usage. There is an urgent need to use data-mining technology to assist carbon accounting from documents produced from the project lifecycle that can be used to develop a granular carbon model. Artificial Intelligence (AI)-enabled granular carbon accounting streamlines workflows and reduces the resources required for carbon assessments. This translates into cost savings for businesses and governments, while improving overall efficiency. With granular insights into carbon emissions, decision-makers can make informed choices that align with sustainability goals and regulatory requirements.

This research had two specific objectives based on the following industry needs:

- **Objective 1: Granular Model of Carbon Accounting Using AI**
  This research aimed to develop a comprehensive and granular carbon accounting method to track and quantify carbon emissions during the construction phase of projects. By leveraging advanced AI technologies, the project analysed construction document data and automatically extracted relevant carbon-related information. The goal was to accurately estimate actual carbon emissions, compare them with planned emissions, identify discrepancies and provide actionable insights to reduce carbon footprints in current and future construction projects.

- **Objective 2: Comprehensive Framework for Identifying Reduction Opportunities**
  To effectively identify and implement carbon-reduction opportunities, this research aimed to develop a holistic framework encompassing cost, social impact, environmental sustainability, performance of asset and resilience. This comprehensive approach ensures that all aspects of carbon reduction are considered, leading to more sustainable and equitable solutions.

Four case studies were conducted to achieve the above objectives, including:

- **Case Study 1: Automating Construction Carbon Tracking Through AI-Powered Invoice Interpretation**
  This case study developed a tool (EasyCarbon) to automate interpretation of invoices using AI to extract carbon-relevant data and map them to standard national carbon emissions databases.

- **Case Study 2: Carbon Estimation and Tracking Using MetaBIM**
  This case study was used to develop a step-by-step guide to integrating EasyCarbon and MetaBIM to carry out Building Information Modelling- (BIM) based carbon estimation focusing on embedding carbon-relevant information directly into BIM objects and automating life-cycle carbon calculations using predefined rules and recognised emissions factor databases.

- **Case Study 3: Lifecycle Energy Assessment for Residential Buildings Using Remote Sensing and AI**
  This case study developed a Geographic Information System and AI-based bottom-up framework to analyse lifecycle energy/carbon across residential building portfolios at both the building and regional scales.

- **Case Study 4: AI-Enabled Multi-Class Road Asset Detection and Automated Barrier Measurement Using LiDAR and Image Data**
  This case study developed an AI-enabled, multi-class road asset detection and measurement framework that could operate directly on raw LiDAR point clouds and aligned imagery.

The outcome of these case studies will provide insights into better provision and use of lifecycle asset information to conduct carbon accounting and asset management in the digital era. This in turn will support identifying ways of achieving net zero carbon emissions and decreasing the cost of operation and maintenance, and improving the return on investment of asset management.

1.0 Case Study 1: Automating Construction Carbon Tracking Through AI-Powered Invoice Interpretation

1.1 Introduction

As the construction sector accelerates its pursuit of national and global decarbonisation targets, the demand for accurate and verifiable tracking of actual carbon emissions has become increasingly critical. Despite advancements in carbon estimation during the design phase, a substantial gap persists in the methods used to monitor, report and audit emissions generated throughout the construction stage.

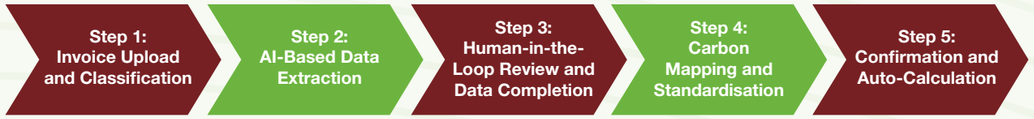
The current industry practice for tracking actual carbon emissions typically involves general contractors distributing spreadsheet templates to subcontractors, suppliers and logistics companies. These templates are intended to capture carbon-relevant data such as materials delivered, transport modes, energy consumed onsite and waste generated. However, this manual method suffers from a number of critical limitations. First, many subcontractors and suppliers are small or medium-sized enterprises, where staff may lack the technical knowledge to accurately report carbon data. As a result, incorrect or incomplete entries are common. Second, manually completing and consolidating spreadsheets across dozens of stakeholders consumes valuable time and often results in delays in reporting. Lastly, since the data is manually entered, it is difficult to trace individual entries back to their original data sources such as invoices or receipts, which complicates the audit process.

As reporting and auditing requirements become more stringent, there is a growing demand for an efficient, scalable and data-driven approach to carbon tracking. To address this need, we trialled an Artificial Intelligence (AI)-Based Carbon Emissions Tracking System, EasyCarbon, that uses construction invoices – ubiquitous documents already produced in all procurement and operational workflows – as the primary data source.

1.2 AI-Based Carbon Emissions Tracking from Invoices

Our method centred on the automated interpretation of invoices using AI to extract carbon-relevant data and map them to standard national carbon emissions databases. This approach presents several advantages. Invoices are already generated for procurement, delivery and operational activities, requiring no additional data entry. Each invoice typically contains validated transaction data, improving traceability. Moreover, AI models can be trained to recognise and extract the required fields, dramatically reducing the human workload and ensuring consistency.

The workflow for this AI-based method consists of five key steps:



Step 1: Invoice Upload and Classification

Users can upload individual invoices or perform batch uploads for an entire construction project, streamlining the data intake process. Once uploaded, the system automatically classifies each invoice into one of three categories based on its content. Type 1 invoices relate to material deliveries and are used to quantify embodied carbon (A1–A3) and transportation emissions (A4). Type 2 invoices pertain to construction energy use – such as diesel fuel or electricity consumption – and contribute to emissions under A5. Type 3 invoices correspond to waste treatment and disposal services, also falling within the A5 emissions category. This automated classification enables efficient sorting and downstream processing of large volumes of project documentation.

Step 2: AI-Based Data Extraction

In this step, we employ agentic AI – an intelligent system capable of autonomous task execution with contextual awareness – to interpret and extract carbon-relevant information directly from construction invoices. The process begins with Optical Character Recognition (OCR) to convert invoice documents, whether scanned or digital, into machine-readable text. The agentic AI then uses Large Language Model (LLM) techniques to understand the structure, semantics and intent of the content.

For Type 1 (material delivery) invoices, the AI identifies and extracts details such as material type, description, quantity, units, weight, delivery date, origin and destination locations, and the delivery method. For Type 2 (construction energy use) invoices, the system recognises energy types (for example, diesel or electricity), their quantities, units and usage dates. For Type 3 (waste treatment) invoices, the AI extracts waste categories, quantities, treatment methods and service dates. By mimicking human-like understanding and decision-making, the agentic AI continuously adapts to varying invoice formats and terminology, ensuring accurate data capture across diverse suppliers and service providers.

Step 3: Human-in-the-Loop Review and Data Completion

While the AI model achieves high accuracy in data extraction, human oversight remains essential to ensure contextual correctness and completeness. Through an intuitive review interface, users can inspect the AI-interpreted data, correct any misinterpretations and validate key entries. Additionally, if certain critical information, such as the material source location, is missing from the invoice, users can manually input this data to enable accurate carbon calculations. This human-in-the-loop mechanism not only ensures data integrity, but also supports edge cases where essential carbon-related details are absent from the original documents.

Step 4: Carbon Mapping and Standardisation

Once the extracted data is verified, the system proceeds to match each material or energy entry with corresponding categories in recognised carbon emissions databases. At present, the system integrates the Australian Life Cycle Inventory (AusLCI), with plans to expand to additional databases. Because suppliers may describe similar materials in different ways, users are provided with an interface to review and, if necessary, adjust the automated mapping. This step ensures that each item is accurately aligned with the correct emissions factor, maintaining consistency and reliability in carbon accounting.

Step 5: Confirmation and Auto-Calculation

Following the mapping stage, the system performs automatic carbon emissions calculations based on established lifecycle assessment methodologies. The results encompass embodied carbon from material production and transport (A1–A4), as well as emissions from onsite energy use and waste treatment activities (A5). The calculated emissions are compiled into structured reports that support project-level auditing, compliance documentation and sustainability performance reviews.

1.0 Case Study 1: Automating Construction Carbon Tracking Through AI-Powered Invoice Interpretation (cont'd)

1.3 Testing and Findings

To assess the effectiveness and reliability of the AI-enabled workflow, we conducted a series of experiments using real construction invoices provided by Sunshine Coast Council. These documents were used to both train and fine-tune the AI models and to validate the complete end-to-end carbon tracking process.

Digitally generated PDF invoices – those produced directly from accounting software – exhibited strong structural consistency and formatting, enabling the AI to extract key fields with over 98% accuracy (see Figure 1). These high-quality documents allowed for precise interpretation of quantities, units, material types and associated metadata.

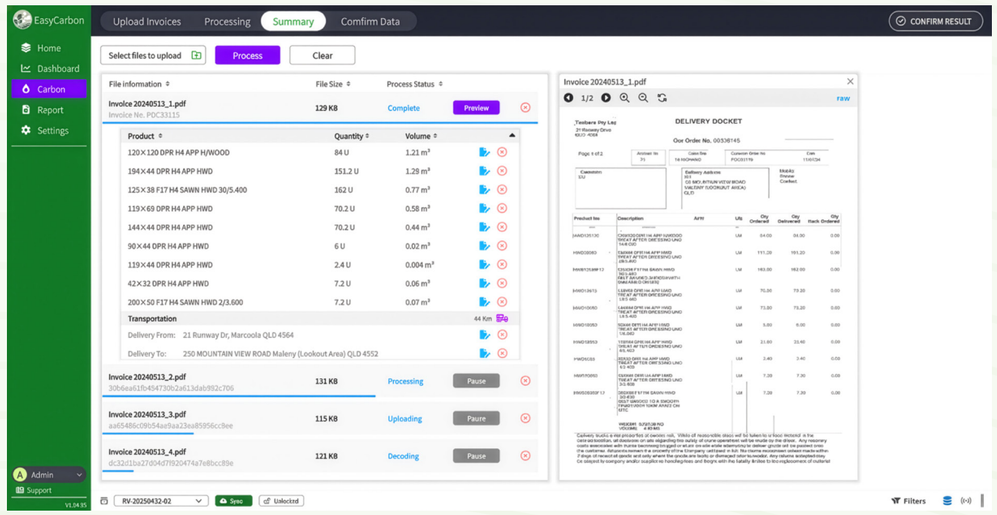


Figure 1. Processing raw invoices to extract carbon-related information

In contrast, the system's performance declined significantly when processing scanned handwritten invoices. Due to irregular fonts, blurred text and varied layouts, accuracy dropped to around 68%. These limitations highlight the importance of document quality in achieving reliable AI performance and suggest that additional training on diverse invoice formats, including the use of handwriting recognition models, may be necessary.

Another key challenge uncovered during testing was the inconsistency or absence of essential carbon-related information in some invoices. A common example occurred with Type 1 material delivery invoices, where the origin location was often missing, providing only the delivery address of the project site. As an interim solution, the system defaulted to using the supplier's company address, typically extracted from the invoice header or logo section. However, this assumption may introduce inaccuracies, particularly when suppliers operate from multiple distribution centres or branch locations.

