

Athithya S. Loganathan<sup>1,2</sup>, Saim Muhammad<sup>1</sup>, Sander Oude Elberink<sup>2</sup>  
<sup>1</sup> Statistics Netherlands (CBS), <sup>2</sup> University of Twente

## BACKGROUND

- Reliable land use information is essential for spatial planning, infrastructure monitoring, and environmental reporting.
- In the Netherlands, this is provided by the *Bestand Bodemgebruik (BBG)* dataset.
- BBG integrates registry data, topographic information, and aerial imagery, but its production remains **partly manual and resource-intensive**.
- Earth Observation (EO) and deep learning offer opportunities to **automate and scale land-use mapping workflows**.

## OBJECTIVES

- Develop an operational deep learning framework to classify 14 built-up land use classes using high-resolution aerial imagery.
- Evaluate the added value of integrating registry-derived attributes to improve classification of functionally distinct but visually ambiguous classes.
- Produce parcel-linked raster predictions aggregated to official statistical reporting units for BBG production.

## KEY TAKEAWAY

### RGB-Only Pipeline

**64.3%**

Macro-averaged F1 score

Fusion improves transport classes (rail, metro/tram, main roads); RGB-only suffices for visually distinct land uses.

### Multimodal Fusion Pipeline

**65.8%**

Macro-averaged F1 score

## DATA

### Study Area

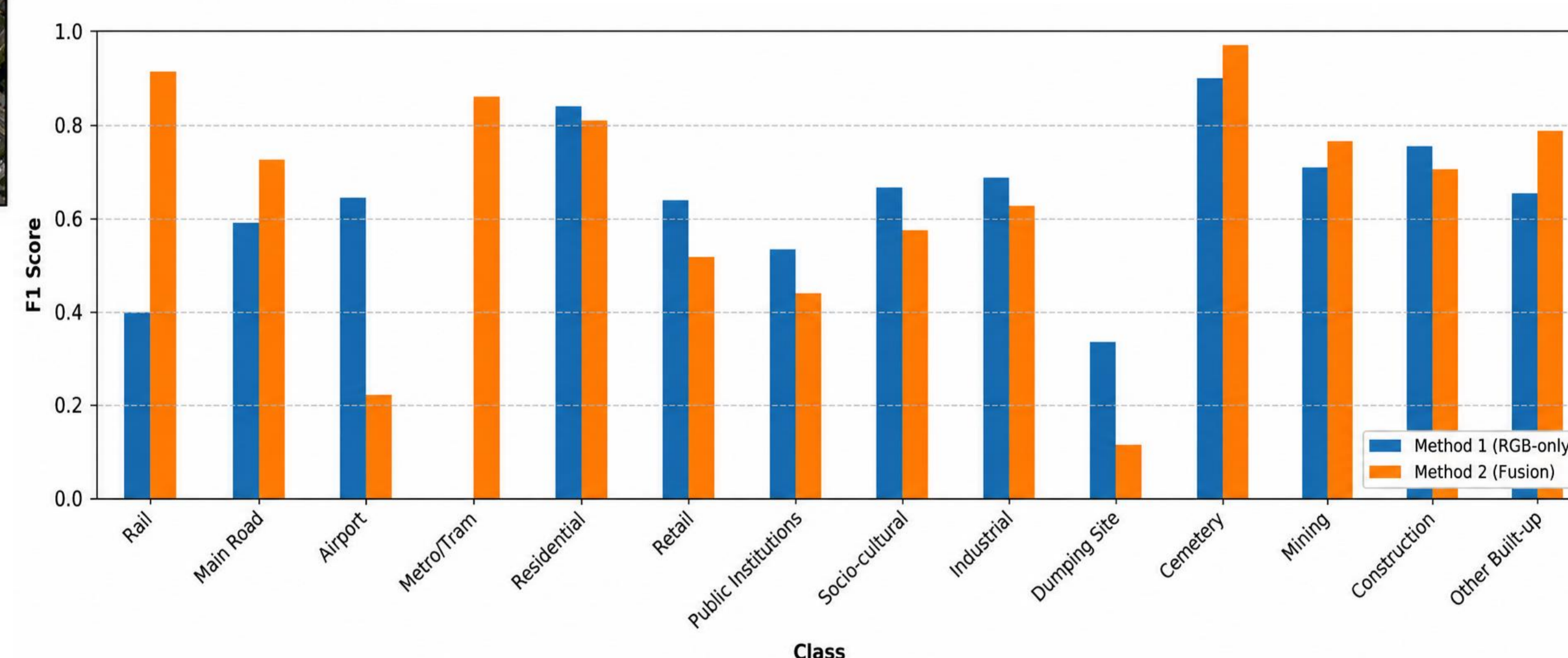
The Netherlands (BBG 2020)

