THE ART OF ROUGHNESS: AI FOR HIGH-PRECISION MODEL DEVELOPMENT

J Maultby[1], **A Mosely[2]**, Hester van Zijl[2], Richard Corbett[1]
[1]AECOM Australia Pty Ltd, Rockhampton, QLD
[2]Moreton Bay Regional Council, Strathpine, QLD

Abstract

Development of roughness and imperviousness data for flood modelling presents a tedious, time-consuming challenge. These inputs directly influence simulated flood behaviour and risk analysis. As such, their preparation must be given due care to avoid error and bias. Traditionally, practitioners have manually digitised landuse features with low detail and abundant inconsistency. Manual approaches also rely on the assumption that visually dense canopy correlates with dense understory.

Moreton Bay Regional Council (MBRC) acquired new aerial imagery and LiDAR in 2019. Rather than manually update regional models, MBRC engaged with AECOM's specialists to develop a data-driven, high value method for the definition of land use layers. The team made use of technological advances in GIS and Artificial Intelligence (AI) to automate preparation of these crucial layers.

AI was used to delineate features such as building extents, roads and vegetation with high precision and minimal bias at a massive scale. Critically, the project team developed a new approach that uses x-ray vision (literally) and point cloud data science to calculate vegetation density below the canopy. This new approach was successfully ground-truthed and significantly improves Council's understanding of hydraulic roughness where flood waters traverse.

These new regional databases (landuse, fraction impervious, hydraulic roughness) boast a 1m resolution and span 2,500km^2 of the LGA, promoting consistent model practice throughout the region. The project demonstrates that harnessing the full potential of GIS and AI in flood modelling is key to our industry's future. It also highlighted the discrepancy between traditional and new approaches to fraction impervious estimation and the follow-on effect for hydrograph estimation.

This paper will discuss the methods used for creating MBRC's new regional databases, the positive impacts of the approach for Council, and the opportunities available for the broader industry.

Introduction

Practitioners within the floodplain management industry all recognise the trend towards ever-more detailed flood modelling, supporting increasingly detailed queries on floodplain infrastructure function and emergency management methods. In discussing the philosophy of hydraulic modelling, Australian Rainfall and Runoff (ARR) guidelines note that, “use of the most sophisticated modelling approach available will not, in itself, guarantee success” for several reasons, including that “the quality of the data used as model input can be equally (or even more) important in determining the success of a modelling exercise” (Book 6 4.1, ARR19).

Traditional approaches to creating landuse input layers and parameters commonly sees a manual broad-brush approach based on comparatively coarse planning information and landuse assumptions. Refinements take the form of manual adjustment based on limited site verification, and is subject to human error, bias, and inconsistency. So, whilst model resolution (i.e. grid cell size) has seen rapid improvement over recent years, creation of land use layers and its derivatives (hydraulic roughness and fraction impervious) has not changed significantly. As the expectations regarding detailed model outputs increase, there is a need to develop a justifiable method for creation of improved landuse input layers which still respects time and budget constraints.

Moreton Bay Regional Council (MBRC) elected to challenge industry norms and collaborate with AECOM Australia Pty Ltd (AECOM) to implement a novel approach to their latest round of hydrologic and hydraulic model updates.

This paper will present the use of geo-AI (supervised machine learning and point cloud data science) in creating a new, scalable method for estimation of fraction impervious and hydraulic roughness distribution model input layers.

Project Background and Objectives

Moreton Bay Regional Council (MBRC) have developed an extensive and detailed Regional Flood Database (RFD), covering fourteen basins within the MBRC local government area (LGA). Developed in 2009 and updated in 2014 / 2016, MBRC’s region-wide library comprises coupled WBNM hydrologic and TUFLOW hydraulic models, which are primarily based on Australian Rainfall and Runoff 1987 (ARR87).

Release of the 2019 update to ARR (ARR19), together with LiDAR and Aerial Imagery collected over 2018-2019 across the region, meant the time was right for MBRC to undertake a major update to their RFD. MBRC have commenced the RFD update across three stages, as shown in Figure 1 below.

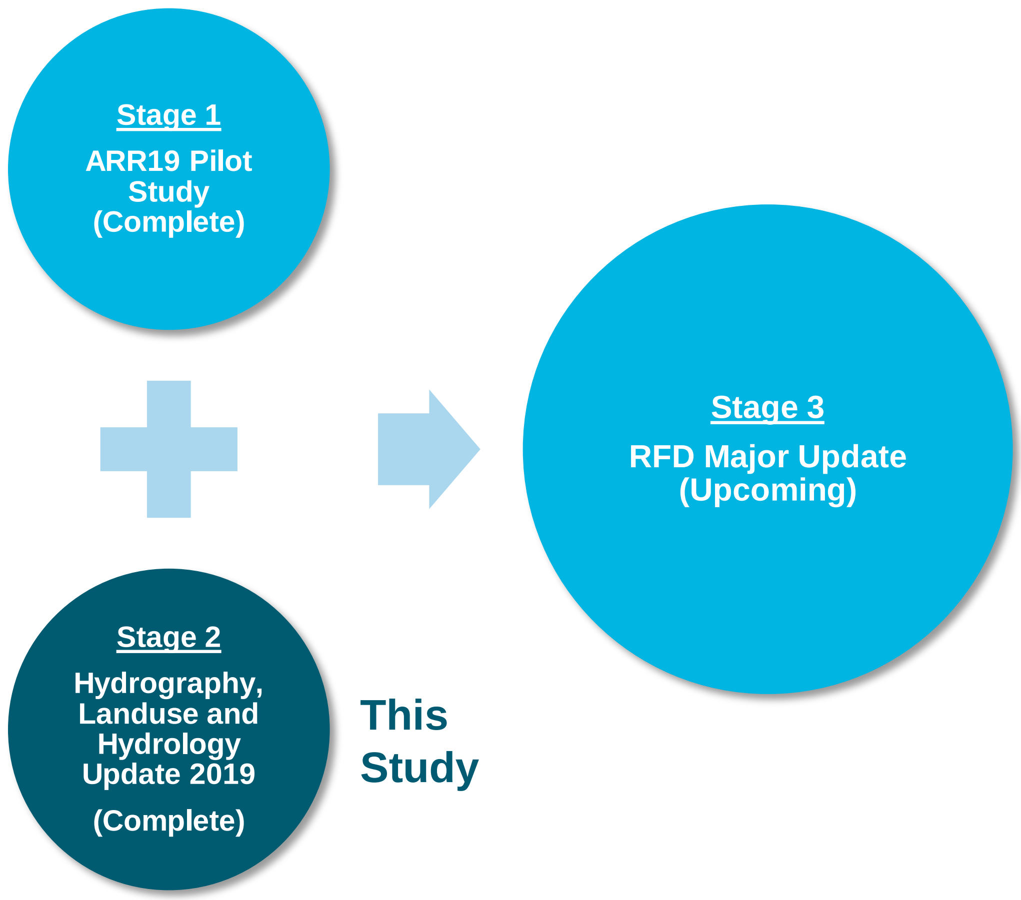

Figure 1 RFD Update Project Stages

In December 2019 MBRC engaged AECOM Australia Pty Ltd (AECOM) to undertake the RFD Hydrography, Landuse and Hydrology Update (Stage 2).