Once the extracted data are confirmed, the system maps each invoice item to a material type with its emission factor and reports the calculated carbon by detailed material type (Figure 2) and by material category (Figure 3).

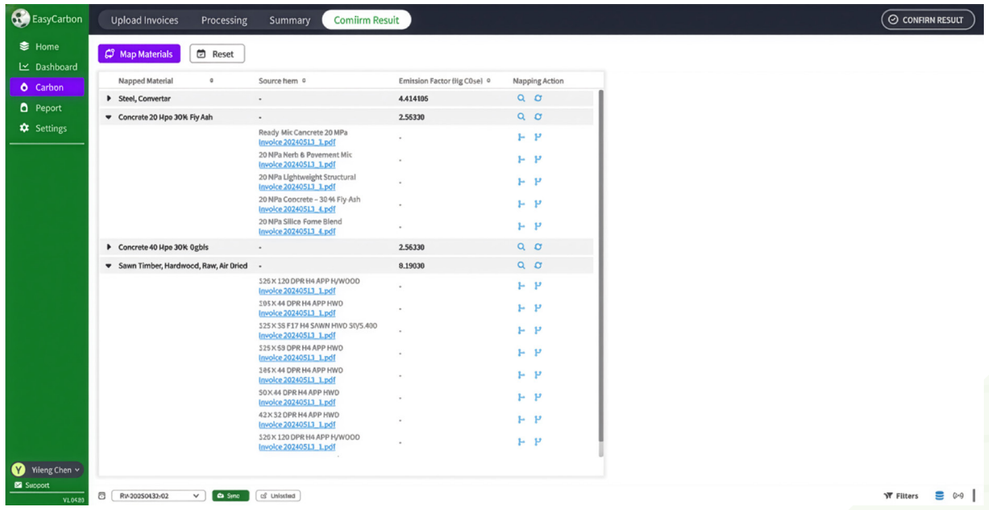


Figure 2. Reporting of calculated carbon by detailed material types

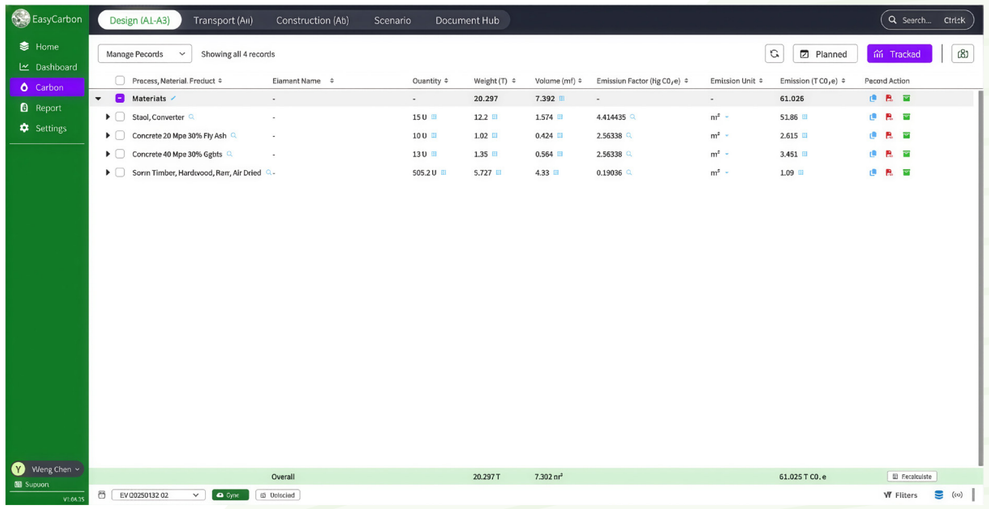


Figure 3. Reporting of calculated carbon by material categories

1.4 Conclusions and Future Work

The AI-driven invoice interpretation approach presents a compelling alternative to traditional spreadsheet-based methods for tracking carbon emissions in construction projects. By leveraging transaction documents that are already generated throughout project delivery, this system minimises manual effort, strengthens data traceability and improves the accuracy and reliability of carbon reporting and audits.

Nonetheless, further development is required to extend its applicability and robustness. One key area involves expanding the dataset used to train and validate the model. To date, the majority of test cases have involved Type 1 invoices related to material delivery. For a more complete view of construction carbon emissions, additional data from Type 2 (energy use) and Type 3 (waste treatment) invoices must be collected and integrated.

In parallel, support for additional carbon databases is essential. Currently, only the AusLCI database is integrated. Future versions will incorporate the NSW Embodied Carbon Databook and NABERS National Material Emissions Factors Database, providing more comprehensive and regionally appropriate emissions factors.

Advancing semantic recognition and context-aware mapping remains a key focus of our ongoing development. By integrating construction-specific terminology into the agentic AI framework, we aim to enhance the system's ability to automatically align invoice data with standardised carbon categories. To support continuous improvement, a user feedback mechanism will be introduced, allowing real-world corrections to inform and refine the AI's performance over time – ensuring the system adapts dynamically to evolving industry practices and documentation standards.

In conclusion, this AI-enabled approach marks an important step towards scalable, verifiable and efficient granular carbon tracking in construction. As regulatory and client demands grow for transparent sustainability reporting, automated systems like this one will become essential tools for modern carbon accounting in the built environment sector.



2.0 Case Study 2: Carbon Estimation and Tracking Using MetaBIM

2.1 Introduction

Accurate carbon estimation and continuous carbon tracking are now fundamental requirements for modern construction project delivery. Increasing regulatory pressure, growing client demand for transparency and industry-wide commitments to net zero targets have collectively driven the need for robust, auditable and scalable carbon management methodologies across the project lifecycle.

Traditional carbon assessment approaches often rely on fragmented data sources, manual calculations or post hoc assessments, limiting their usefulness for real-time decision-making and compliance auditing. In response to these challenges, this research provides a step-by-step digital-first workflow that integrates:

- Building Information Modelling- (BIM) based embodied carbon estimation
- AI-enabled carbon emissions tracking from construction invoices.

Together, these two components form a closed-loop carbon management approach, enabling carbon performance to be quantified, monitored and verified continuously – from early design-stage estimation (A1–A5) through to construction-stage evidence-based tracking and auditing.

The workflow is built on the seamless integration of MetaBIM and EasyCarbon. By combining structured BIM data, recognised carbon databases and agentic AI technologies, the workflow delivers transparent, standard-aligned and scalable carbon outcomes suitable for both project-level management and portfolio-level reporting.

2.2 MetaBIM-Based Carbon Estimation

BIM-based carbon estimation focuses on embedding carbon-relevant information directly into BIM objects and automating lifecycle carbon calculations using predefined rules and recognised emissions factor databases. This approach ensures that carbon estimation is object-based, repeatable and auditable, rather than reliant on disconnected spreadsheets or manual entries and assumptions.

Step 1: Create a Project and Upload the BIM Model

- Log in to the MetaBIM platform.
- Create a new project.
- Upload your 3D BIM model in Industry Foundation Classes (IFC) format.

As illustrated in Figure 4, this step establishes the digital foundation for carbon estimation by ensuring that all building or infrastructure elements are available in a structured, machine-readable form. The use of IFC ensures interoperability across authoring tools and downstream carbon analysis platforms.

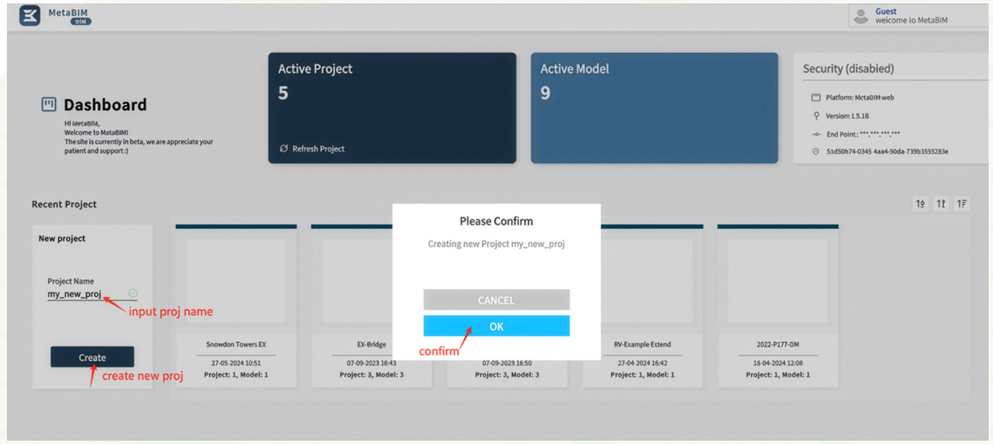


Figure 4. Create a project and upload the BIM model

Step 2: Open the Project and Review Object Properties

- Open the newly created project.
- Inspect object properties for key elements such as columns, beams, slabs, walls or road components (as shown in Figure 5).

At this stage, users review existing attributes attached to BIM objects and identify missing or inconsistent data relevant to carbon estimation. This quality-check step is critical to ensuring reliable downstream calculations.

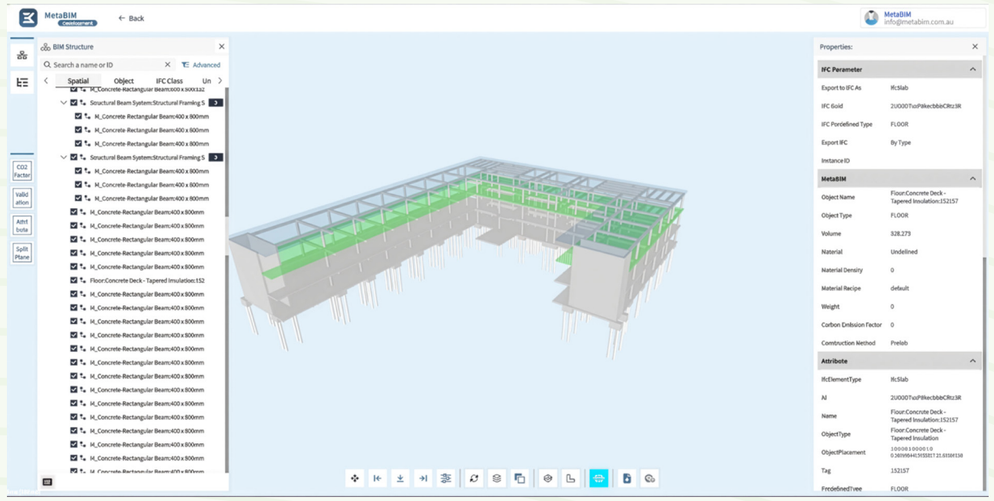


Figure 5. Open the project and review object properties

Step 3: Create a Carbon-Specific Property Set

- Create a new property set named Carbon_Common (as shown in Figure 6).
- Add a group of properties relevant to carbon estimation, such as:
  - material
  - construction method
  - supplier
  - waste management.

