Exploring the Use of Machine Learning and Remote Sensing for Traffic Map Generation at Large Scale

Machine learning for feature detection and user applications

ECMWF ML workshop, virtual

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Introduction

- **Carbon dioxide** is the largest constituent of road traffic greenhouse gas emissions [1]:
  - Local Government Authorities (LGAs) are typically responsible for facilitating mitigation of these emissions.
  - Critical to this task is the ability to assess the impact of transport interventions on road traffic emissions for a whole network.
- **Sustainability problem** that could be generated from transformation of traditional cities to smart cities becomes increasingly important. Urban growth trends expected to increase by 70% in 2050 of the world population will live in cities [2].
- Organisations like World Health Organization (WHO) or the European Environment Agency have reported that being exposed to air pollutants (generated from road vehicles) **increases the risk of early death** [3].
- Air pollution is the biggest environmental threat to health in the UK, with **between 28,000 and 36,000 deaths a year attributed to long-term exposure** (Public Health England (PHE), 2019).

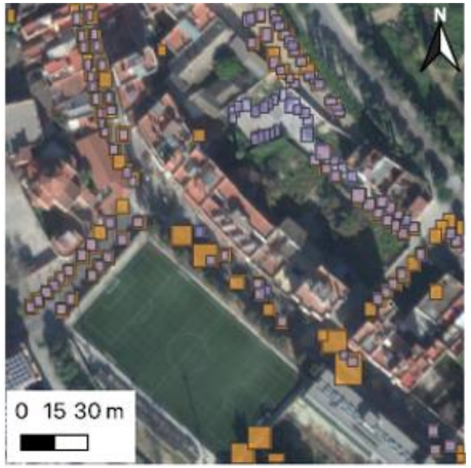
Main motivations

1-Frequent revisits of earth imaging satellite constellations with providing high spatial resolution support the available efforts for updating traffic maps when combined with advanced machine learning techniques.

2-Support the Local Government Authorities (LGAs) to mitigate road network emissions, and critical to this task is the ability to assess the impact of transport interventions on road traffic emissions for a whole traffic network.

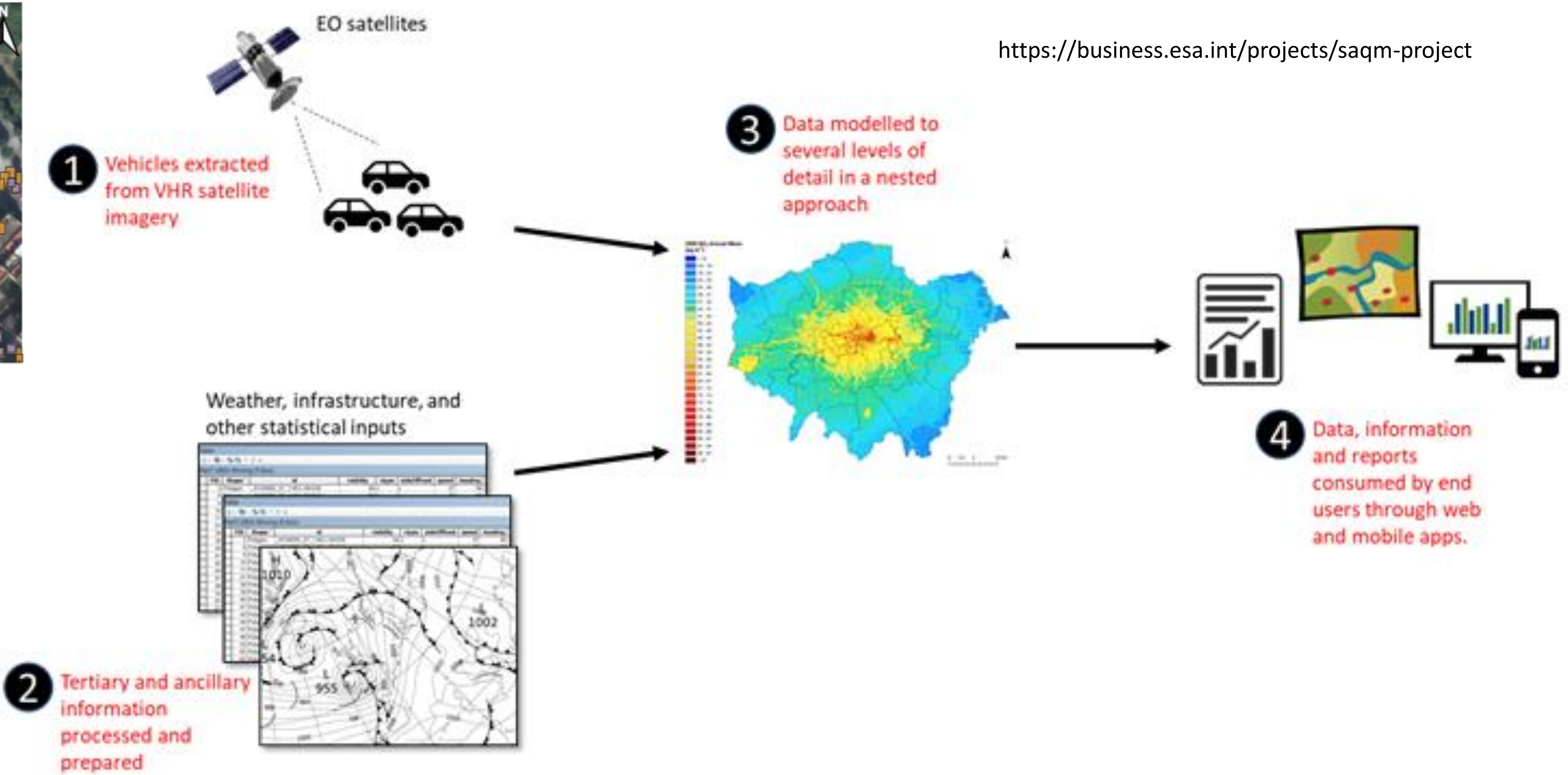
3-Support Air quality prediction tasks by reducing the uncertainty level in answering the main question: Where these pollutants originate from.