The key objectives of the Stage 2 works relating to this paper include:

- Updated Hydraulic Roughness – accurate representation of ground conditions and associated runoff characteristics is essential in preparing high quality hydrologic and hydraulic models.
- Updated Fraction Impervious (FI) – identification of imperviousness facilitates translation of rainfall to runoff across differing ground conditions.
- Updated WBNM Models – inputs from the above tasks will allow updates to existing hydrologic models across the MBRC local government area.

The focus of this paper is on the development of a detailed landuse database, which was used to construct hydraulic roughness / fraction impervious layers, and the effect of these updates on design hydrographs.

Technical Approach

The existing RFD models were based on older aerial photography and LiDAR data, with the hydraulic roughness and imperviousness layers largely manually digitised. At the time of project commencement, MBRC had recently received 2019 datasets of high-resolution aerial imagery, semi-classified LAS point clouds and a 1m LiDAR DEM. These databases were supplied to AECOM alongside MBRC's existing flood models and GIS databases.

The MBRC LGA is a broad expense with a total area (including external incoming basins) in excess of 2,500km^2. Land within the LGA sees a range of uses and natural conditions (e.g. coastal vs highlands), which called for a tailored approach to re-delineating land use. A precise, detailed land use database is the pivotal information required to re-delineate hydraulic roughness and fraction impervious.

To make best use of MBRC's available data, AECOM proposed implementation of Artificial Intelligence (AI) supported by other automated GIS workflows. This suggested approach posed both risk and reward;

- Traditional approaches (even with automated GIS feature extraction) weren't able to provide the level of detail required. Earlier independent research and development (R&D) by AECOM indicated that machine learning (ML – a subarea of AI) was able to achieve the level of detailed required at scale.
- Though ML could provide good results, it could also become unreliable when faced with new information (such as unidentified land uses).
- ML methods were limited to the quality of input data. Inconsistencies with shadows and tidal levels can introduce error or misclassification.
- A solution couldn't be initially guaranteed at the onset of the MBRC project, as a precedent in the hydrologic / hydraulic modelling field did not yet exist.
- AI approaches often cannot create a 100% solution. Rather, AI is best used with the Pareto Principle in mind – 80% progress with 20% of the budget. The remaining 20% can be achieved via other methods.

How Does AI Work?

IBM (2020) provides a good definition of AI:

> Artificial intelligence refers to the ability of a computer or machine to **mimic the capabilities of the human mind**—learning from examples and experience, recognizing objects, understanding and responding to language, making decisions, solving problems—and combining these and other capabilities to perform functions a human might perform.
>
> Think of *artificial intelligence* as the entire universe of computing technology that exhibits anything remotely resembling human intelligence.
>
> *Machine learning* is a subset of AI application that learns by itself. It actually reprograms itself, as it digests more data, to perform the specific task it's designed to perform with increasingly greater accuracy.

In short (from the Author's perspective), AI uses the efficiency of computers and the flexibility of applied mathematics to copy some of the simpler tasks human minds complete. Imperative to its task is good quality data, without which ML (or any form of AI) is of little use. The better the data, the more that can be done through AI to achieve project objectives (see Figure 2). Importantly, it's not only the quality of the data that matters, but also the way in which it is used.

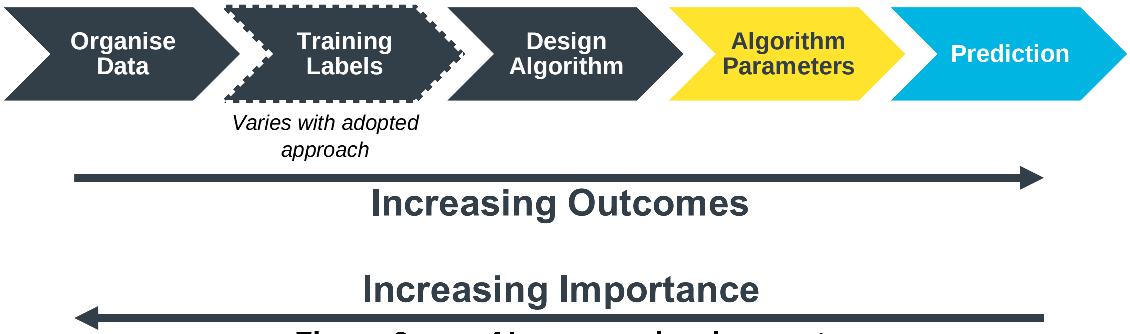

Figure 2 AI process development

Training Labels

Commonly heard in the modelling world is the catchphrase "garbage in = garbage out". Indeed, AI is more reliant on good input data than any predecessor. The type of ML applied in the MBRC project scenario is 'supervised' ML. This method uses a handful of pre-defined labels (e.g. 'this is a house') to guide the algorithm as it teaches itself to mimic human processes.

The other type is called unsupervised ML, which is able to detect patterns in data (such as types of land use classifications) by itself (almost)! For the MBRC project, the right tool was supervised ML, which gave better control over the results and allowed for adoption of consistent land use classes as previously used within the RFD.

As mentioned above, supervised ML methods require a training dataset. This training dataset is what the algorithm uses to construct itself and replicate the process at larger scales. In this project, in the order of 1,000 land use samples were collected and labelled to inform the algorithm. These samples were used to define specific land use classes, such as 'vegetation' or 'road' (see Figure 3).

Figure 3 Land use training dataset example

The area captured under each label is used by the algorithm to link data characteristics (such as Red-Green-Blue patterns) to land use classes. When using aerial imagery as the input training data, the algorithm has to struggle against clouds, shadows, variable lighting and changing tides. Whilst human minds are able to readily recognise and factor in these variables, the endless combinations introduce confusion for the algorithm. More often than not, this causes the algorithm to predict the wrong land use class.