- Land Use Labels:** CBS – BBG (14 built-up classes + background)
- Aerial Imagery:** PDOK RGB orthophotos (25 cm resolution)
- Registry Data (fusion):** BAG, BRT, NWB, BGT, ProRail
- Dataset**
  - ~39,000 image patches Nationwide coverage
- Split**
  - Train: 72% | Val: 14% | Test: 13%
  - Geographically separated

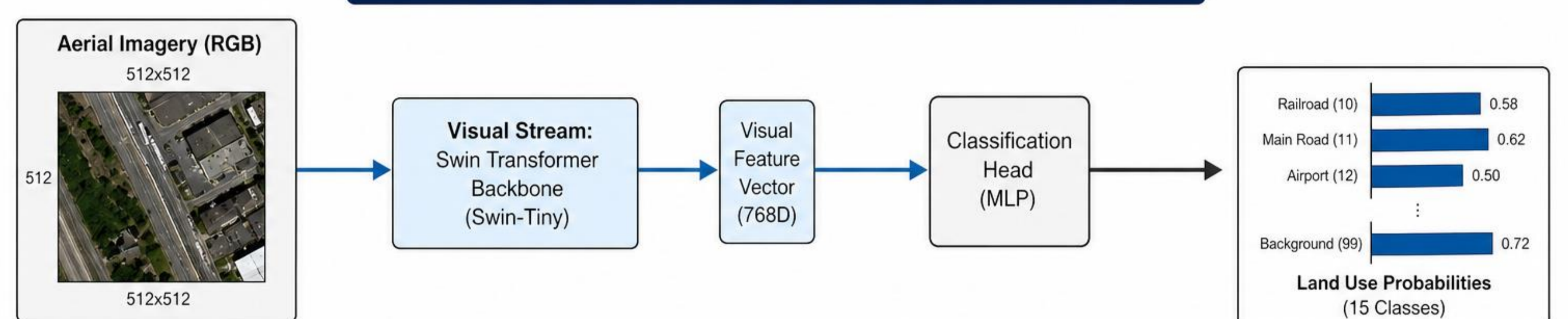


## CONCLUSION

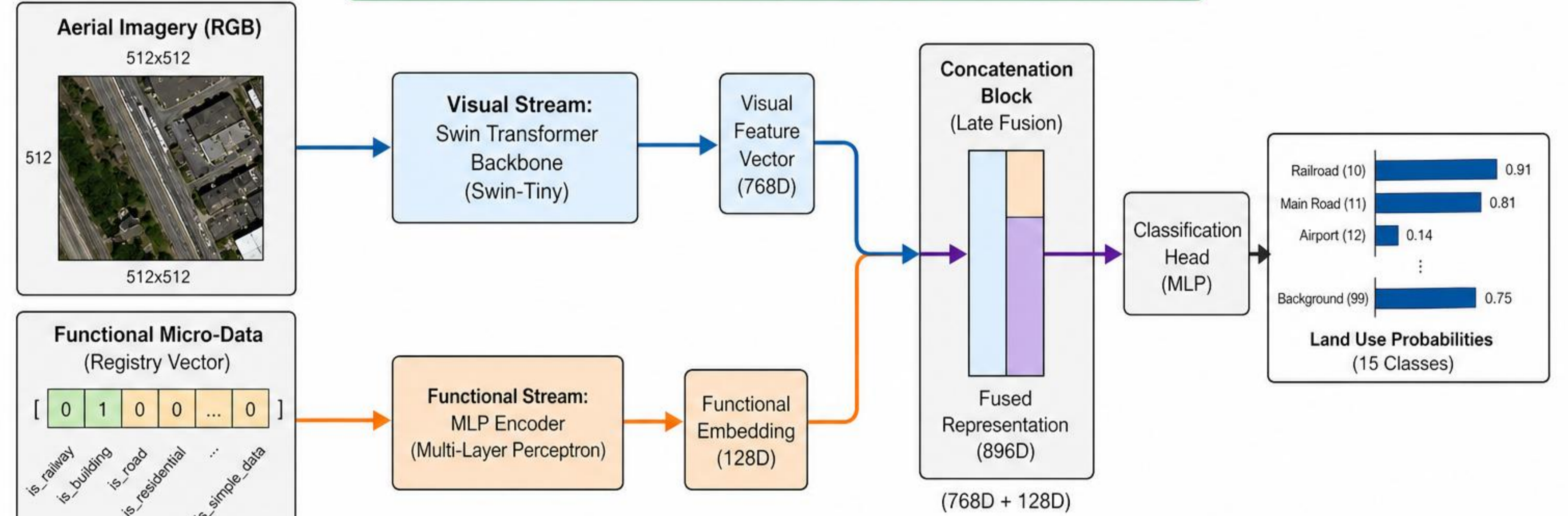
- Scalable deep learning framework enables parcel-level land-use mapping for national statistics (BBG).
- For BBG production: registry fusion is most worthwhile where visual cues alone fall short, i.e. transport classes.
- Headline F1 gain looks small (+1.5 pts), but per-class gains for transport classes justify the added pipeline complexity.
- Recommendation: hybrid deployment — RGB-only by default, registry fusion selectively for transport classes.