4 Earth Intelligence-Satellite Air Quality Model (SAQM) project



Satellite images@2019 Maxar Tech.
World View 2/3 Barcelona city

https://business.esa.int/projects/saqm-project



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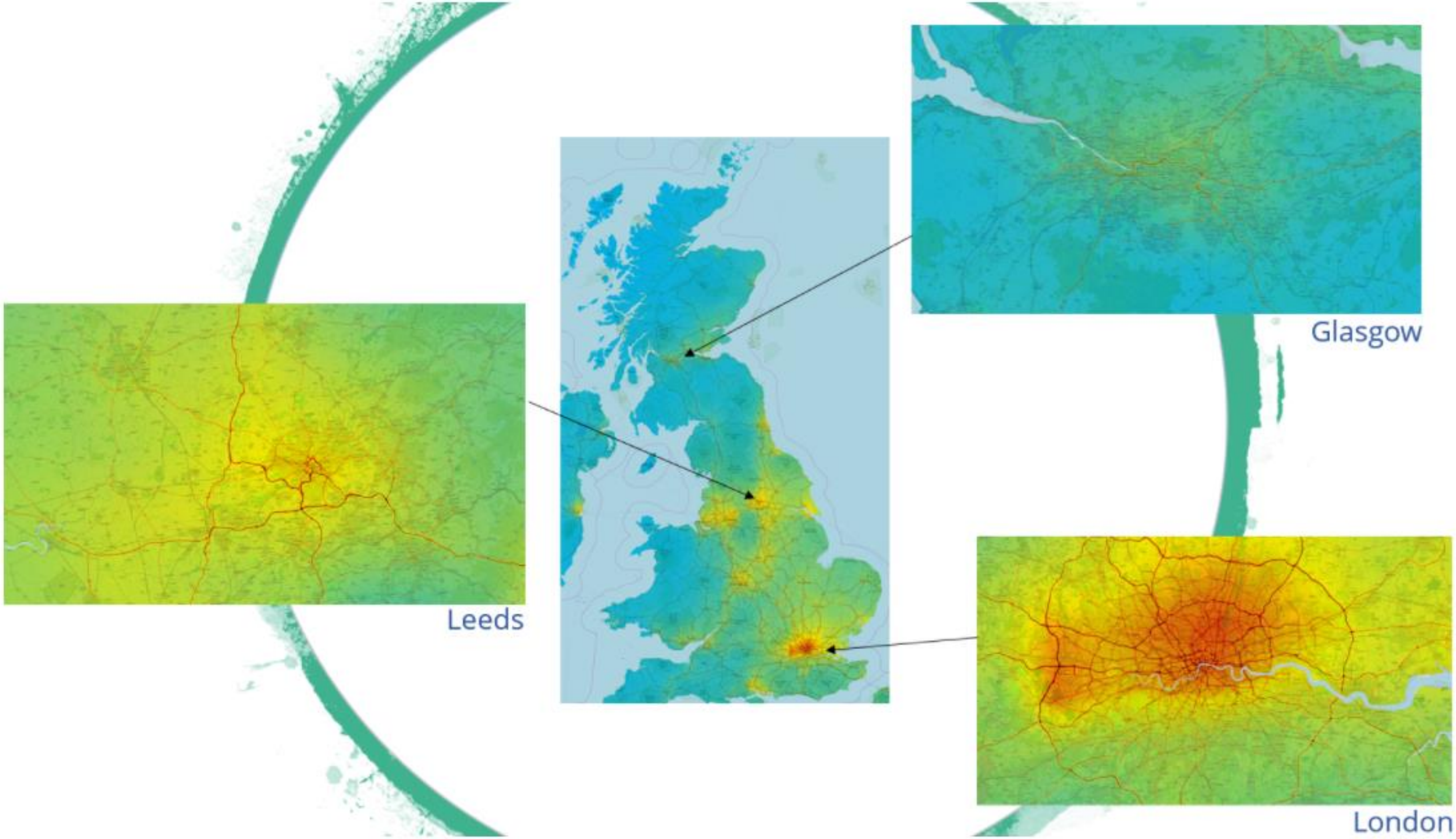
4EI Intelligence-Satellite Air Quality Model (SAQM) project



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Agenda

Multi model ML:

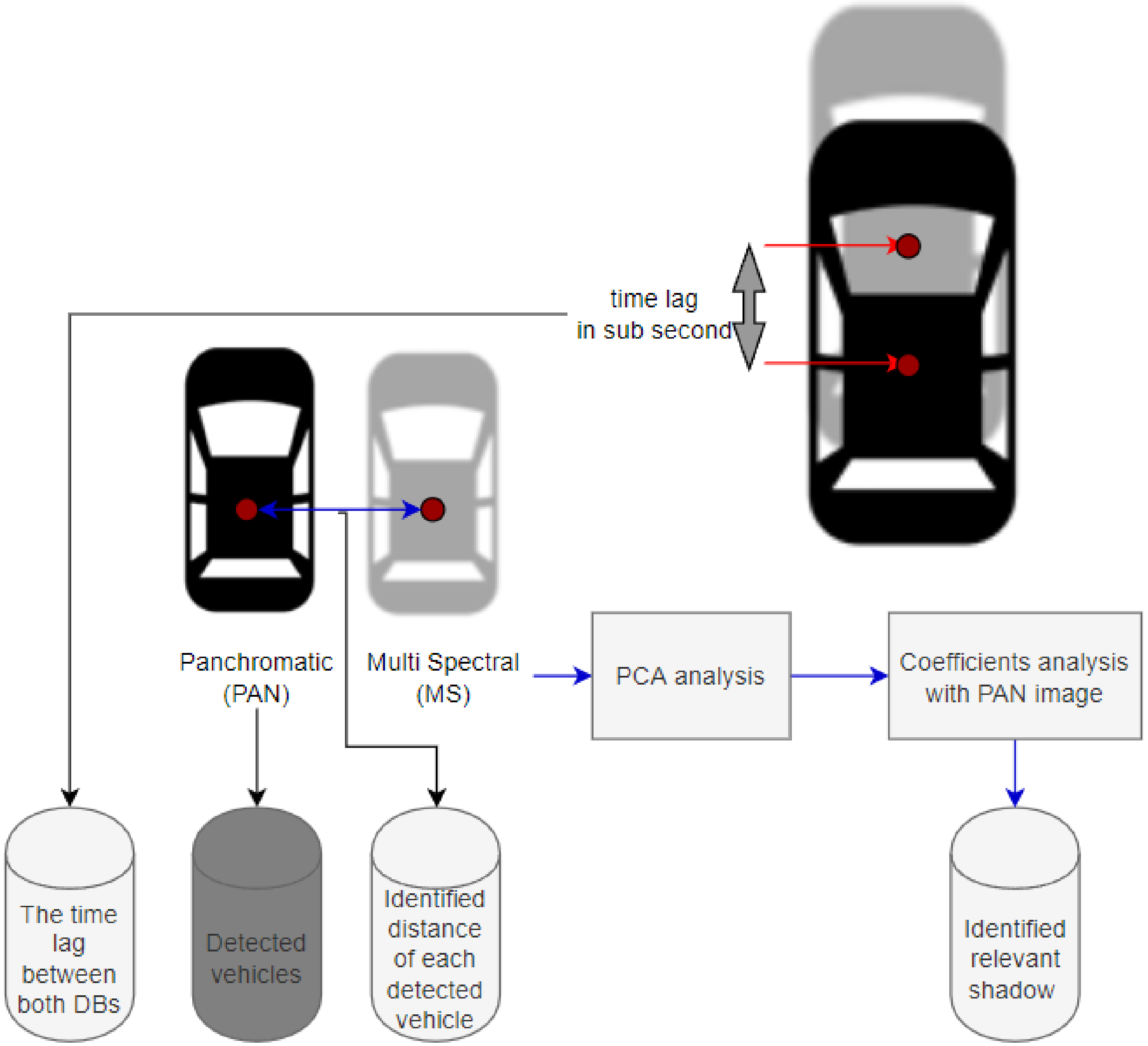
Road segmentation and Vehicle localisation

Data analysis platform:

Average speed estimation and verification

Potential use cases applications

Speed calculation concept



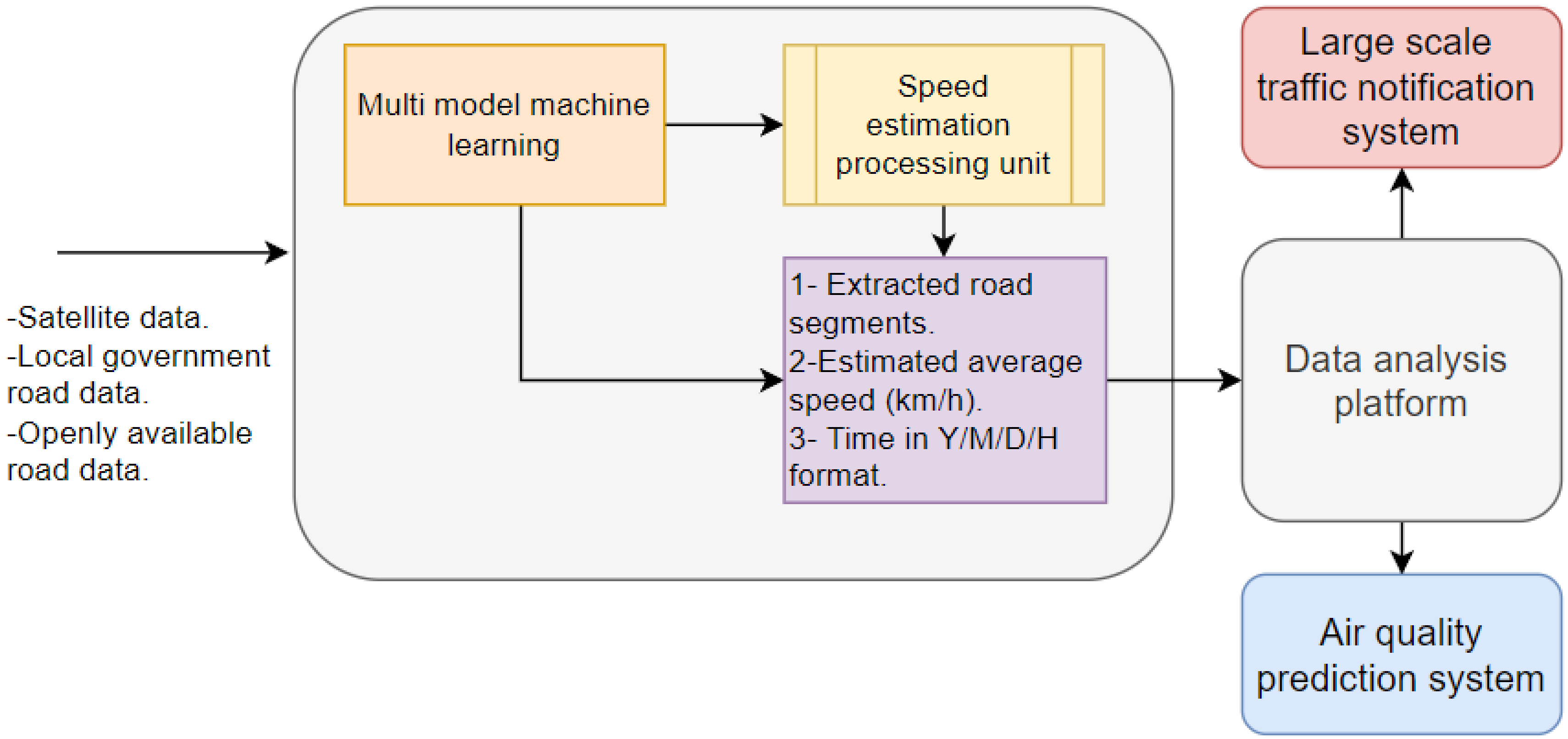
The idea of speed calculation using spaceborne data