To combat this challenge, AECOM made use of the LAS point cloud to construct a Digital Surface Model (DSM). A DSM follows the shape of the highest feature as the crow flies – in other terms, it follows the tree canopy and tops of buildings, rather than the underlying land. LiDAR DEMs as floodplain practitioners know them are Digital Terrain Models (DTM), and better represent where surface water traverses. When we minus the DTM from the DSM, we get a 'normalised DSM' (nDSM) (see Figure 4). This nDSM is able to describe the heights of each feature on the ground (such as a building) and changes the units from mAHD (absolute) to m (relative).

A secret to the MBRC project method's success was the use of aerial imagery, combined with an nDSM, to create a robust dataset with which to train the model. The combination of both datasets allows each land use classification to have four unique characteristics:

1. Red (R) colour band
2. Green (G) colour band
3. Blue (B) colour band
4. Height above ground

In this way, complexities such as buildings with dark rooftops can be separated from roads by the height band. Similarly, open spaces can be separated from roads and concrete by the R-G-B combination.

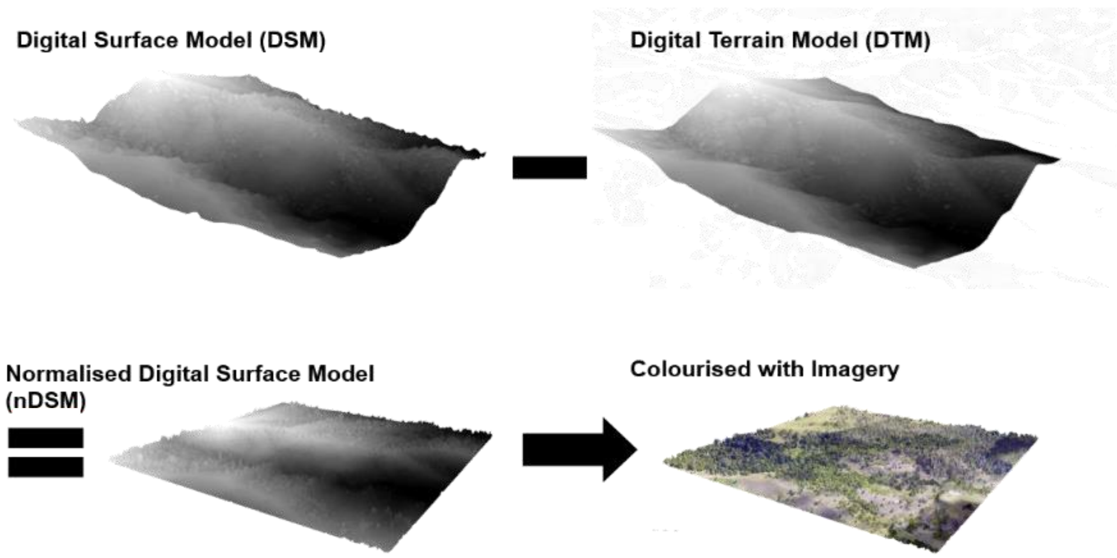

Figure 4 Training data preparation

Algorithm Selection

An important step in implementing AI is selection of an appropriate algorithm. Choosing a less applicable algorithm can result in very limited outputs or long computation times. Some algorithms are also more suited to a particular task or type of data.

Aerial and LAS datasets are 'noisy' by nature. This means the data can have significant amounts of unseen variability or meaningless information. Based on previous R&D, AECOM adopted the Random Forest algorithm for the MBRC project. This algorithm entails a vast quantity of decision trees (Figure 5) that operate as an ensemble being simultaneously applied and compared to give the most probably output (Figure 6).
Since this method uses a 'most likely' method to predict the result, the answers are generally more explainable. When the answer isn't what we expect it to be, there is usually an obvious reason (such as 'the colour combination is very similar to another land use class').

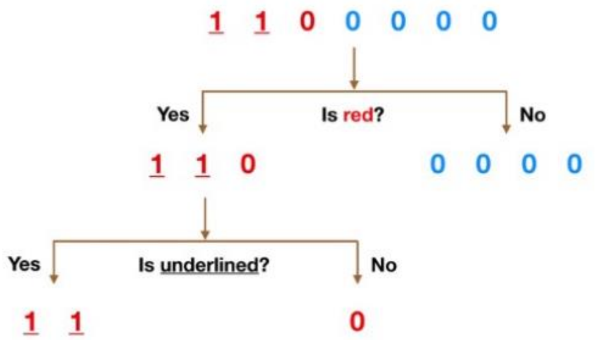

Figure 5 Simple decision tree example (towards data science, 2019)

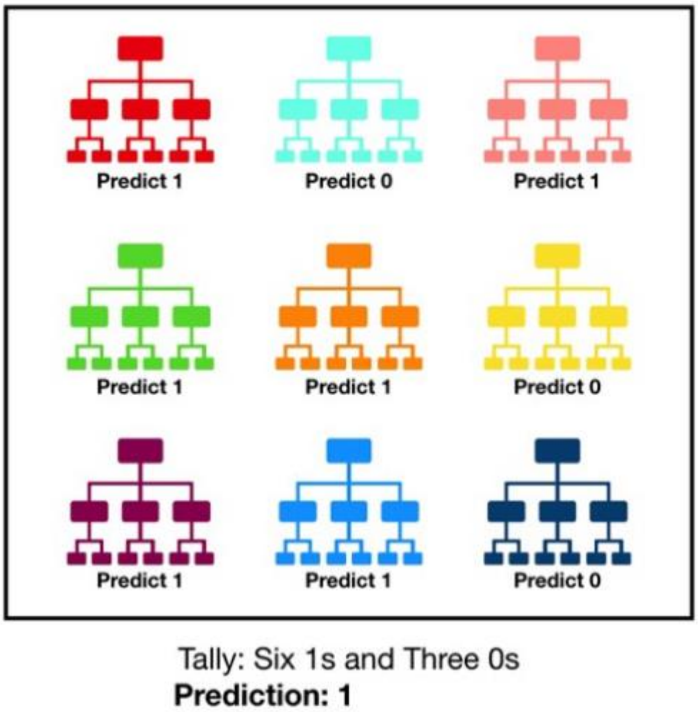

Figure 6 Simple visualization of a Random Forest model making a prediction (towards data science, 2019)

Algorithm Parameters Prediction

Once the algorithm type and its boundaries (such as the number of decision trees) have been set and the training labels are prepared, AI is able to ‘take control’ and design the algorithm parameters in such a way that it can replicate the process at scale. ArcGIS Pro, which was used for the MBRC project, has a suite of pre-programmed tools that automate this process with minimal input. These tools also reduce the need for complex coding capabilities, opening this technology to a considerably broader audience of professionals.