The Carbon_Common property set functions as a standardised carbon data container, ensuring consistent data structure and semantics across all project objects. This standardisation is essential for scalable automation and cross-project comparability.

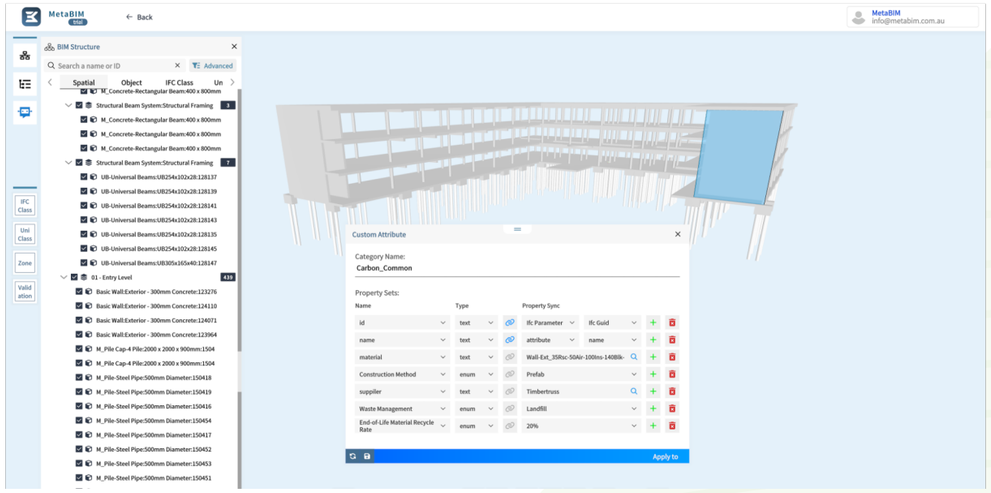


Figure 6. Create a carbon-specific property set

Step 4: Assign Carbon Properties to Project Objects

- Assign the Carbon_Common property set to all relevant objects (for example, columns, beams, pavements).
- For each object, select material values from recognised carbon databases such as NABERS Embodied Carbon (as shown in Figure 7).

By explicitly linking BIM objects to authoritative emissions factors, carbon estimation becomes transparent, repeatable and auditable, while also supporting scenario comparison during design development.

2.0 Case Study 2: Carbon Estimation and Tracking Using MetaBIM (cont'd)

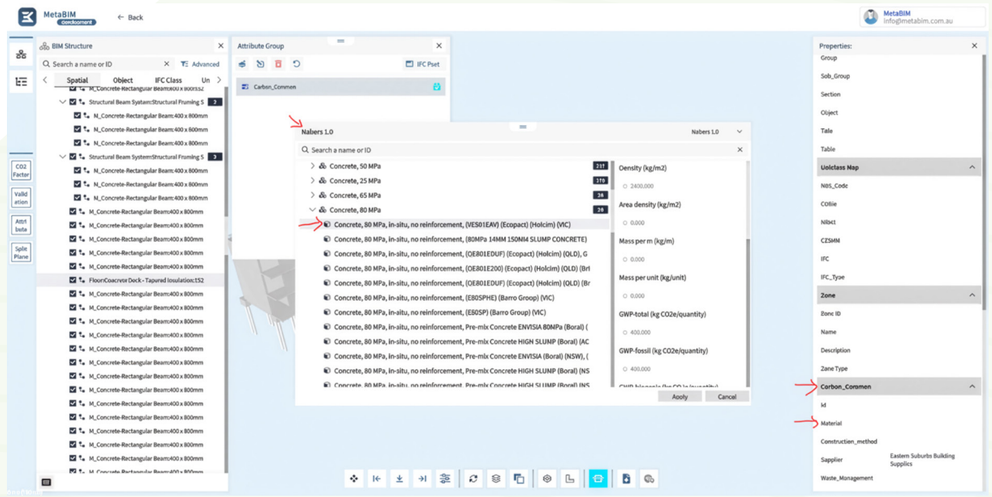


Figure 7. Assign carbon properties to project objects and select material values from NABERS Embodied Carbon Database

Step 5: Share the Project with EasyCarbon

- Generate a project share link within MetaBIM (as shown in Figure 8).
- Share the link with EasyCarbon to enable carbon calculation workflows.

This step establishes a seamless data handover between BIM-based data conditioning and automated carbon computation, eliminating manual data transfer and reducing error risk.

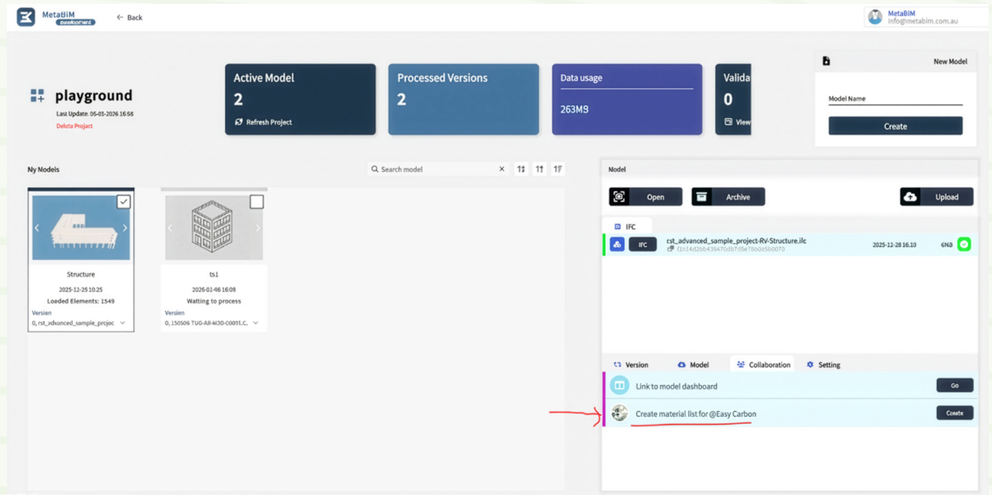


Figure 8. Share the project with EasyCarbon

Step 6: Automated Carbon Calculation (A1–A5)

Using predefined carbon estimation rules and databases, the system automatically calculates:

- A1–A3: Material production and manufacturing
- A4: Transportation to site
- A5: Construction and installation activities.

As shown in Figure 9, the results provide a baseline embodied and construction-stage carbon footprint, supporting early-stage design decisions, option comparison, benchmarking and reporting against regulatory or client requirements.

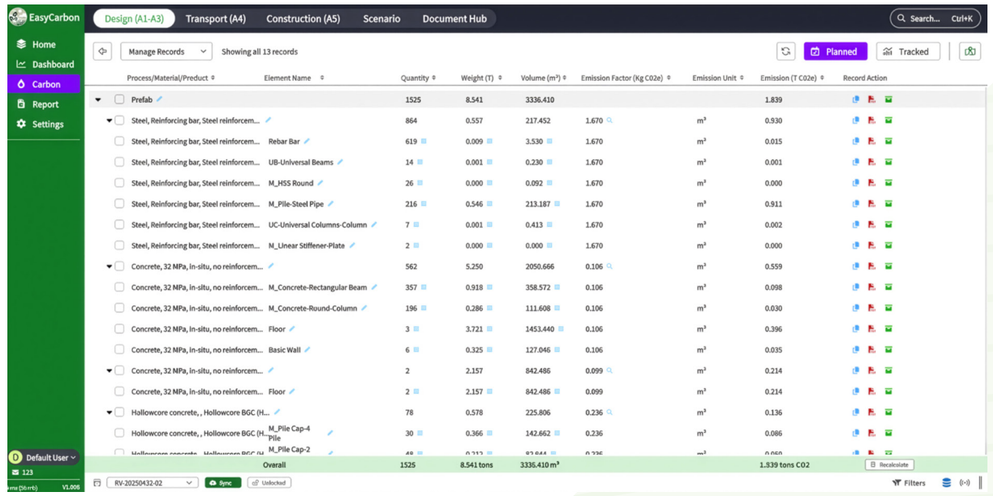


Figure 9. Automated carbon calculation (A1–A5) within EasyCarbon

2.3 AI-Based Carbon Emissions Tracking from Invoices

While BIM-based carbon estimation provides planned or expected emissions, actual construction-stage emissions often deviate due to changes in suppliers, logistics, energy use and waste management practices. AI-based invoice tracking addresses this gap by capturing real, evidence-based carbon data directly from construction records.

Once the MetaBIM model is shared, EasyCarbon stores the design-stage results as the project's planned carbon baseline (the 'Planned' view, Figure 9). Invoices uploaded during construction are processed within the same EasyCarbon project and recorded as tracked carbon (the 'Tracked' view, Figure 14). This allows planned and actual emissions to be compared and discrepancies identified as construction progresses.

Step 1: Invoice Upload and Automatic Classification

Users can upload invoices individually or in batches for an entire project (as shown in Figure 10). Once uploaded, the system automatically classifies invoices into three types:

- **Type 1 – Material Delivery Invoices**
  Used to quantify embodied carbon (A1–A3) and transport emissions (A4).
- **Type 2 – Construction Energy Use Invoices**
  Cover diesel, electricity or other energy consumption contributing to A5 emissions.
- **Type 3 – Waste Treatment and Disposal Invoices**
  Capture emissions from waste processing, also under A5.

Automated classification enables efficient processing of large volumes of heterogeneous project documentation.

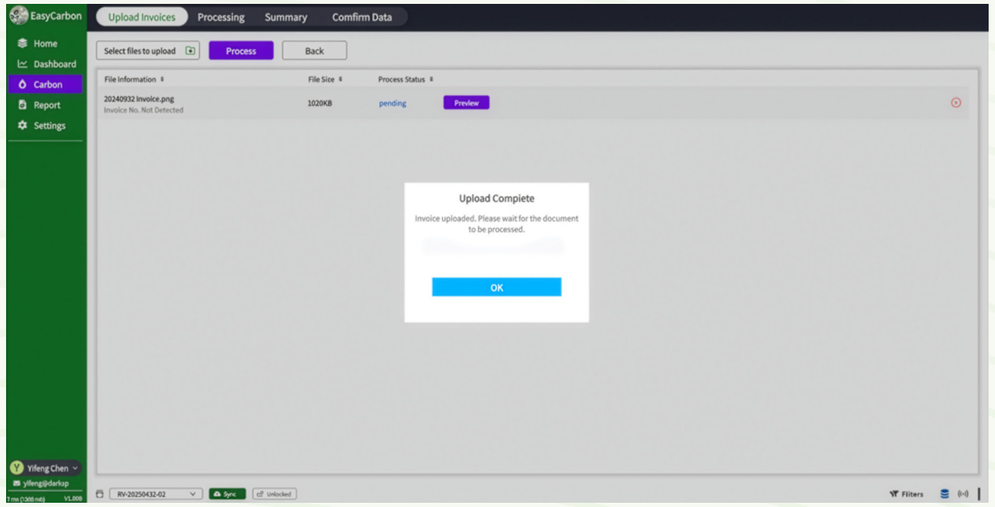


Figure 10. Invoice upload and automatic classification

Step 2: AI-Based Data Extraction Using Agentic AI

The system employs agentic AI, combining OCR and LLMs, to interpret diverse invoice formats (as shown in Figure 11).