Promising speed calculation approach

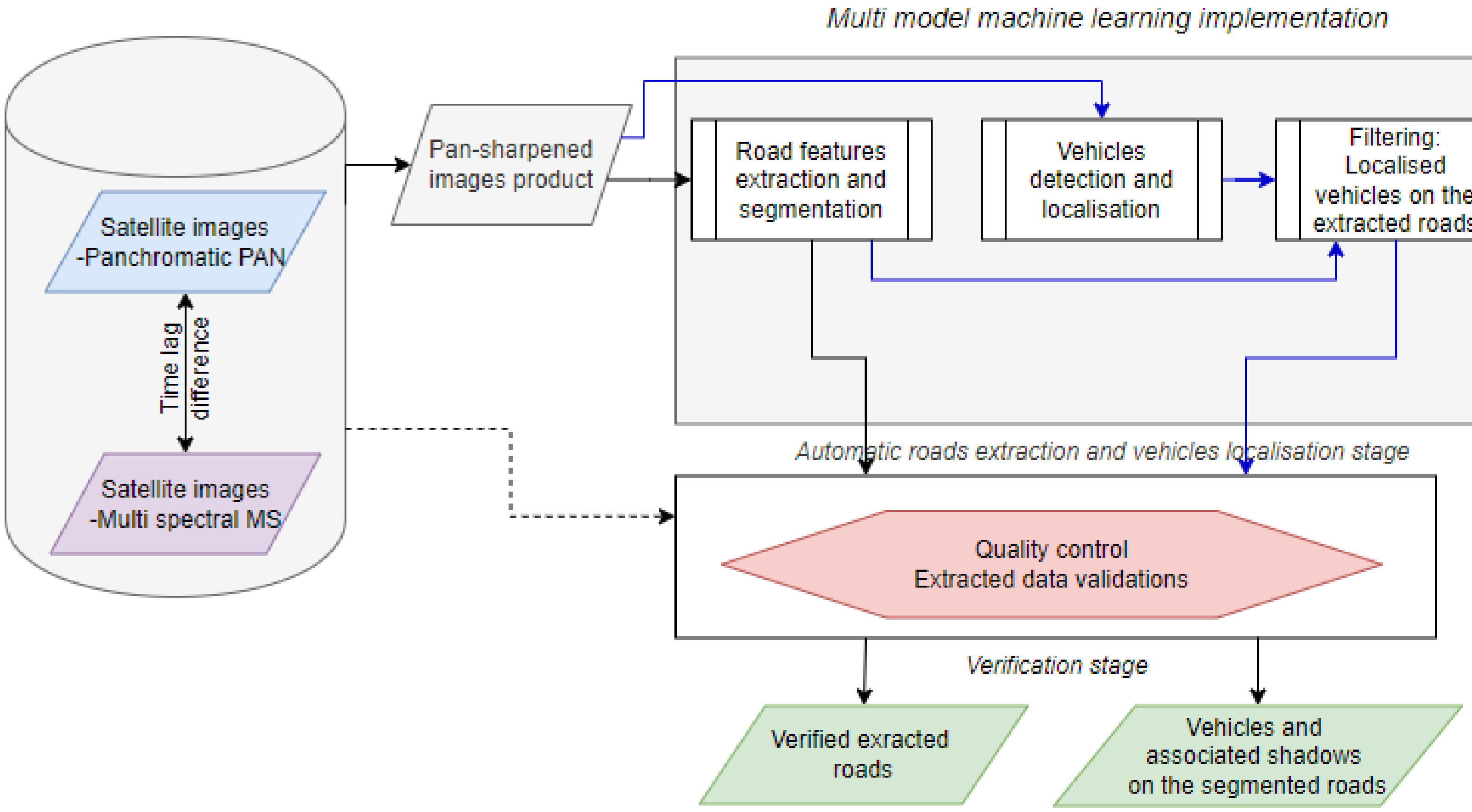
Reference	Year	Title
[4] Liu et al.	2007	Speed Detection of Vehicles From Arial Photographers.
[5] Yamazaki et al.	2007	Speed Detection for Moving Objects from Digital Aerial Camera and QuickBird Sensors
[6] Liu et al.	2011	Automated Vehicle Extraction and Speed Determination From QuickBird Satellite Images

1. Road environmental conditions: road lines, vegetation, signboards etc.
2. Low accuracy of vehicle extraction and localisation.
3. Low spatial satellite resolution in 2011 compared to 2022.
4. Limited optimised ML approaches for road segmentation and vehicles detection tasks.