Once parameters have been determined, the output model (i.e. the parameterized Random Forest algorithm) can then be applied to larger datasets to predict the land use in a consistent manner. These results are then reviewed manually to check for errors and identify opportunities to improve the outputs. This output takes the form of a gridded raster which can then be post-processed further to be made appropriate for uses like hydraulic roughness delineation and fraction impervious.

Staged Delivery

To overcome some of the technical challenges and uncertainties, the project team elected to adopt a staged approach to delivering an updated land use database and associated derivatives. This allowed AECOM to develop and refine their methodology whilst collaborating with MBRC to ground-truth outputs, enabling improvements with each iteration.

Staged application of the proposed approach took shape across three phases:

1. Proof of Concept – demonstrate viability of the proposed approach through application to local conditions and datasets (applied to approximately 0.2% of the project area).
2. Basin-Scale – increase scale to a full basin to validate the process independent of ‘training locations’ (explained later) and allow for detailed ground-truthing (applied to 2% of the project area, or 10x the proof of concept area).
3. LGA-Scale - increase scale to the full LGA using refined, validated process.

Land Use Database Development

Phase 1: Proof of Concept

Prior to accepting the supervised ML approach for the Stage 2 project, MBRC and AECOM agreed to undertake a proof of concept process at six locations of varying land use in the LGA (roughly xxkm2 in area each). These locations included:

- Residential
- Industrial
- Rural
- Coastal
- Estuarine
- Highlands

Each of these locations were used to train the AI to identify basic land use classes (such as buildings, roads, vegetation etc.). At first, only aerial imagery was used as input data. As noted above, this proof-of-concept process quickly identified deficiencies in the outputs, leading to the use of an nDSM as well as aerial imagery as input data. Immediate improvements in the clarity between predicted land use classes were realised in the predictions.

At this point in the process, the algorithm was able to develop land use outputs at a rate of 42 seconds per km^2. Proof of concept outputs for rural and industrial areas are shown in Figure 7 and Figure 8.

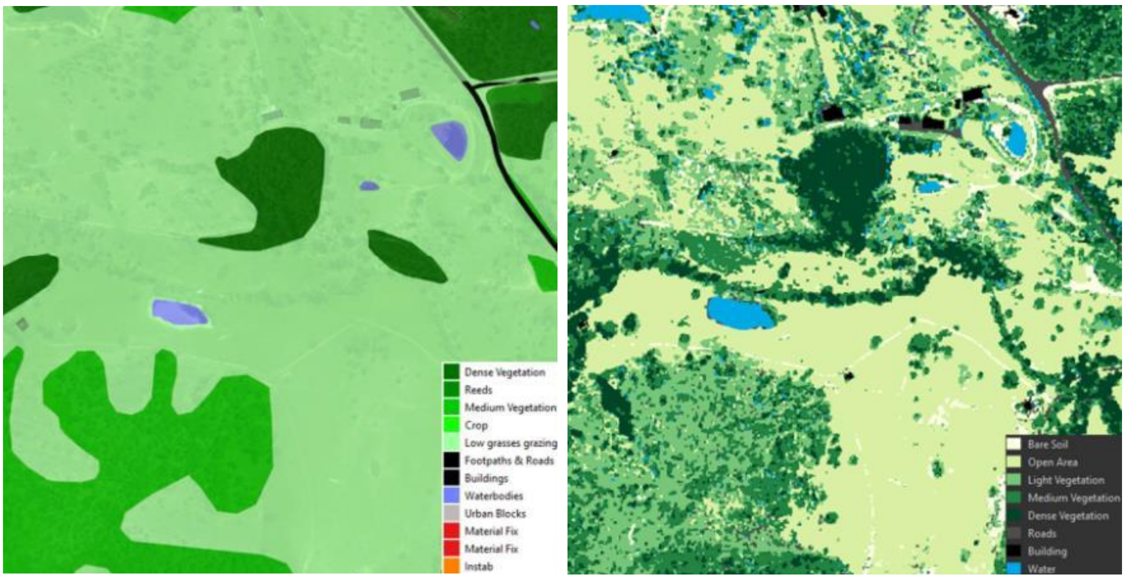

Figure 7 Pilot Study Sample – Rural (LHS – Previous Land Use | RHS – Predicted Land Use)

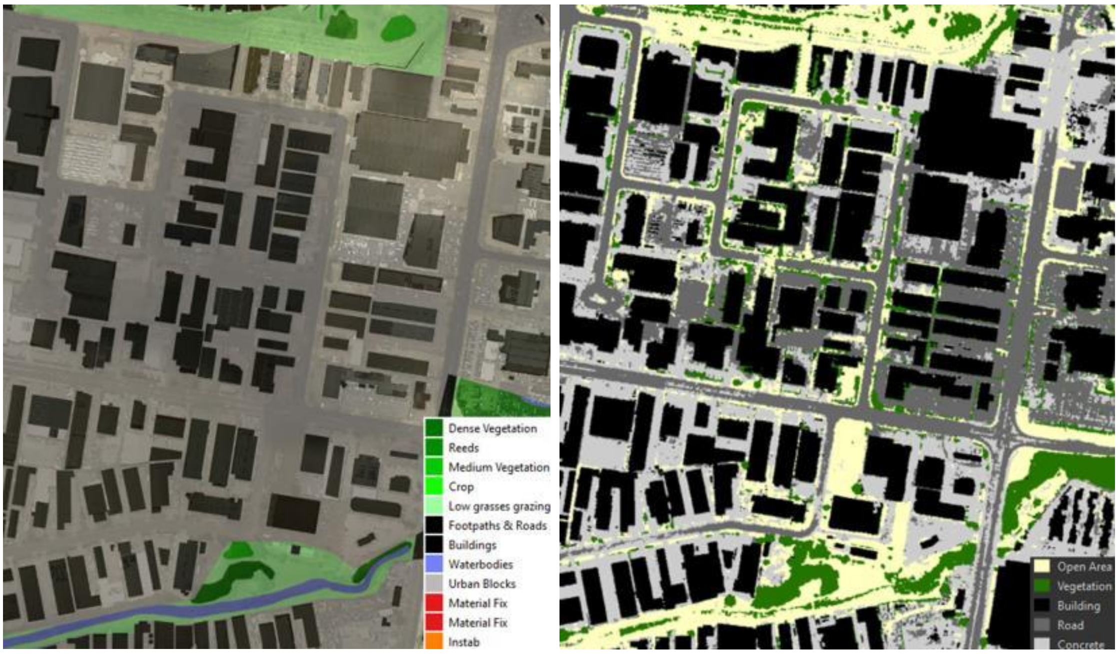

Figure 8 Pilot Study Sample – Industrial (LHS – Previous Land Use | RHS – Predicted Land Use)

MBRC and AECOM staff attended a site visit at each of the pilot study areas to ground truth the predicted land use outputs and note discrepancies. From these visits it was concluded that the process gave reasonable results and was worth pursuing further, though noting low-medium-high vegetation classification did not always correlate with the observed vegetation understory density, and 'noisy pixels' (speckling) should be managed carefully in post processing.