- OCR converts scanned or digital invoices into machine-readable text.
- The AI understands invoice structure, semantics and intent.

Extracted information includes:

- Type 1: material type, quantity, units, weight, origin, destination, delivery method.
- Type 2: energy type, quantity, units, usage period.
- Type 3: waste category, quantity, treatment method, service date.

This approach replicates human-level interpretation, while enabling scalable, automated processing across suppliers and projects.

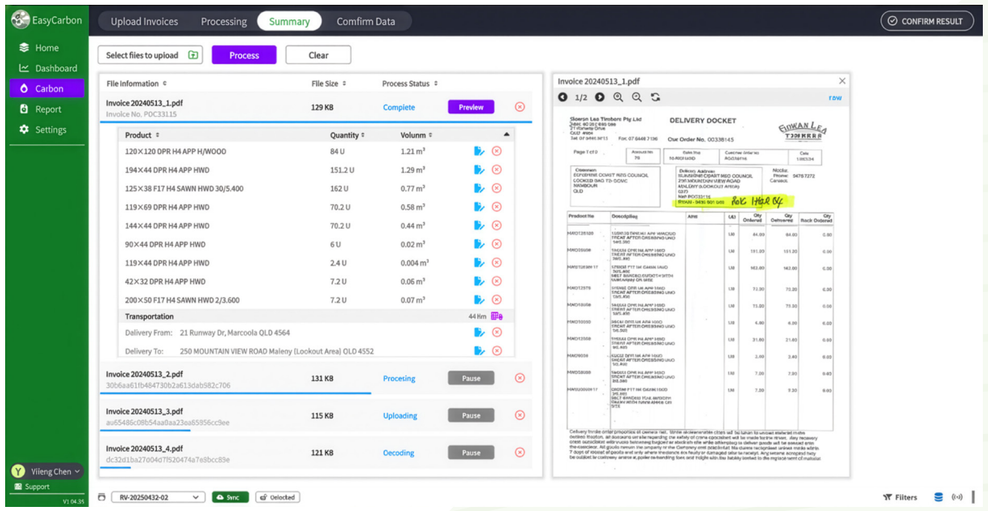


Figure 11. AI-based data extraction using agentic AI

Step 3: Human-in-the-Loop Review and Data Completion

Despite high AI accuracy, a human-in-the-loop ensures reliability:

- Users review and validate extracted data through an intuitive interface (as shown in Figure 12).
- Misinterpretations can be corrected easily.
- Missing information (for example, transport distance or source location) can be manually added.

This human-in-the-loop mechanism ensures contextual correctness and audit-ready data quality.

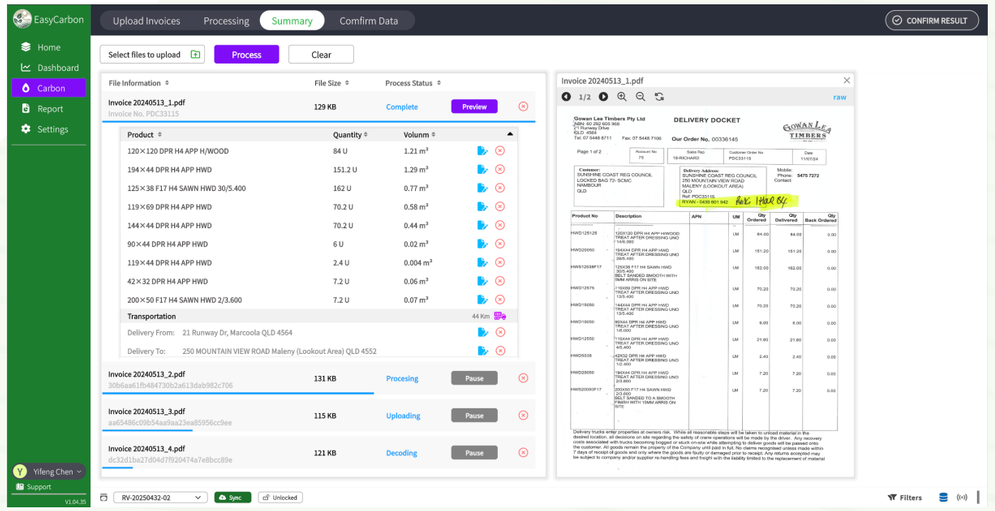


Figure 12. Human-in-the-loop review and data verification

Step 4: Carbon Mapping and Standardisation

Verified data is mapped to recognised emissions factor databases (as shown in Figure 13), currently including AusLCI, and NABERS Embodied Carbon Database.

Because supplier descriptions vary, users can:

- review automated mappings
- adjust categories where necessary.

This step ensures consistency, comparability and methodological alignment across suppliers and projects.

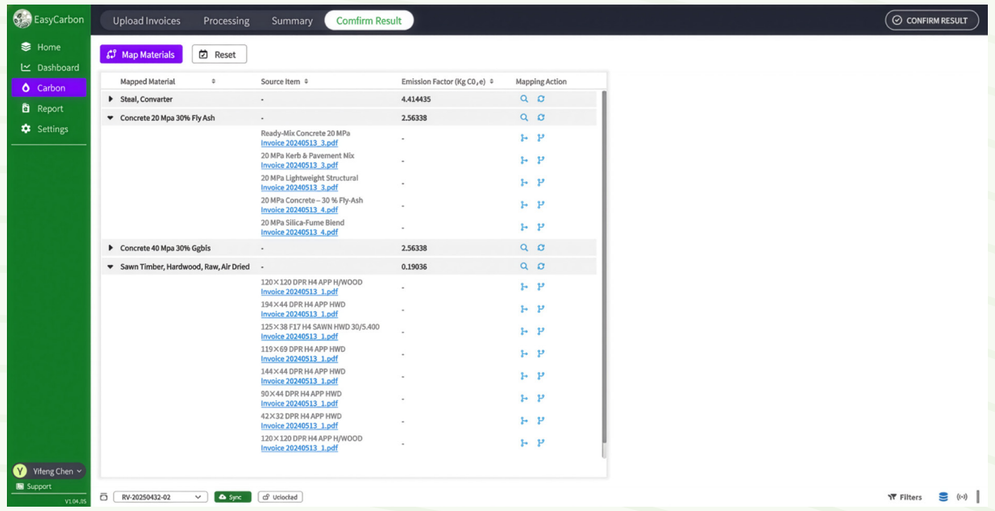


Figure 13. Carbon mapping and standardisation

Step 5: Confirmation and Automated Carbon Calculation

Once mapping is confirmed, the system automatically calculates:

- A1–A4 emissions from materials and transport (as shown in Figure 14)
- A5 emissions from onsite energy use and waste treatment.

Results are compiled into structured reports suitable for:

- carbon auditing
- regulatory compliance
- sustainability reporting
- project-level performance reviews.

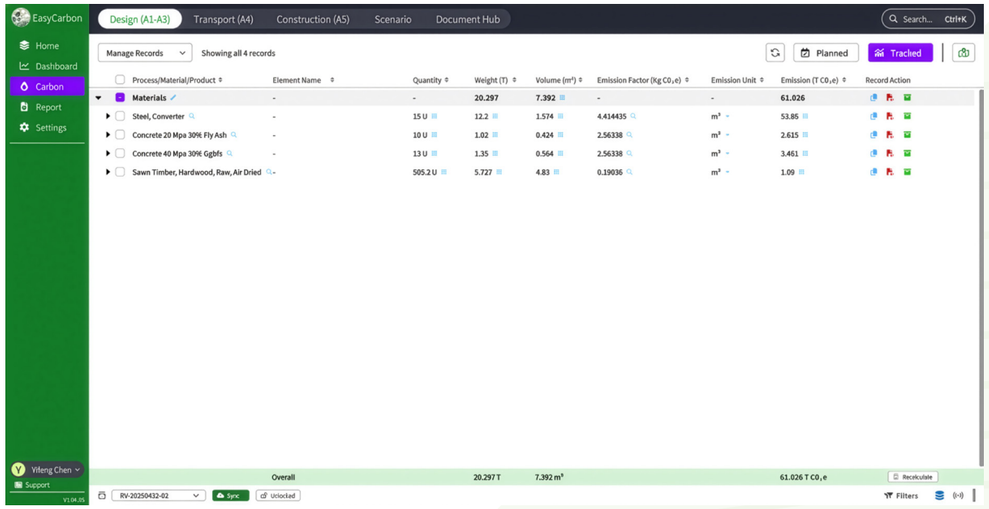


Figure 14. Automated actual carbon calculation based on the uploaded invoices

2.0 Case Study 2: Carbon Estimation and Tracking Using MetaBIM (cont'd)

2.4 Conclusions and Future Work

This research provides a comprehensive, step-by-step workflow for carbon estimation and tracking in construction projects, integrating BIM-based embodied carbon estimation with AI-enabled carbon emissions tracking from construction invoices. By combining these two complementary approaches, the proposed workflow establishes a closed-loop, data-driven carbon management framework that spans from early design intent to construction-stage reality.

At the design and planning stage, BIM-based carbon estimation enables project teams to embed carbon-relevant information directly into model objects and to quantify embodied and construction-stage carbon emissions (A1–A5) in a structured, object-based and repeatable manner. This approach allows carbon considerations to be integrated into design decision-making, option comparison and benchmarking, rather than treated as a post-design compliance exercise.

During construction, AI-based carbon-emissions tracking from invoices captures actual, evidence-based carbon emissions associated with material procurement, transportation, onsite energy use and waste treatment. By leveraging agentic AI, OCR and LLMs, the system is able to interpret heterogeneous invoice formats at scale, while the human-in-the-loop review mechanism ensures contextual correctness, data completeness and audit-ready reliability. This significantly reduces the manual effort traditionally required for carbon data collection and verification.

Critically, the integration of MetaBIM and EasyCarbon enables seamless data flow between BIM models, invoice-based evidence and recognised carbon databases. The result is a transparent, standard-aligned and scalable carbon-management solution that supports regulatory compliance, sustainability reporting and continuous performance monitoring at both project and portfolio levels.

Overall, this workflow shifts carbon management from a fragmented, retrospective activity to a continuous, evidence-driven process, providing a robust foundation for decarbonised construction delivery and informed decision-making across the project lifecycle.

The MetaBIM platform represents a significant advancement in the field of carbon emissions estimation and analysis for construction projects. Its comprehensive, accurate and flexible approach provides a solid foundation for promoting sustainable practices in the industry. It can categorise the calculated carbon into different groups to accommodate various reporting requirements; for example, by materials (Figures 2 and 3). To further enhance the capabilities of the MetaBIM platform and continue driving innovation in carbon emissions estimation and analysis, several key areas of development have been identified. These future works aim to integrate advanced technologies, expand the platform's database and enhance reporting and compliance tools, ensuring the MetaBIM platform remains at the forefront of sustainable construction practices.