Machine Learning implementation approach



Multi model Machine Learning implementation



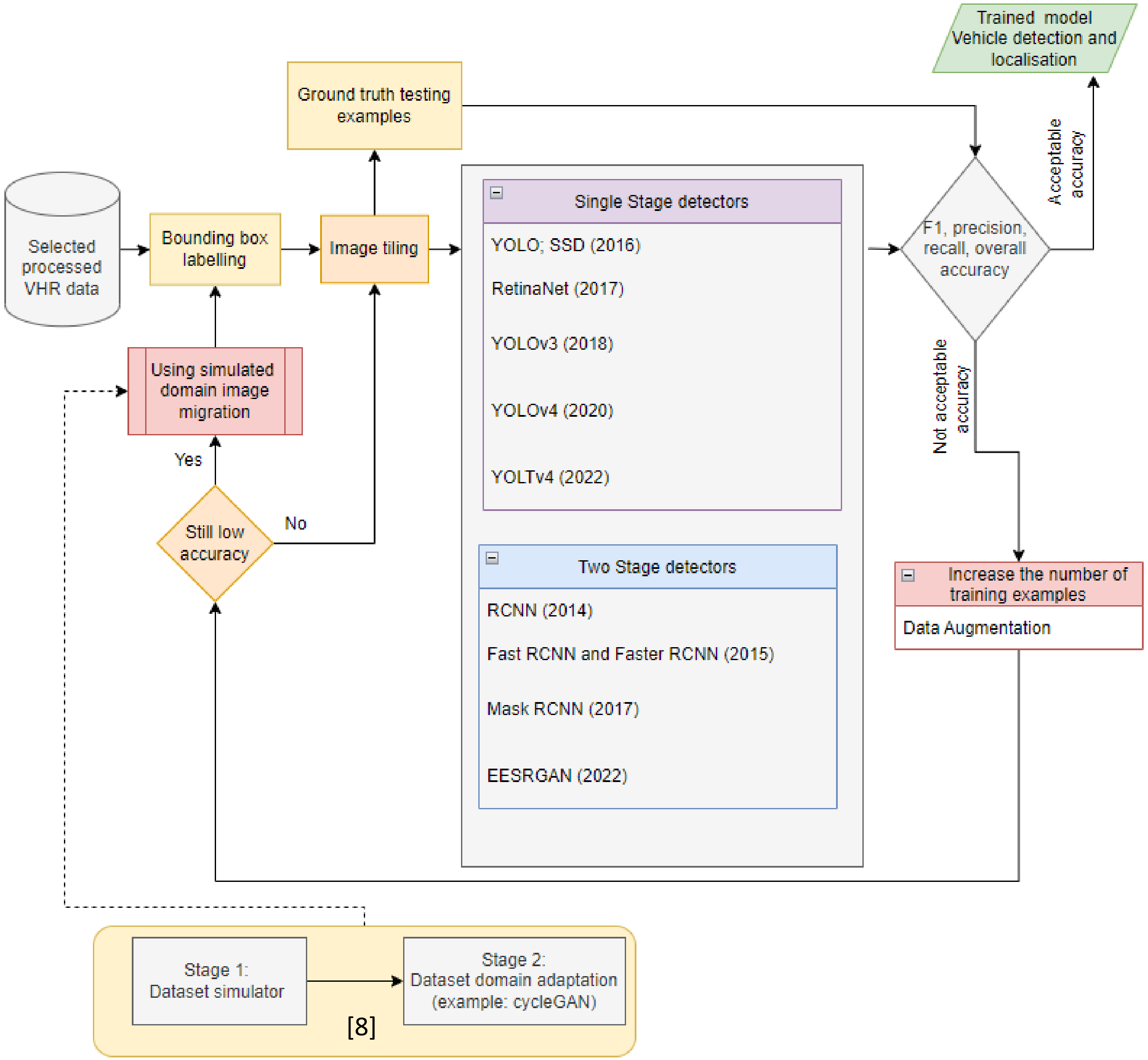
Automatic roads extraction and vehicles localisation tasks