Phase 2: Basin-Scale

The approach used to undertake the proof of concept was scaled up and applied to the ~40km^2 Brisbane Coastal Creeks (BCC) basin. The Random Forest algorithm was re-trained based on learnings gathered from the proof of concept process. Improvements took the form of better consistency in training samples (which reduces confusion and incorrect predictions), and a larger range of land use classes. Shadows were also captured as their own land use class, to prevent misclassification as 'roads' or 'buildings' in undeveloped, vegetated areas.

Post-processing was then applied to carefully filter out noisy pixels and simplify boundaries between land use classes; for instance, smoothing edges of roads and buildings towards a more realistic, sensible shape.

Excluding process refinements and data preparation, the land use for the BCC basin (Figure 9) was predicted and post-processed in less than two hours.

Figure 9 BCC basin scale land use prediction

Ground truthing was again undertaken for the revised prediction. Site visits in this implementation phase focused on vegetation and found the following:

- Singular tall trees were classified as mixed areas of high/medium/low vegetation, with the 'high' areas being the tallest part of the canopy and 'low' areas being the fringes of the leaves. Whilst this somewhat correlates with the greater vegetation density being centred around the tree trunk, it was apparent the classification reflected canopy conditions more so than ground conditions (ground conditions being of greater importance to hydraulic modelling).
- Multiple examples of areas with tall trees but limited undergrowth (e.g. urban trees) being classified as 'high' vegetation were noted.
- Multiple examples of areas of very dense reeds/long grass being classified as 'low' vegetation were noted.

Consequently, the project team concluded that, whilst non-vegetation land use classes were suitable to take forward, more confidence was desired concerning vegetation. MBRC posed the question:

"Are there some additional smarts we could apply to the process to achieve better representation of vegetation understory density?"

A Novel Method to Understory Density

A new approach was developed to better estimate vegetation density close to the ground where water flows. The logic behind the new approach drew on an intrinsic understanding of multi-return point cloud data. LiDAR is able to penetrate all but the densest of tree canopies and will return a number of locations throughout the vertical plane. For standalone trees, almost the full tree structure can be appreciated when viewing the LAS point cloud in a 3D workspace. Similarly, a dense understory will show a maze of points as they intersect low-profile branches and shrubs (see Figure 10).

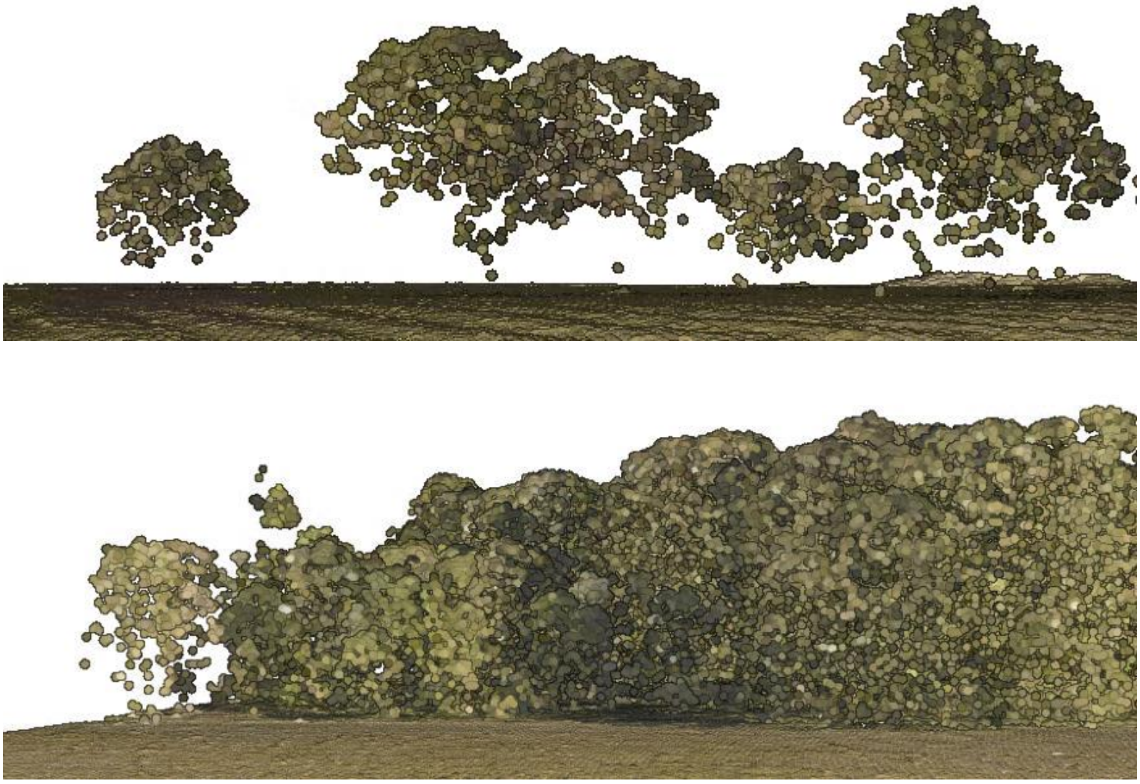

Figure 10 Point cloud data for standalone trees (top) and densely vegetated areas (bottom)

To make best use of this valuable information, point cloud data science was employed to compare the quantity of low-lying (i.e. within 2m above ground) vegetation points against ground points in a specified area. Where most points in the area were vegetation, it could be assumed the vegetation was medium to high density. Where most points in the area were ground, it could be assumed that the vegetation was low density or predominantly open space (which was the case for isolated trees with no underlying vegetation).