InfiniteFlow (Source: Adobe Stock)

3.0 Case Study 3: Lifecycle Energy Assessment for Residential Buildings Using Remote Sensing and AI

3.1 Introduction

Residential buildings account for a large share of national energy use in Australia. Some residential building portfolios in Western Australia (WA) lack adequate energy efficiency and thermal comfort features, contributing significantly to energy consumption. As cities expand and more dwellings are constructed, understanding how much energy these buildings use has become important.

Energy consumption in buildings includes the energy used during operation and the energy embedded in construction materials. Existing assessment methods often focus on one aspect of energy use and do not provide a lifecycle analysis. Many studies rely on small samples or manual surveys. These methods have a scaling limit and they do not support consistent comparison across suburbs or building types. Some approaches use top-down models that estimate energy at the regional level, but such methods do not show how individual buildings and components contribute to total energy use. As a result, there is a gap between the information required by planners, industry and government agencies and the information provided by existing models. Leveraging remote sensing AI can enable scalable, data-driven lifecycle energy (LCE) evaluations across large building stocks, supporting informed decision-making and advancing Australia's commitment to net zero emissions by 2050.

3.2 Case Study Objectives

The motivation for this project comes from the growing need for spatially detailed and technically robust information about residential energy use. Agencies responsible for planning and development require data that shows how energy use varies across different neighbourhoods. Energy utilities need to understand long-term demand trends and the effect of different housing forms. Developers and industry groups need guidance on the energy impacts of construction materials and building designs. These needs cannot be met using high-level or sample-based data alone. However, remote sensing and Geographic Information Systems (GIS) allow the extraction of building information at a large scale. Combined with AI-based classification, these tools can identify residential typologies, estimate building heights and detect changes in the built environment. This creates an opportunity to build an automated and scalable framework for LCA.

Therefore, this project developed a GIS and AI-based bottom-up framework to analyse LCE assessment across residential building portfolios at both the building and regional scales in WA. The objectives were: (a) to classify residential building typologies using remote sensing and spatial data; (b) to assess and compare LCE across different building typologies at the individual level and characterise the LCE profile of building portfolios at the regional scale; and (c) to identify key drivers of energy use and provide strategic insights for decarbonisation pathways across residential building portfolios.

3.3 Methods and Results

This method combines spatial data, remote sensing information and building energy modelling to provide a practical way to analyse the LCE performance of residential buildings (Figure 15). It supports automated building classification, estimation of embodied and operational energy and spatial assessment at different scales. The process begins with building classification, utilising GIS and remote sensing to categorise residential buildings by building type, construction type, climate zone and construction year. At the building level, material intensities and operational energy are simulated iteratively using AusZEH software for each building typology, then multiplied by relevant coefficients to derive corresponding energy. Regional assessments are achieved through a bottom-up method, aggregating building-level results by typology-specific floor areas, enabling spatiotemporal analysis at both building and regional scales. This approach is suitable for planners, developers and policymakers who need reliable, detailed information to guide their decisions.

3.0 Case Study 3: Lifecycle Energy Assessment for Residential Buildings Using Remote Sensing and AI (cont'd)

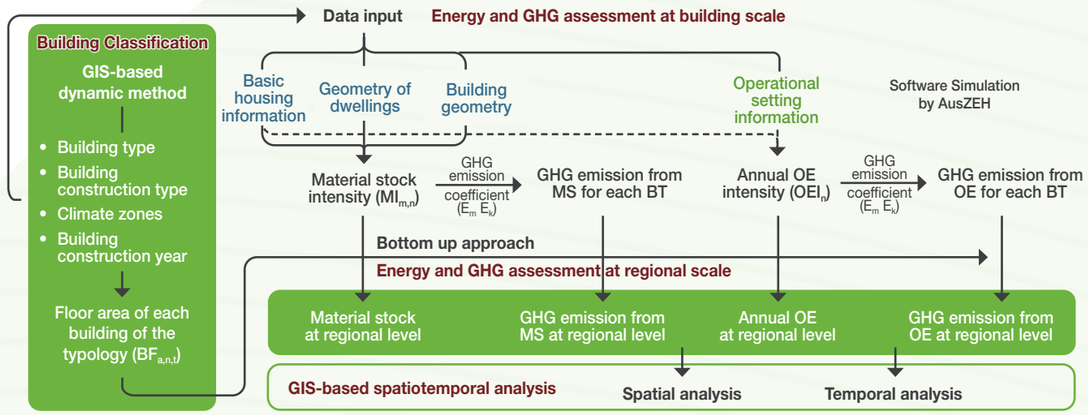


Figure 15. Geographic Information System and AI-based bottom-up framework for lifecycle energy assessment

Legend:
BF: Building floor area (a=area, n=building type, t=construction year)
BT: Building type
E: GHG emission coefficient (Em=material m; Ek=energy type k)
GHG: Greenhouse gas
MI: Material stock intensity (m=material, n=building type)
MS: Material stock
OE: Operational energy
OEI: Operational energy intensity

3.3.1 Building Data and Automated Residential Classification

The analysis begins with the assembly of a set of spatial datasets that describe the residential building stock in WA. Building footprints are used to define the size and outline of each structure. Three-dimensional building-height data helps distinguish low structures from multi-storey forms. Land cover dynamics derived from satellite observations allow the identification of construction periods by locating the first appearance of impervious surfaces. Construction types are linked to buildings using Local Government Area statistics, and climate zone boundaries provide the environmental context for energy simulation.

These datasets are combined to classify WA's residential buildings into main dwelling types. The classification process follows clear geometric rules based on footprint area, height bands and building proportions. Detached houses, semi-detached houses, low-rise apartments and high-rise apartments are identified through this procedure. The same spatial inputs support the assignment of construction periods, grouped into pre-2006, 2006 to 2011, and 2012 to 2022, which reflect significant changes in energy performance requirements.

By bringing these elements together, the method produces a set of representative residential typologies. Each typology captures a dwelling type, a construction period and a typical construction system. These typologies form the basis for both embodied and operational energy modelling, and they allow the analysis to be applied across large areas in a consistent way. The classification also ensures that the energy assessment reflects the physical and temporal variation present in the actual housing stock in WA.

3.3.2 Embodied, Operational and Lifecycle Energy Profiles

Once the residential typologies are established, they are used to estimate both Embodied Energy (EE) and Operational Energy (OE) at the building level. EE is calculated by linking the material quantity of each archetype with hybrid LCE coefficients. This approach produces an EE intensity that reflects differences in construction systems and material use across housing types. OE is estimated through a simulation model based on the AusZEH framework. The model considers climatic conditions, envelope characteristics and typical occupancy patterns to simulate annual demand for heating, cooling, hot water, lighting and appliances. The outputs provide an OE intensity for each typology. The integration of modelling results across housing types generates a set of energy profiles that show how WA's residential buildings perform at different stages of their lifecycle.

3.3.3 Embodied Energy Intensity of Residential Building Typologies

The EE profile (Figure 16) reflects the influence of construction materials, housing types and construction years. Apartments tend to show higher embodied intensity because they rely more heavily on reinforced concrete. Detached and semi-detached houses usually present lower values due to their lighter construction systems. These patterns follow the typical material composition of Australian housing and give a clear view of how construction choices shape EE outcomes. It reveals that increasing the use of low-EE or energy-efficient materials provides an effective strategy to reduce embodied energy in the building sector.

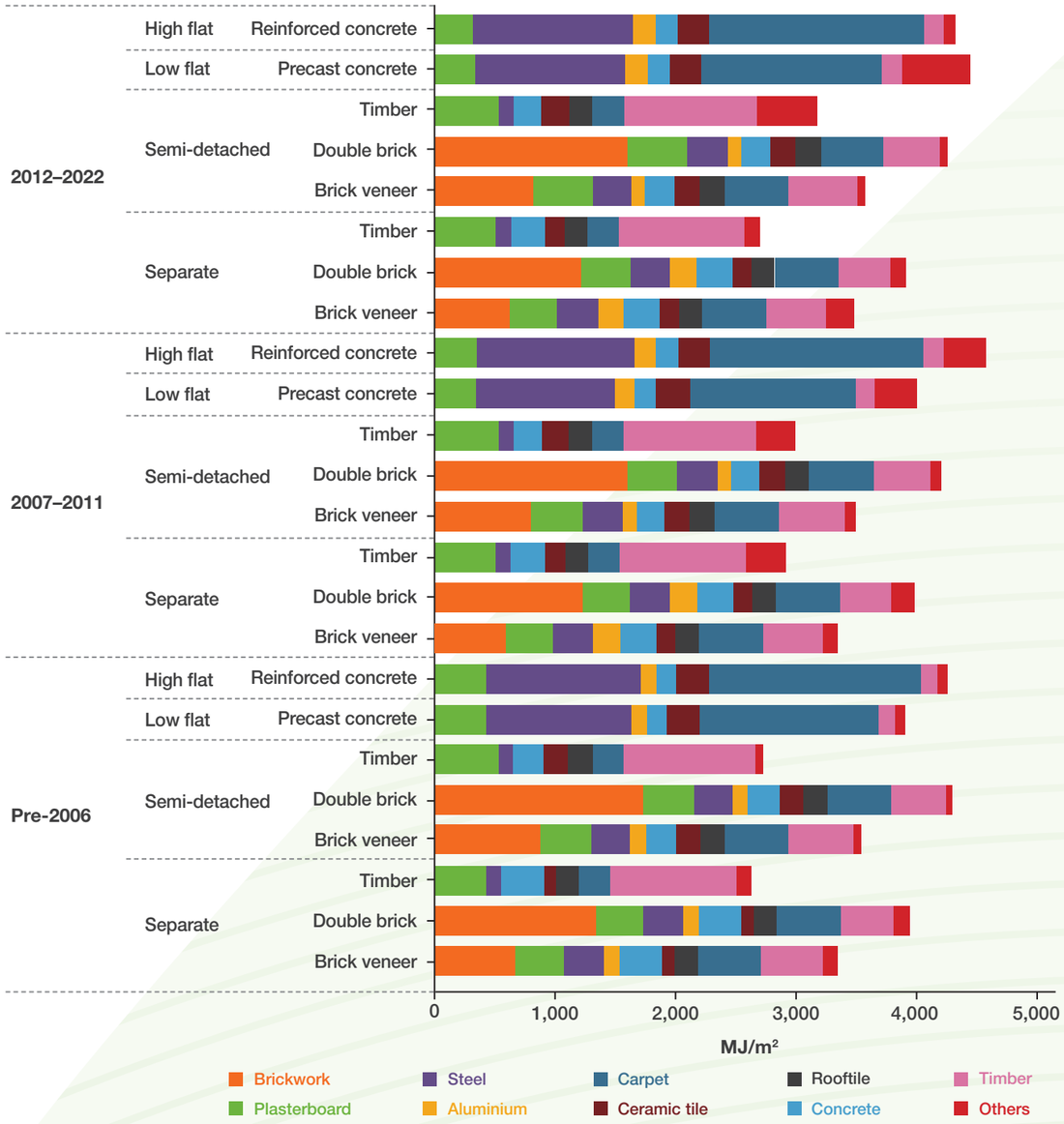


Figure 16. Embodied energy intensity for residential building typologies with material categories

3.0 Case Study 3: Lifecycle Energy Assessment for Residential Buildings Using Remote Sensing and AI (cont'd)

3.3.4 Operational Energy Intensity of Residential Building Typologies

OE profiles (Figure 17) reveal the effect of building form and size on energy demand. Detached houses often have higher operational intensity because of larger floor areas and greater exposure to outdoor temperatures. Apartments benefit from compact layouts and shared walls, which reduce the demand for heating and cooling. The division of OE into end-uses also provides useful insights. It shows how heating, cooling, hot water and appliances contribute to overall energy use in each building type and where improvements may be most effective.