Some of Remote sensing datasets

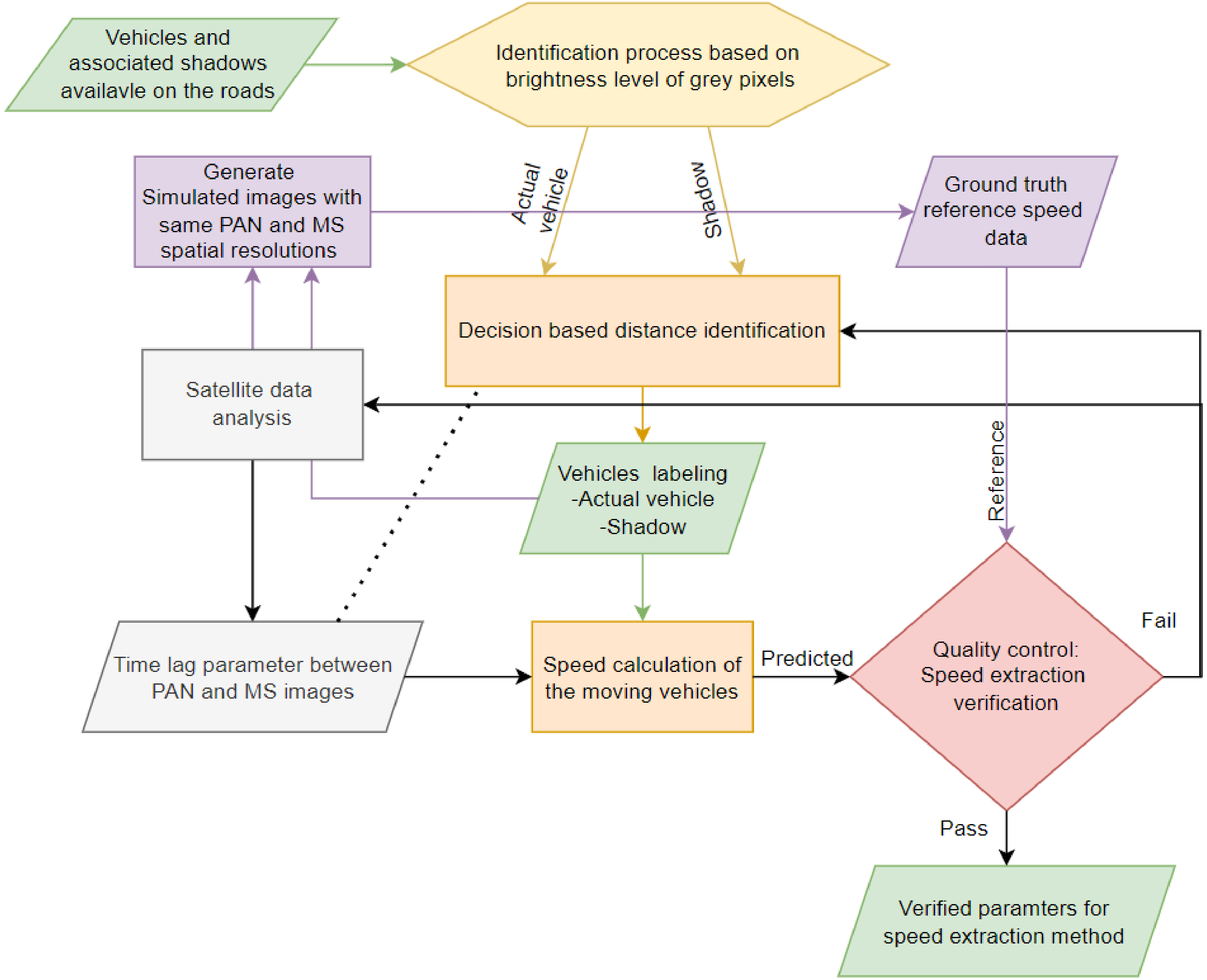
Some of openly available and commercial remote sensing datasets

Dataset source	Description
Massachusetts Roads Dataset	Openly available spaceborne data, 3 channel resolution with 1 m resolution.
Cars Overhead With Context (COWC) dataset	Openly available aerial data, 3 channel resolution with 15 cm resolution.
xView dataset	Openly available and one of the largest overhead data, 3 channel resolution with 30 cm resolution, 60 classes and 1 million object instances.
Worldview-4	Panchromatic, and 4 Multispectral bands (B, G, R, and NIR). Panchromatic nadir: 0.31m Multispectral nadir: 1.24m
Worldview-3	Panchromatic, 8 Multispectral bands, and 8 SWIR Panchromatic nadir: 0.31m Multispectral nadir: 1.24m
SkySat	**[SkySat-1, SkySat-2] -A/B Generation** Panchromatic: 0.86 m Multispectral: 1.0 m **[SkySat-3 - SkySat-15] -C Generation** Panchromatic: 0.65m (0.72 m before 30/06/2020) Multispectral: 0.81m (1.0 m before 30/06/2020) **[SkySat-16 - SkySat-21] -C Generation** Panchromatic: 0.57m Multispectral: 0.75m