This new method of quantifying vegetation density classes was applied to the 350km^2 Lower Pine River (LPR) basin which features a range of vegetation types (such as mountainous, urban, riparian, aquatic). To validate the AI classification of vegetation, MBRC undertook several site visits within the LPB basin, with focus on visiting:

- Areas within the catchment known to have been previously miss-classified by the manual classification method owing to hydraulic model calibration challenges.
- Areas with different types of vegetation e.g. eucalypt bushland vs weedy urban creek vs native forest.
- Areas known to have dense vegetation with different canopy heights e.g. dense grass/reeds vs dense native bushland adjoining creek.
- Areas classified as dense and light mangrove, to justify multiple mangrove classifications.

During the field inspection, the new classification of the locations was assessed using a simple ranking system (good, fair, poor). MBRC staff feedback confirmed that the new classification was achieving very good classification of the relative vegetation density beneath the canopy, with 85% of sites achieved a ‘good’ or ‘fair’ score.

The 15% of ‘poor’ locations resided where LiDAR was unable to effectively penetrate the tree canopy. Assumptions (which were agreed with MBRC) had been built into the automated process to overcome data limitations in a consistent, reasonable manner. To assist MBRC in developing confidence in future hydraulic modelling, locations where these assumptions were applied were mapped in a shapefile, to allow sites to be visited and manually checked in the future, particularly within sensitive regions in the catchment.

With respect to the mangrove regions, the site visit made it abundantly clear that there were indeed areas of more-dense mangrove, and areas where the mangrove species were taller with the canopy extended largely outside the waterway. This supported the proposed density classifications for the mangrove areas.

Ultimately, the project team agreed the novel approach to estimating vegetation density for the purpose of hydraulic roughness was dependable and suitable for application to the broader LGA. Figure 11 presents a sample of the outputs from both ‘as the crow flies’ and ‘as the water flows’ perspectives.

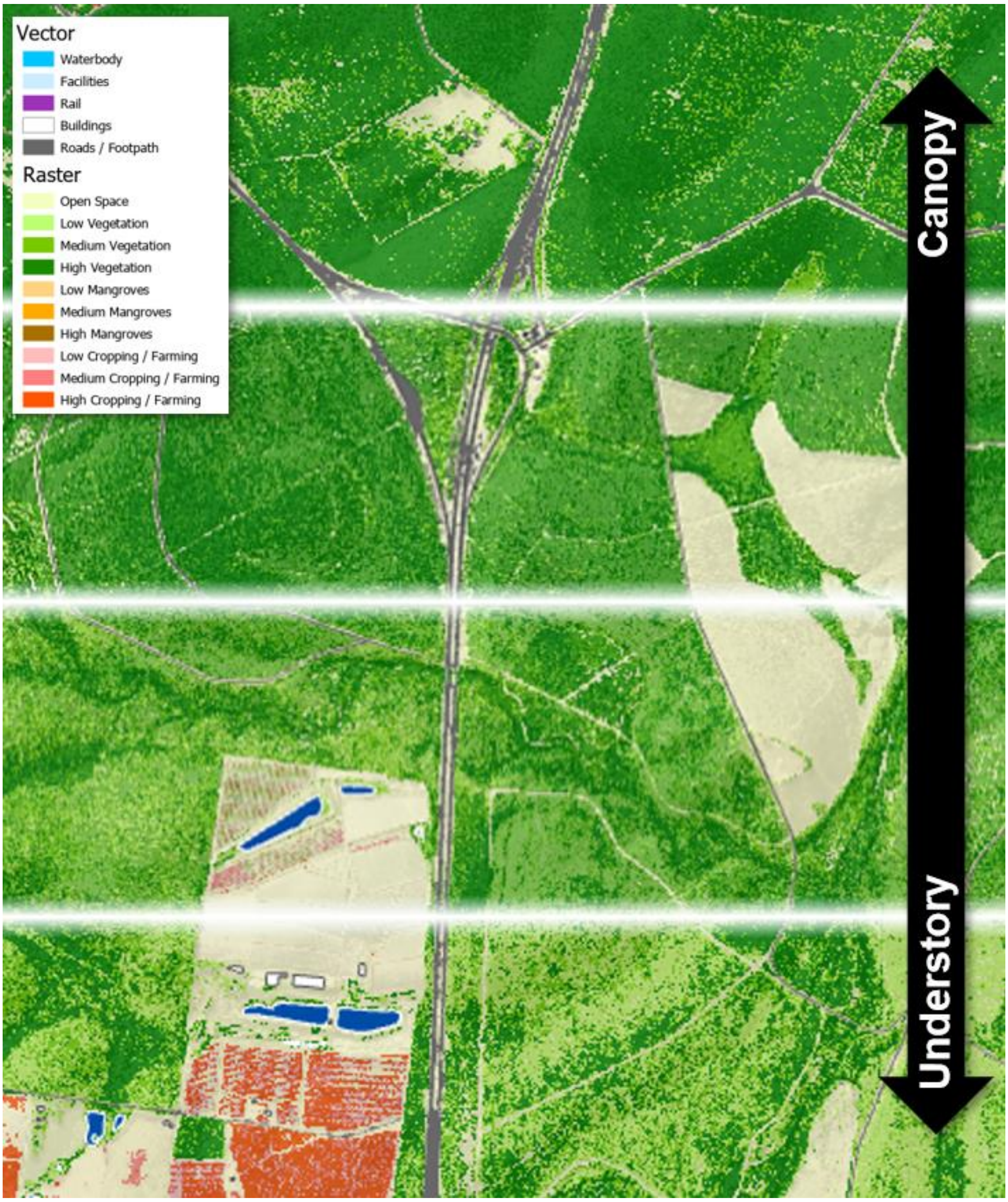

Figure 11 Vegetation classification sample

Phase 3: LGA-Scale

The final Random Forest algorithm, together with the point cloud data science recipe for vegetation understory density and post-processing, were applied to the full LGA. Initial outputs (before post-processing) for the 2,500km^2 area were computed in approximately 32 hours, with the final product being completed in approximately 72 hours. Figure 12 presents the final land use database.