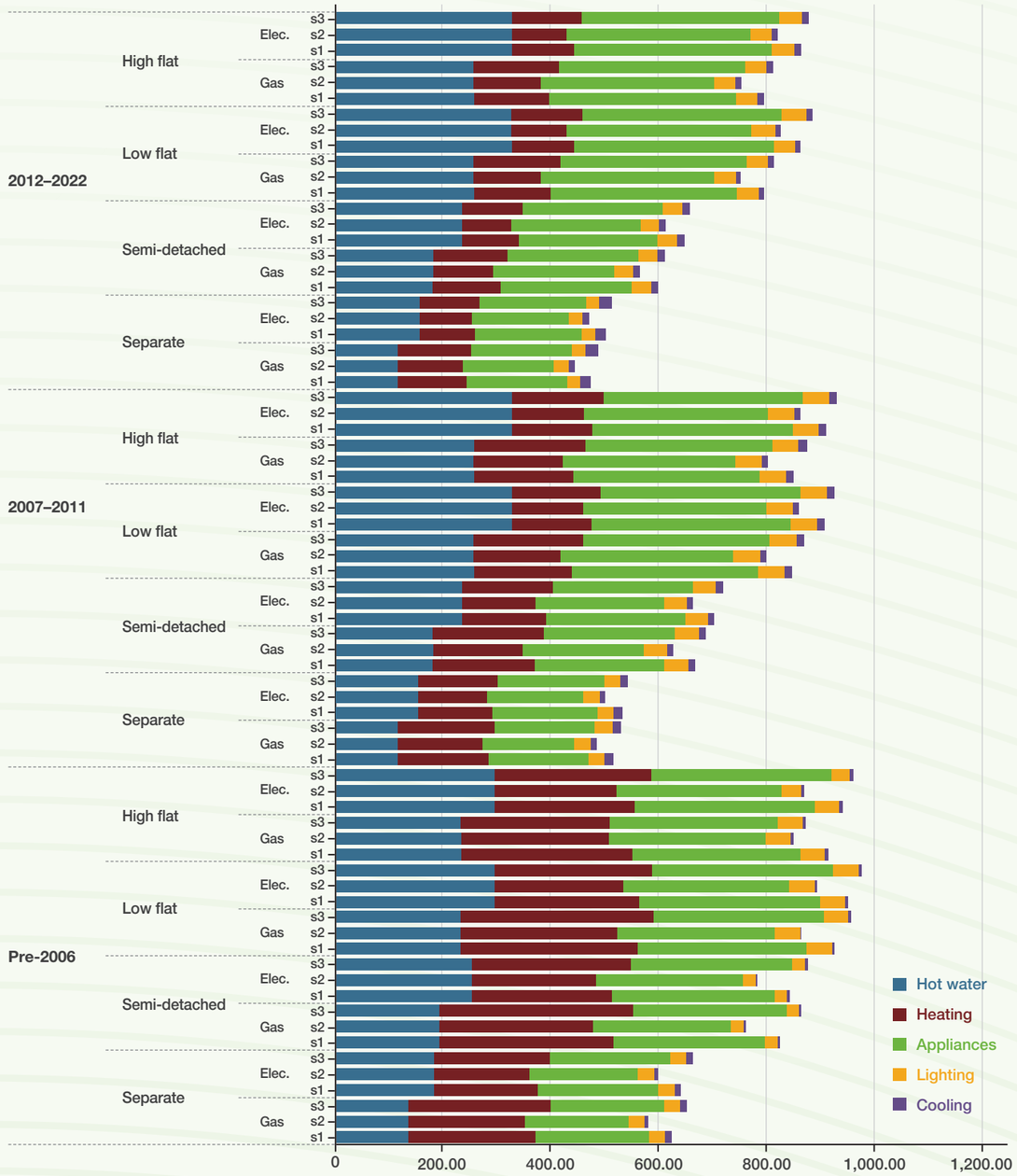


Figure 17. Operational energy intensities by housing typologies with end-use categories

3.3.5 Lifecycle Energy Intensity of Residential Building Typologies

The LCE profile brings both components together (Figure 18). The apartment has a higher LCE intensity than the house because the apartment has a larger embodied and operational energy intensity. In addition, the construction year has a significant impact on LCE. EE will account for a larger proportion of new housing due to the development of energy-efficient technologies. It is significant to evaluate the energy of buildings from a lifecycle perspective. The comprehensive lifecycle profile helps explain how energy performance varies across the housing stock and where the most significant gains could be made through design improvements, material selection or energy upgrades.

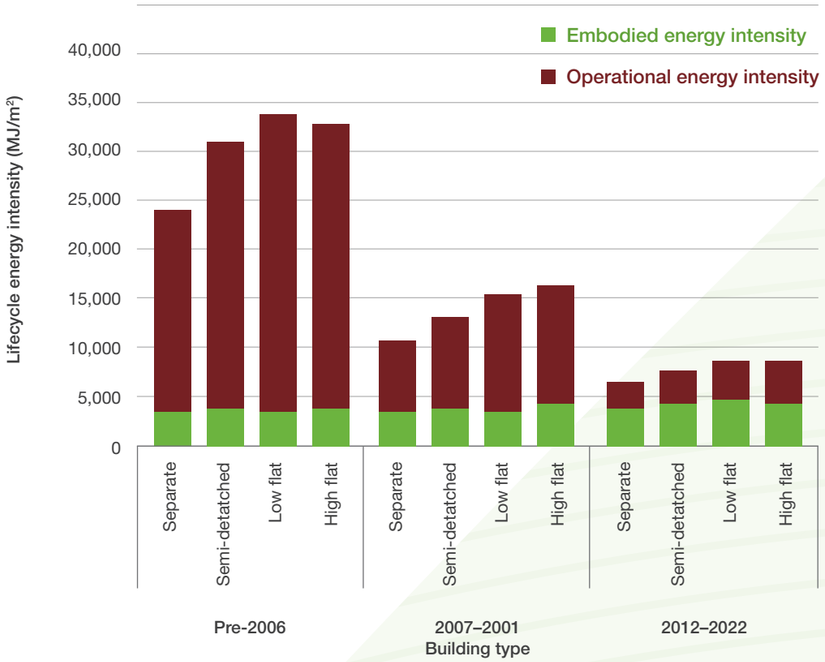


Figure 18. Lifecycle energy intensity for residential buildings by housing typologies

3.3.6 Spatial Assessment and Suburb-Level Results

The spatial assessment links LCE values to individual buildings and aggregates them to the suburb level. This process reveals variations that cannot be seen through building typology. By mapping the LCE of housing at the Statistical Area Level 1 (SA1), the assessment shows how construction period, dwelling type and material use interact across neighbourhoods.

Figure 19 illustrates the spatial distribution of LCE across residential building stocks in the Canning Vale, WA, case study at the SA1 level. Areas with more detached houses and older dwellings tend to show higher LCE. Newer developments or areas dominated by compact housing exhibit lower values. The spatial output highlights which parts of the suburb may benefit from targeted retrofit programs or design improvements. It also supports local planning by providing evidence of where energy demand is concentrated and where interventions could have the most impact.

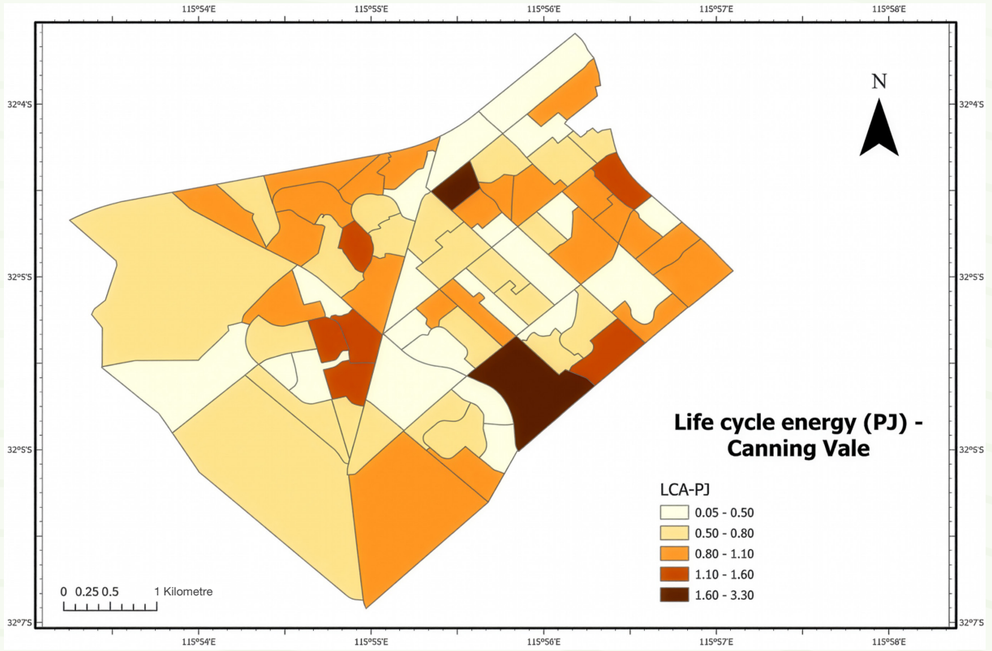


Figure 19. Case study of lifecycle energy of residential building stocks in Canning Vale, WA, at SA1 level

The spatial component has broader relevance for industry and government. It allows analysis to move beyond individual dwellings and present neighbourhood level patterns that support planning and policy decisions. By linking modelling outputs with spatial insight, the tool becomes practical for large-scale application and long-term planning needs. These spatial results help planners assess the performance of existing housing stock and identify areas where upgrades may be most effective. They also assist developers in understanding how construction materials influence LCE outcomes across different suburbs. The same information supports policymaking by showing how housing types contribute to local energy demand and enables scenario testing through changes in materials or energy-efficiency assumptions.