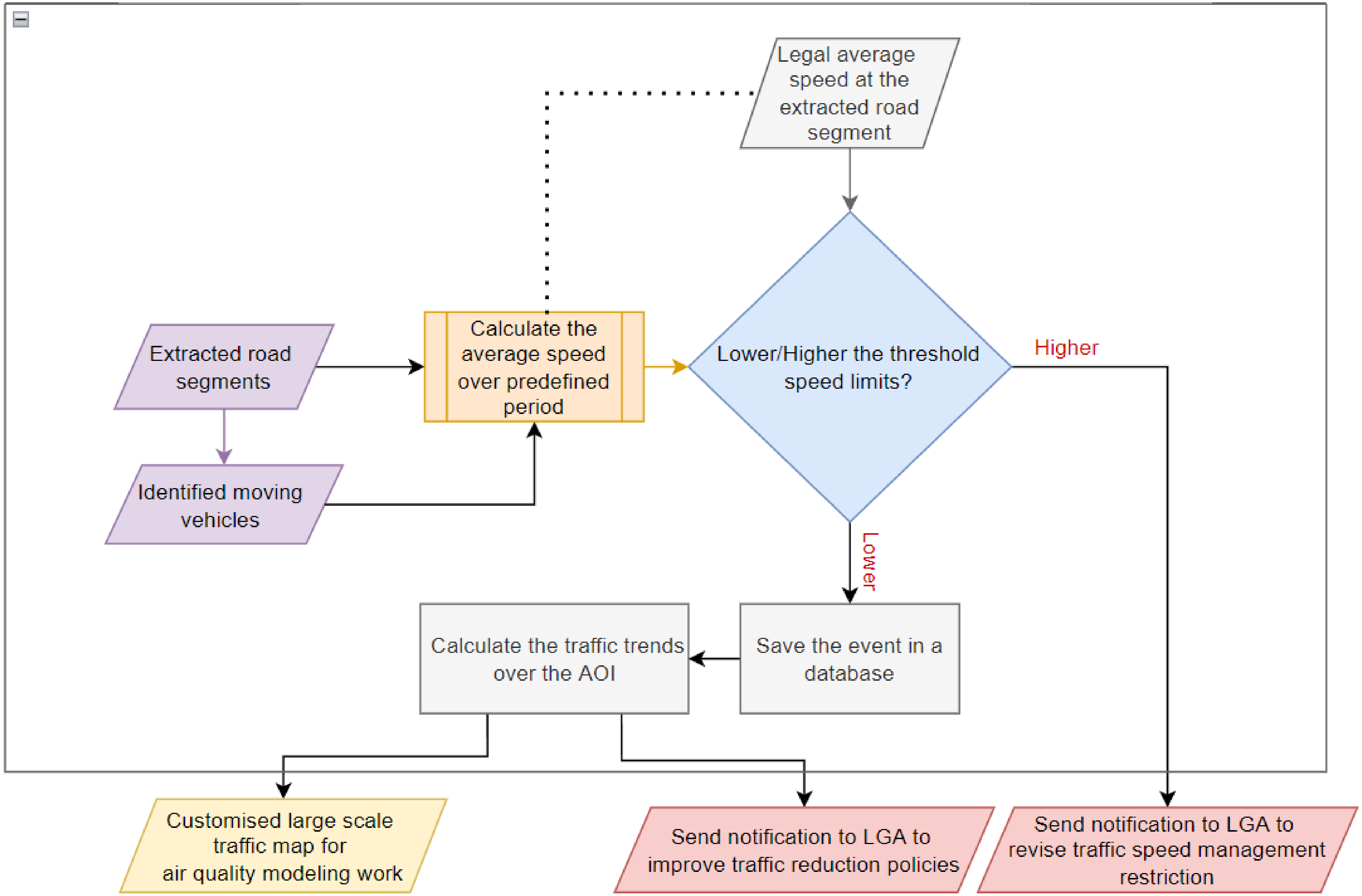
Vehicles detection and localisation



Data Analysis platform: Speed calculations and verification



Large scale roads traffic notification system:
Multi model Machine Learning Integration Stage

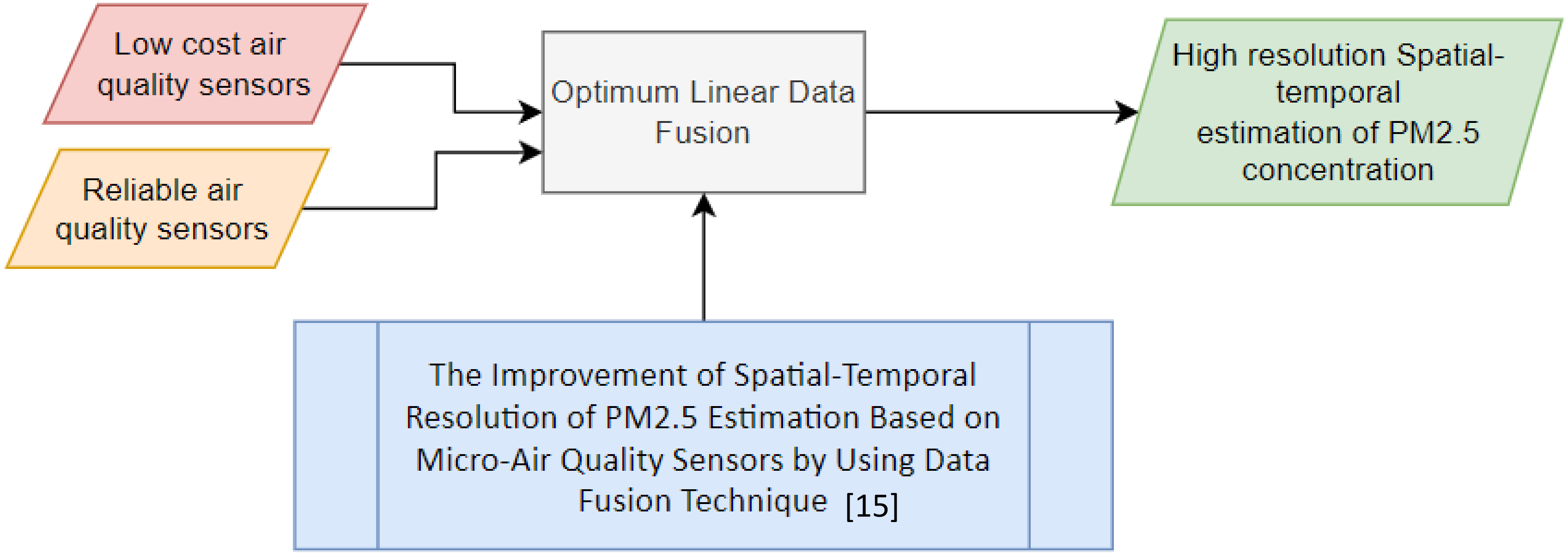


High spatial resolution air pollution prediction large scale map

- On site measurements stations/ **Lack of spatial coverage**:
  - On the Earth's surface, networks of measurement stations record the concentration of various chemicals predefined locations. Such networks are commonly run by environmental agencies and provide frequent measurements while often lacking in spatial coverage.
- Remote sensing spectrometers:

  The higher spatial resolutions could reach is **in kilometres range** and with little information about the pollutant's vertical distribution.