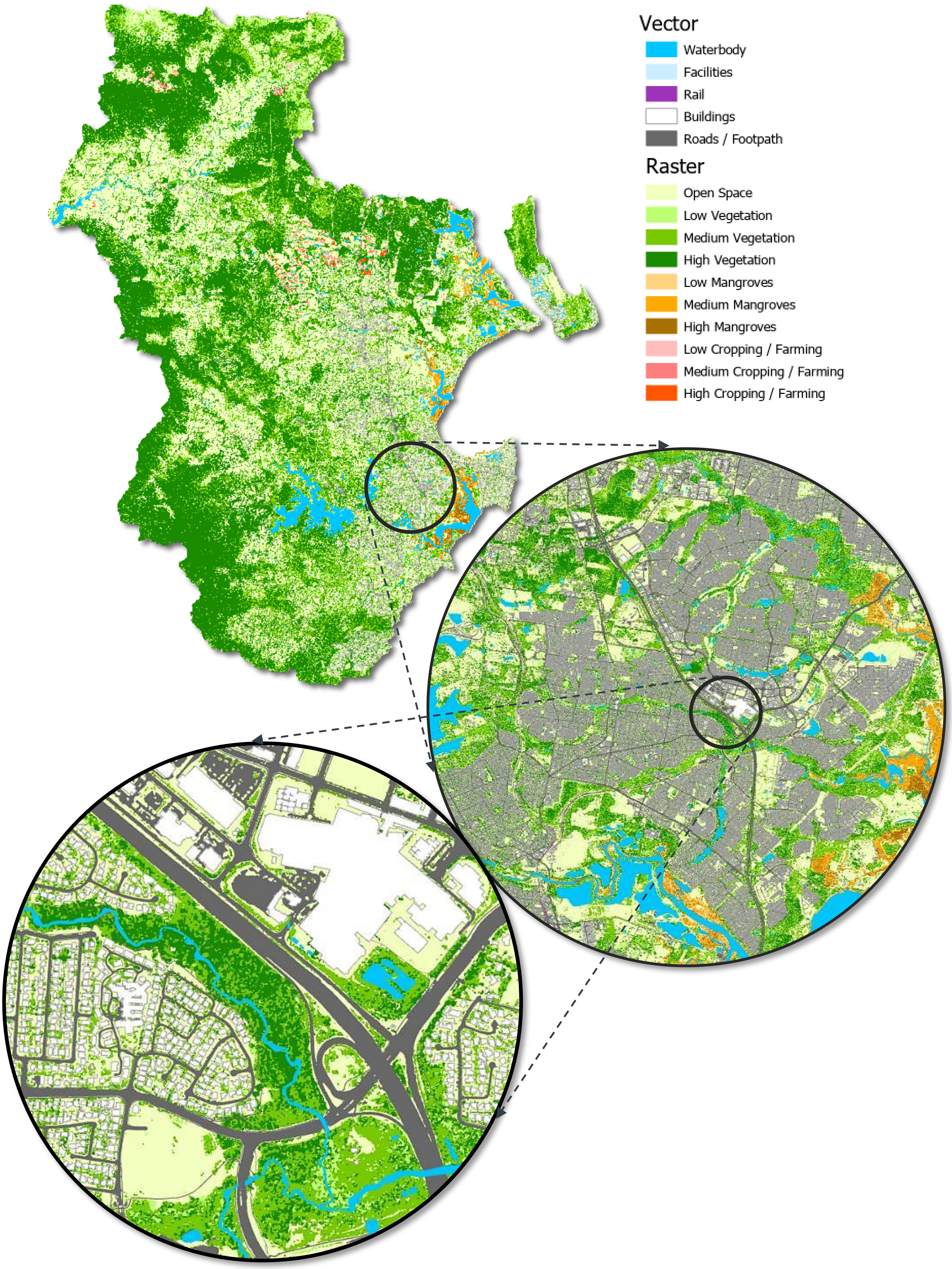

Figure 12 Final MBRC LGA land use database

Fraction Impervious Layer Development

Each land use class was assigned an agreed FI in order to create an LGA-wide database;

- Buildings (100% impervious).
- Roads (100% impervious).
- Facilities, e.g. tennis courts (100% impervious).
- Concrete, including footpaths and carparks (100% impervious).
- Waterbodies (100% impervious).
- Railways (70% impervious).
- Open space / vegetation (0% impervious).

The resultant database (Figure 13) was created at a 1m resolution to match the precision of the land use database.

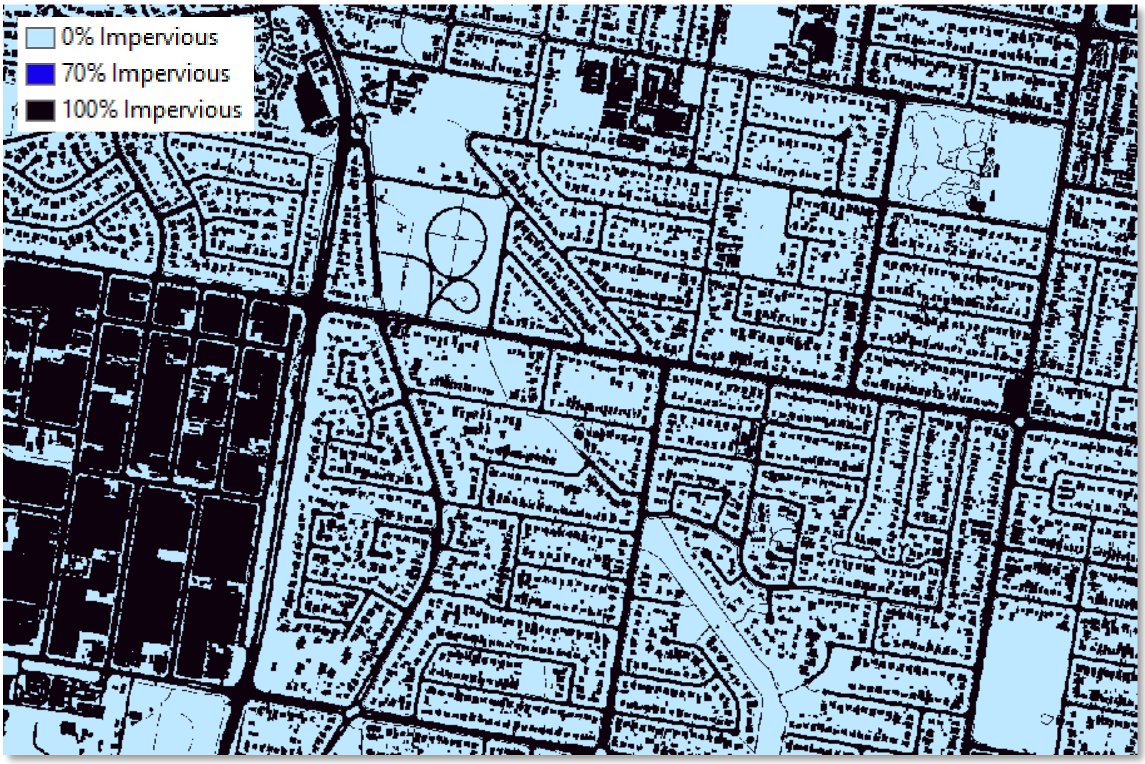

Figure 13 FI database sample

The FI raster was used to quantify the mean FI within each subcatchment of the WBNM models (some 6,634 subcatchments). Each of these polygons was compared to the previously adopted FI developed based on 2009 planning and GIS databases.