3.4. Conclusions and Future Work

This project developed a GIS and AI-based LCE assessment framework for residential buildings by integrating remote sensing, GIS analysis, automated building classification and energy modelling. The framework combines embodied and operational energy within a consistent structure and supports analysis at both building and regional scales. It captures differences in housing types, construction years and material types, which helps more accurately represent the energy characteristics of WA's housing stock.

The tool offers direct value for planning and decision-making. It provides a structured way to interpret how construction materials, building forms and development patterns influence LCE outcomes. The spatial outputs help identify locations where energy intensity is high and where design improvements or retrofit measures may bring the greatest benefit. These capabilities support evidence-based planning and help strengthen local policies related to residential energy performance.

Future work can further enhance the framework in several ways. Incorporating cost-based analysis and end-of-life modelling would provide a more holistic assessment of both environmental and economic impacts. Scenario analysis, testing alternative improvement strategies for residential buildings, could offer practical guidance to industry stakeholders, helping them identify the most effective pathways to improve energy efficiency. Improving the building classification process with higher resolution remote-sensing data or machine-learning methods could produce more detailed archetypes and refine energy estimates. Developing a web-based platform would also expand accessibility and support ongoing updates as new data becomes available. These extensions would increase the robustness of the tool and broaden its use across government, industry and research settings.



Pakin (Source: Adobe Stock)

4.0 Case Study 4: AI-Enabled Multi-Class Road Asset Detection and Automated Barrier Measurement Using LiDAR and Image Data

4.1 Introduction and Background

Road infrastructure networks contain a wide range of safety-critical roadside assets including barriers, signs, lighting, poles and retaining structures. Accurate and up-to-date information about the location, type and geometry of these assets is fundamental for effective asset management, maintenance planning and the development of digital twins to support long-term decision-making.

This project builds upon a previous research project – SBEnrc 2.92 Smarter and Greener Built Assets Through Digitalisation and Artificial Intelligence – that focused on road safety barrier detection and geometric dimension measurement using mobile LiDAR point cloud data hosted within the PointTerra platform. In that earlier work, road barriers were first identified through image-based detection and their geometry was then measured manually within the point cloud environment. While this approach demonstrated technical feasibility and achieved a high detection precision of approximately 93%, it also revealed several critical limitations that constrained its scalability and operational usability.

Most notably, the trained detection model exhibited a low recall rate, meaning that a significant proportion of barriers present in the scene were not detected. Detailed analysis showed that this issue was primarily caused by the training dataset. The model was trained almost exclusively on positive examples of barriers and was not explicitly exposed to a sufficient range of non-barrier objects. As a result, the model learned to recognise barrier-like patterns but did not effectively learn what should not be classified as a barrier. During inference, this led to overly conservative predictions, where the model only produced detections when visual features closely matched the training samples, causing many valid barriers to be missed.

4.2 Motivation and Objectives

The limitations identified in the earlier single-class detection workflow highlighted the need for a more comprehensive and robust solution. From an infrastructure owner's perspective, focusing on a single asset type is insufficient, as road authorities manage complex environments containing many interrelated asset classes. Furthermore, reliance on proprietary platforms constrained flexibility, automation and integration with broader digital engineering ecosystems.

The core motivation of this case study was therefore to move beyond isolated barrier detection and develop an AI-enabled, multi-class road asset detection and measurement framework that could operate directly on raw LiDAR point clouds and aligned imagery. A key objective was to migrate from the PointTerra environment to a custom-built point cloud data platform, allowing full control over data structures, AI training pipelines, inference workflows and downstream analytics.

4.0 Case Study 4: AI-Enabled Multi-Class Road Asset Detection and Automated Barrier Measurement Using LiDAR and Image Data (cont'd)

4.3 Methods

4.3.1 Point Cloud Data Labelling and Semantic Taxonomy

A critical foundation for reliable AI-based asset detection is the availability of high-quality, semantically labelled training data. To support transparency, reproducibility and scalability, this project adopted CloudCompare, an open-source point cloud processing platform, as the primary tool for data editing and annotation (as shown in Figure 20). Rather than limiting the scope to safety barriers alone, a comprehensive road asset semantic taxonomy was developed to reflect real-world road environments. This taxonomy includes pavement surfaces, concrete and steel safety barriers, traffic signs, power poles, street lights, traffic signals, roadside vegetation, shoulders, sidewalks, retaining walls, noise barriers, roundabouts and various median types. By explicitly modelling this diversity, the dataset enables AI models to learn both target assets and surrounding context, which is essential for reducing false positives and improving recall.

To date, 25 out of 271 raw road segments have been fully annotated. Each raw segment is further subdivided into more than 10 smaller sub-segments to improve navigation, annotation accuracy and memory efficiency during training. In total, approximately 25 km of roadway have been labelled, representing around 10% of the overall dataset. Although partial, this coverage already captures a wide range of asset configurations and environmental conditions, providing a strong initial foundation for model development.

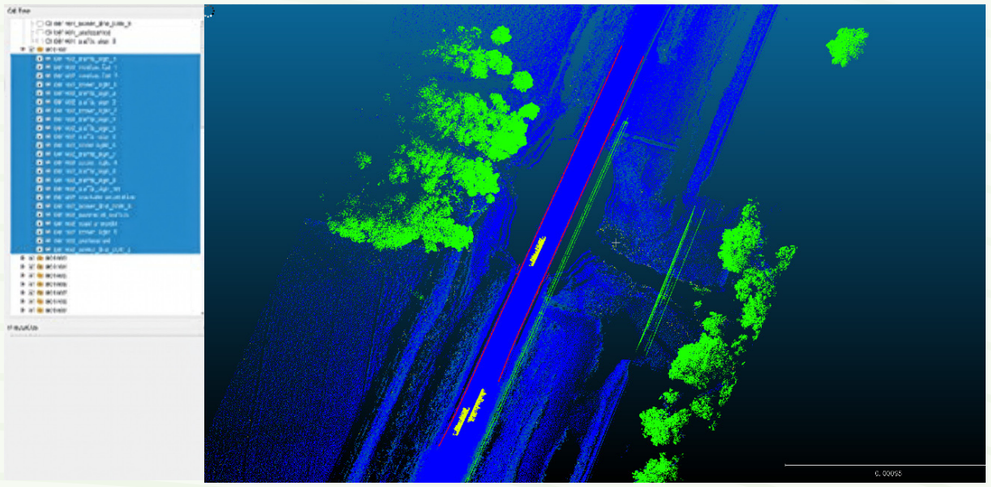


Figure 20. Point cloud data editing and annotation with CloudCompare

4.3.2 Data Structuring and AI Training Pipeline

Beyond annotation, a major technical challenge lies in transforming labelled point cloud data into a format suitable for large-scale AI training. To address this, an automated data structuring pipeline was developed to bridge the gap between the labelling environment and the AI models.

Labelled point clouds are automatically exported from CloudCompare into a structured database, where class labels, spatial indices and metadata are standardised (as shown in Figure 21). This process ensures consistency across training runs and allows rapid experimentation with different model architectures without having to repeat manual preprocessing. Importantly, this pipeline also supports future extensions, such as incremental dataset updates and semi-automated label refinement, which are essential for long-term operational deployment.

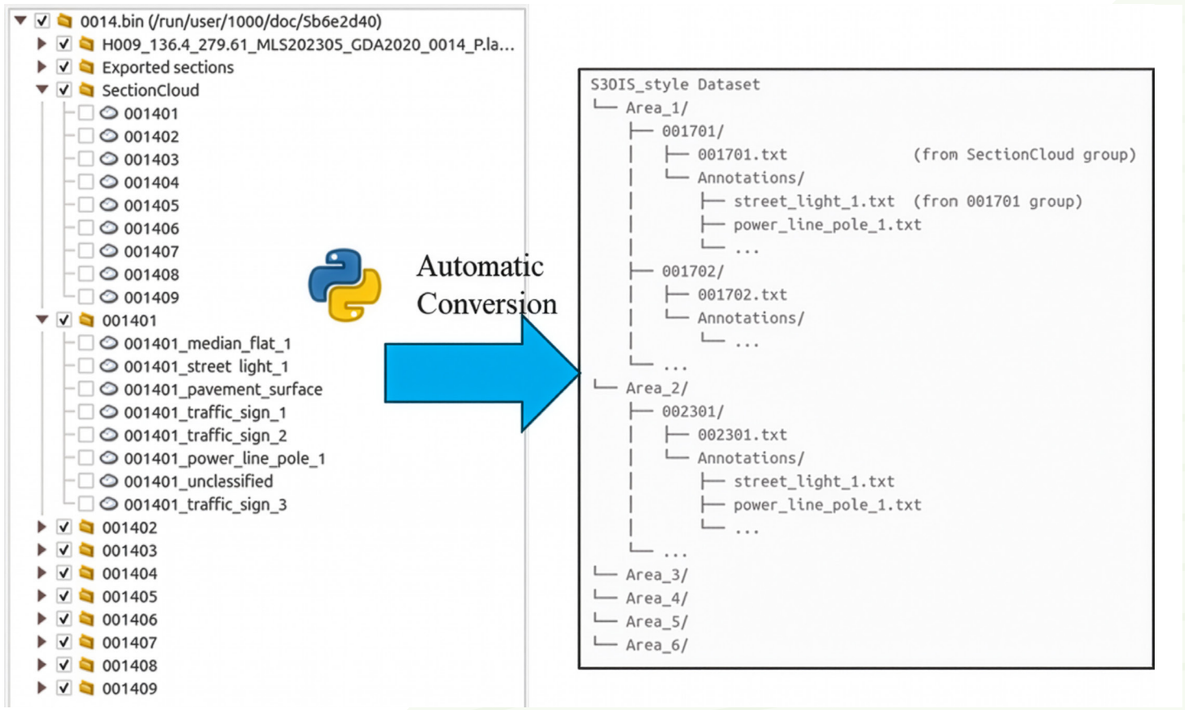


Figure 21. Automatic conversion of labelled point clouds

4.3.3 AI Models and Geometry-Aware Learning

To evaluate the effectiveness of different deep learning approaches for road asset segmentation, four state-of-the-art point cloud semantic segmentation models were trained and compared. These include PointNet++, PointTransformer V3 and RandLA-Net, which are widely recognised benchmarks in 3D scene understanding. In addition to these baselines, the project developed a customised approach based on RandLA-Net enhanced with geometry priors.

The introduction of geometry priors represents a key methodological contribution of this work. Rather than relying solely on data-driven feature learning, geometry priors embed simple but powerful physical knowledge about road environments directly into the detection pipeline. For example, road surfaces tend to be flat and horizontally continuous; poles are predominantly vertical and slender; and safety barriers exhibit linear, elongated structures aligned with road edges. By incorporating these constraints, the model can better resolve ambiguous cases and produce more stable predictions, particularly when labelled data is limited. This hybrid learning strategy is especially valuable in infrastructure contexts, where collecting exhaustive labelled datasets is expensive and time-consuming. Geometry priors effectively act as an inductive bias, guiding the model towards physically plausible interpretations of the scene.