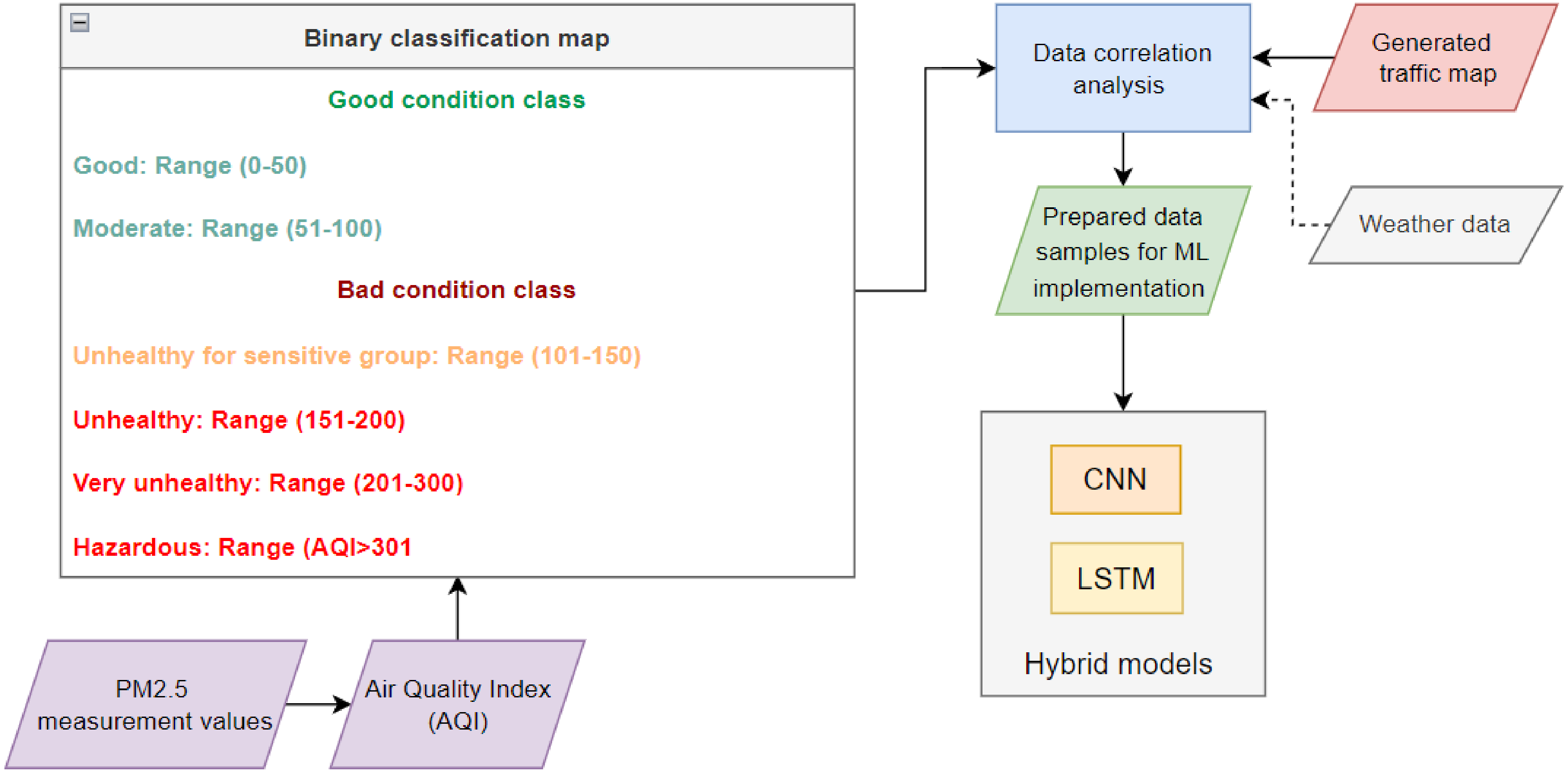
High spatial resolution PM2.5 data preparation



The comparison of basic statistics information of Taiwan EPA Monitoring Station and AirBox $PM_{2.5}$ concentration data from October 14 to 27, 2016. [15]

Variable	Unit	Range	Mean	St. Dev	Sampling Frequency	Number of Stations
$PM_{2.5}$(EPA)	μg/m^3	[2.0, 142.0]	20.985	17.064	1 h	74
$PM_{2.5}$(AirBox)	μg/m^3	[1.0, 211.0]	36.430	23.585	5 min	1176

Use case for air pollution estimation research



Conclusions

- Manage traffic and estimate automobile emissions: Using satellite data with machine learning could provide more reliable decision support ability to address air quality prediction issues.

- With the advancements of satellite remote sensing sensors and ML algorithms in remote sensing industry, the automation of features extraction from spaceborne data could be a valuable input source in the following domains:
  - Large scale traffic monitoring systems.
  - Air pollution forecasting systems.

Thank you

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