### METHOD 1: BASELINE – SWIN-TINY ONLY (IMAGE-ONLY)



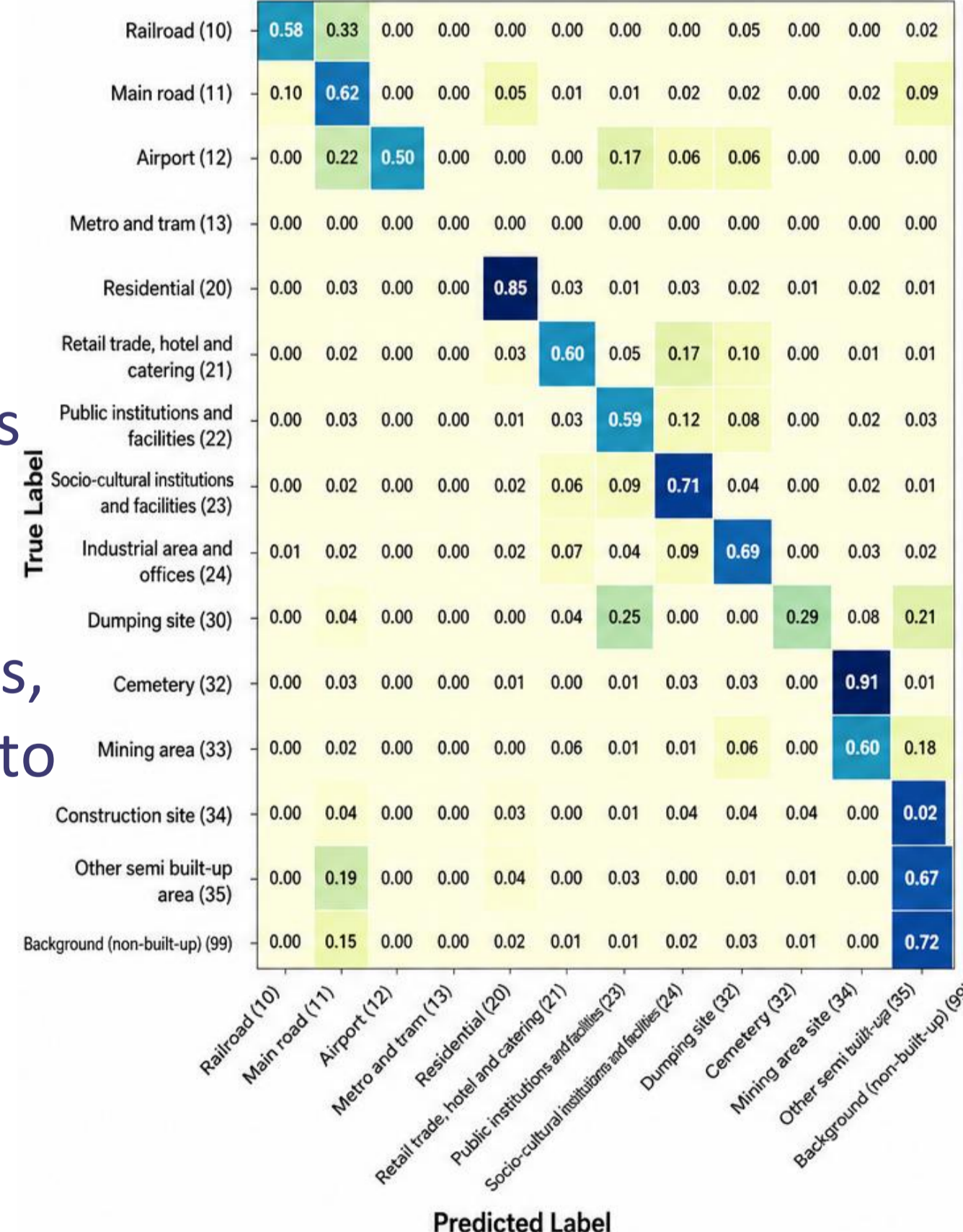
### METHOD 2: PROPOSED – MULTIMODAL (IMAGE + REGISTRY DATA)