4.3.4 Model Performance and Deployment Readiness

Model performance was evaluated using two complementary metrics: overall classification accuracy (Acc); and mean Intersection-over-Union (mIoU). Accuracy measures the proportion of correctly classified points across the entire scene, while mIoU provides a stricter assessment of how well predicted asset regions overlap with ground-truth labels on a per-class basis. Figure 22 shows the model training loss, which measures the error between the model's predictions and the labelled data during training. A declining loss indicates the model is learning. Accuracy on unseen data is reported in Table 1.

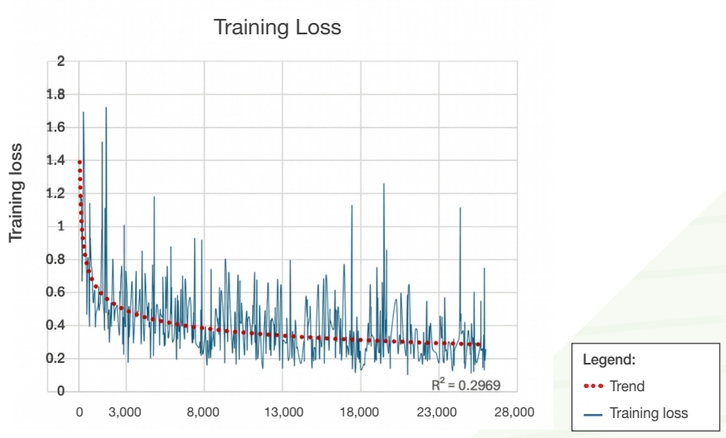


Figure 22. AI model training loss

To systematically assess the effectiveness of the proposed approach, we evaluated four point cloud semantic segmentation models: PointNet++, PointTransformer V3, RandLA-Net and our enhanced version of RandLA-Net incorporating geometry priors (as shown in Table 1). These models represent a progression from early deep-learning architectures to more recent, large-scale point cloud learning frameworks, providing a robust basis for comparison.

The experimental results reveal clear performance differences across the tested models. Traditional approaches such as PointNet++ and PointTransformer V3 exhibit relatively weak performance when trained on the smaller labelled dataset, achieving approximately 15–18% accuracy and around 5% mIoU. These results indicate that, while these models are capable of learning basic geometric features, they struggle to generalise in complex road environments when training data is limited and class distributions are highly imbalanced.

RandLA-Net demonstrates a noticeable improvement over these baselines, reaching approximately 25–32% accuracy on the same dataset. This confirms the advantage of random sampling and hierarchical feature aggregation for large-scale outdoor point clouds. However, despite this improvement, RandLA-Net still exhibits limitations in handling rare or geometrically subtle asset classes, suggesting that purely data-driven learning remains insufficient under constrained labelling conditions.

In contrast, the proposed RandLA-Net with geometry priors delivers a substantial and consistent performance gain. When trained on the 70-segment dataset, the enhanced model achieves 45% accuracy and 22.6% mIoU, demonstrating that the integration of domain-specific geometric knowledge significantly improves both point-level classification and region-level consistency. When the training dataset is expanded to 150 labelled segments, performance improves further, with accuracy rising to nearly 69% and mIoU reaching 35.7%. This trend highlights the complementary roles of increased data volume and geometry-aware learning, with geometry priors enabling more efficient use of available training samples.

4.0 Case Study 4: AI-Enabled Multi-Class Road Asset Detection and Automated Barrier Measurement Using LiDAR and Image Data (cont'd)

These results align well with recognised performance tiers for operational deployment in infrastructure asset mapping. Models achieving 65–75% accuracy and 20–35% mIoU can be considered to have reached baseline production readiness, suitable for semi-automated workflows where AI outputs substantially reduce manual effort but are still accompanied by targeted human review. When accuracy increases to 75–85% and mIoU to 35–50%, the system becomes operationally deployable, capable of supporting routine asset inventory updates with minimal manual intervention. Beyond this level, exceeding 85% accuracy and 50% mIoU would indicate high-confidence, fully automated capability, comparable to established large-scale benchmarks such as SemanticKITTI and Toronto-3D.

Table 1. Model performance comparison

Algorithm		Dataset size=70 seg	Dataset size=150 seg
PointNet++	Acc	15.3%	20.1%
	mIoU	4.89%	5.47%
PointTransformer v3	Acc	18.77%	N/A
	mIoU	5.13%	
RandLA-Net	Acc	25.2%	32.4%
	mIoU	N/A	3.5%
Ours	**Acc**	**45.3%**	**68.5%**
	mIoU	**22.6%**	**35.7%**

4.3.5 AI Inference and Automated Dimension Measurement

Beyond semantic classification, a major practical outcome of this project is the automation of road safety barrier dimension measurement. Once barriers are accurately segmented from the surrounding environment, their geometric properties – such as length, height and alignment – can be computed directly from the point cloud (as shown in Figure 23).

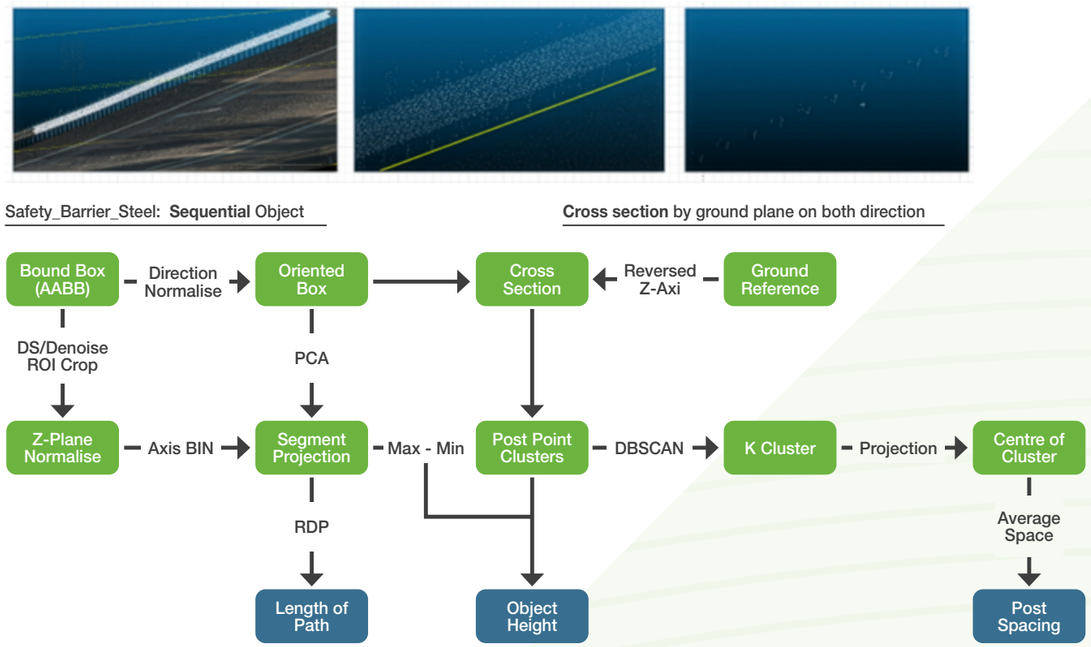


Figure 23. Automated dimension measurement

This capability eliminates the need for manual measurement within third-party platforms and enables consistent, repeatable geometry extraction at scale. For road authorities, this represents a substantial efficiency gain, allowing large networks to be audited more frequently and with greater confidence. The same workflow can also be extended to other linear or vertical assets, such as noise barriers and retaining walls, further enhancing its value.

To support end-to-end deployment, the project has developed a dedicated point cloud AI platform that integrates data management, AI inference, visualisation and geometry analysis. This platform enables users to use raw LiDAR data, view semantic segmentation results, extract asset-level information and export structured outputs for asset management systems or digital twin environments.

By removing dependence on proprietary software and consolidating all processing stages within a single platform, the system provides a flexible foundation for future extensions including real-time updates, cross-project benchmarking and integration with maintenance and inspection workflows.

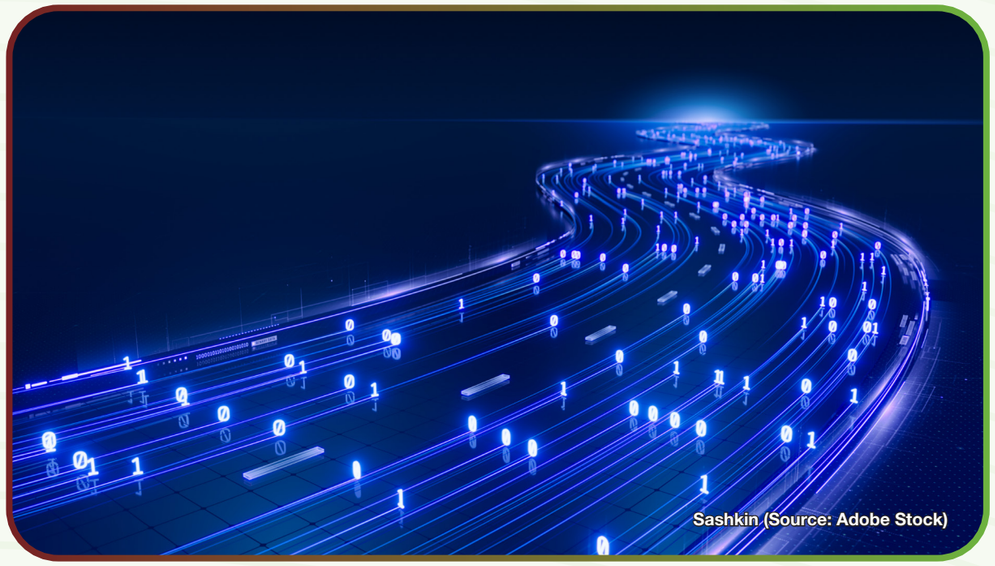
4.0 Case Study 4: AI-Enabled Multi-Class Road Asset Detection and Automated Barrier Measurement Using LiDAR and Image Data (cont'd)

4.4 Conclusions and Future Work

This case study demonstrates a comprehensive AI-driven approach to multi-class road asset detection and automated barrier measurement using LiDAR and image data. By combining open-source data labelling, structured AI pipelines, geometry-aware learning and an integrated deployment platform, the project provides a scalable solution that directly addresses the needs of road authorities.

While current results demonstrate strong potential, several avenues for further improvement have been identified. Expanding the labelled dataset across a broader range of road environments – such as urban, rural and high-speed highways – will improve model generalisation. Addressing class imbalance by collecting additional samples for rare assets, including traffic signals and noise barriers, is expected to further increase mIoU scores.

In addition, the project plans to explore automated label generation techniques, such as weak supervision and self-training, to reduce the manual annotation burden. Geometry priors will also be extended to become adaptive, allowing them to adjust automatically based on road type and context. Finally, integrating temporal data from repeated scans will enable change detection and long-term monitoring of asset condition and deterioration.



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