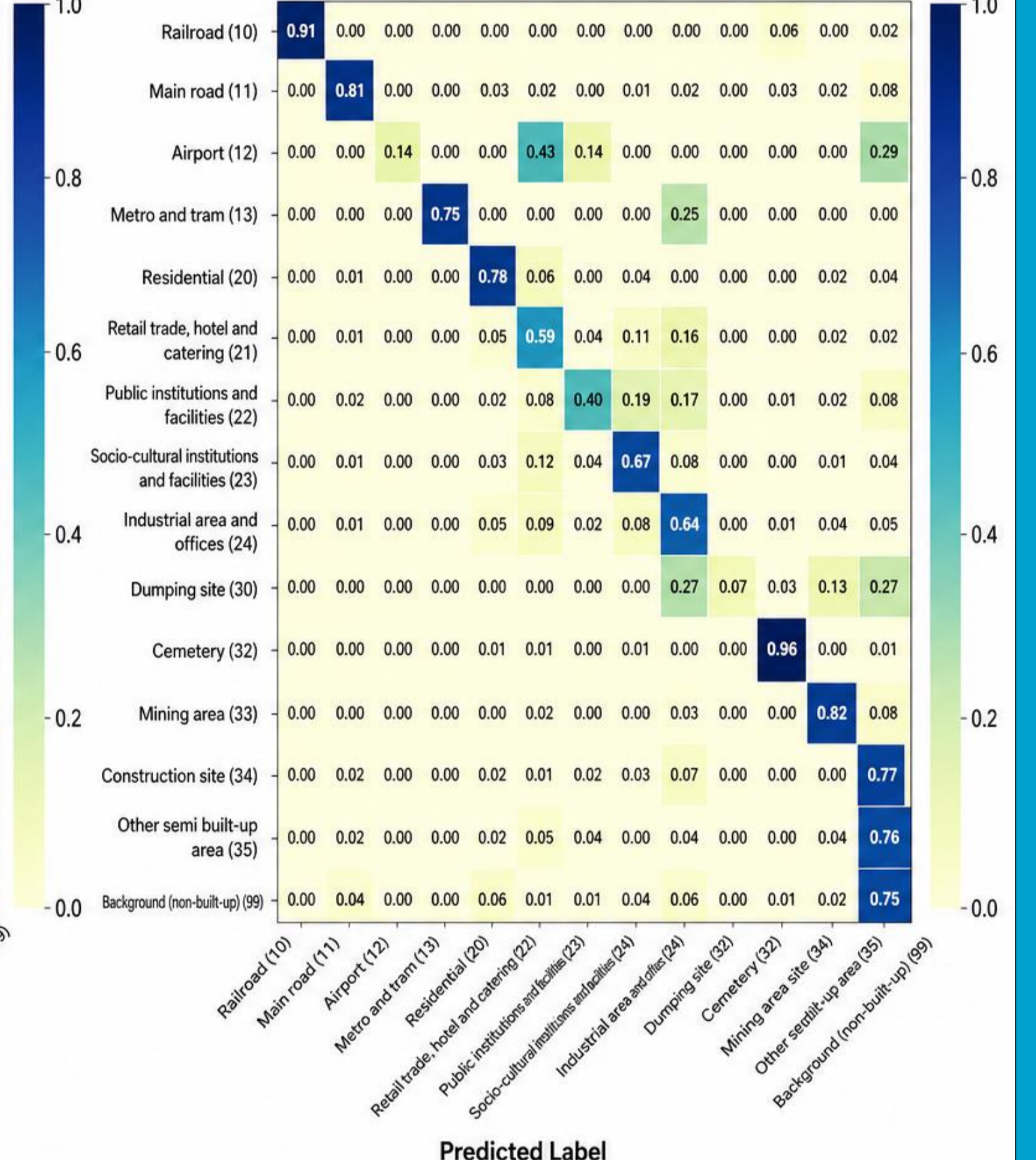
## INSIGHTS

- Stronger diagonal in Method 2 indicates higher class-wise accuracy than RGB-only.
- Misclassification drops sharply in transport classes (rail, metro/tram, main roads).
- Rare classes (dumping sites, airport) stay unstable due to limited samples.

Confusion Matrix – Method 1 (Baseline)



Confusion Matrix – Method 2 (With Registry Data)



## PER-CLASS F1

- Largest fusion gains: rail, metro/tram, main road (transport classes).
- RGB already strong for residential, cemetery, construction — little to add from fusion.
- Dumping sites and airport stay low for both methods (rare-class instability).

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**CONTACT:** Athithya S. Loganathan ([athithya.loganathan@cbs.nl](mailto:athithya.loganathan@cbs.nl)) Statistics Netherlands (CBS) & University of Twente