The comparison (Figure 14) revealed several key observations:

- Changes in FI by ±70% or more were observed where development has occurred, or a waterbody extent had been corrected from pervious to impervious.
- Significant increases to FI (e.g. >20%) were observed where development has occurred, or a waterbody extent had been corrected from pervious to impervious.
- Moderate increases to FI (e.g. 10-20%) were observed where urban density has increased, or where the AI-based approach had identified sheds, paved areas or other impervious areas not previously defined.
- Decreases in FI were generally within rural areas or water storages where the storage level has decreased between this assessment and the previous.
- *Estimates of FI in urban areas are generally 5-10% higher than previous assumptions. For example, FI in Redcliffe increased by an average of 8.7%.*

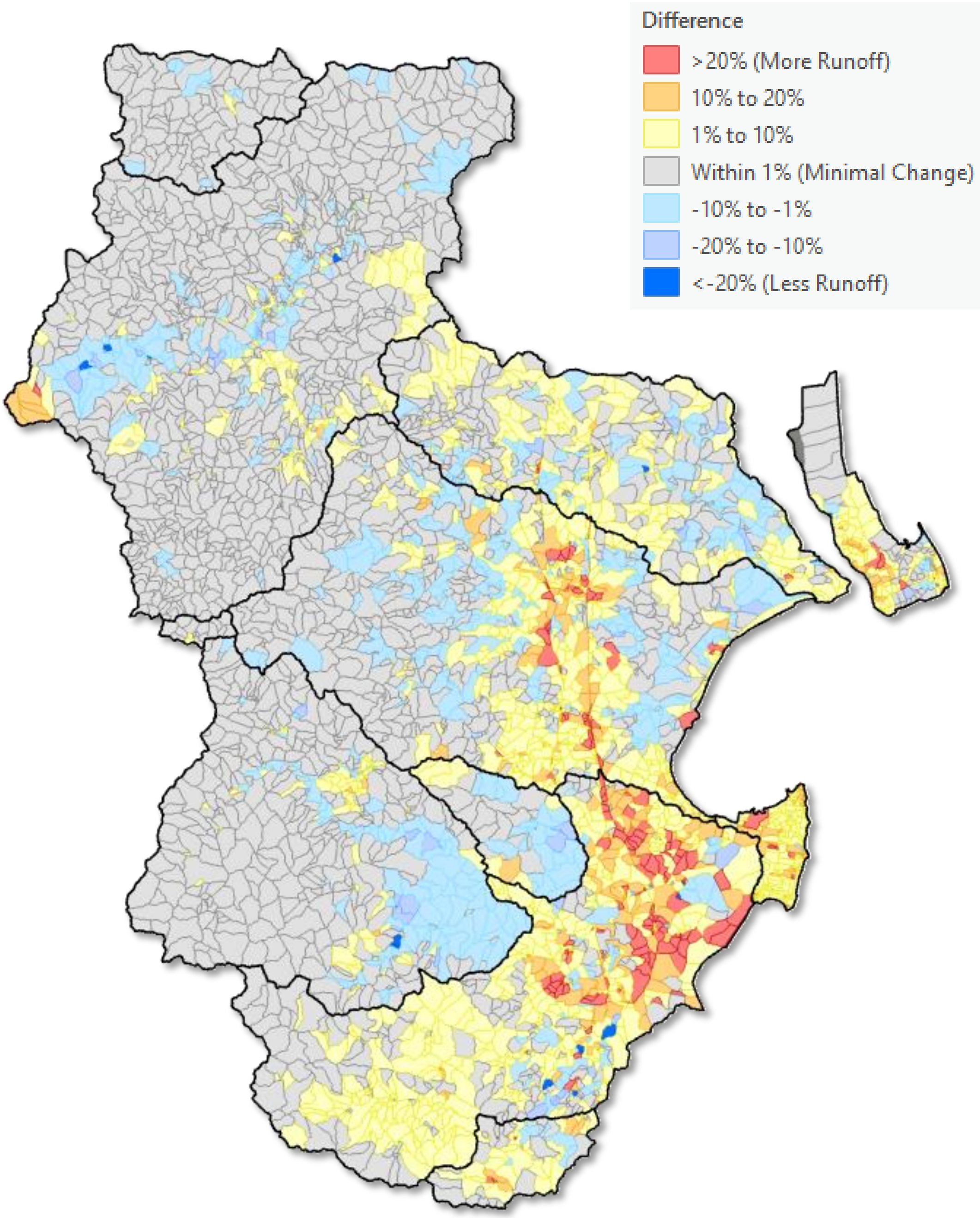

Figure 14 FI change between 2009 and 2019 assessments

Hydrologic Sensitivity Analysis

Finally stages of the project included sensitivity analysis of the new databases on design hydrographs at key locations throughout the LGA. A specific example of Walkers Creek in Redcliffe (a suburb where the FI estimate increased notably) has been included for the purposes of this paper.

The Walkers Creek catchment includes a range of urban topologies, including dense residences, commercial precinct, open parklands and transport corridors. An average FI of 32% was previously estimated for this catchment. Based on the 2019 datasets and AI approach, the average FI has increased by 10% to 42%.

The increased FI results in an accelerated flood wave, 22% increase to peak flow and 18% increase to runoff volume for the 5% and 1% AEP design events.

Whilst this magnitude of increased FI was not always seen, it demonstrates the sensitivity of model results to parameters such as FI.

It is noted that this hydrologic sensitivity calculation was a straightforward like-for-like assessment utilising the RFD WBNM models, with only the FI updated. ARR2019 provides new guidance regarding Effective Impervious Area, which may impact upon the way FI layers are incorporated into the RFD models. Nonetheless, the observed outcomes of the sensitivity calculation demonstrate the importance and potential impact of improved FI layers.

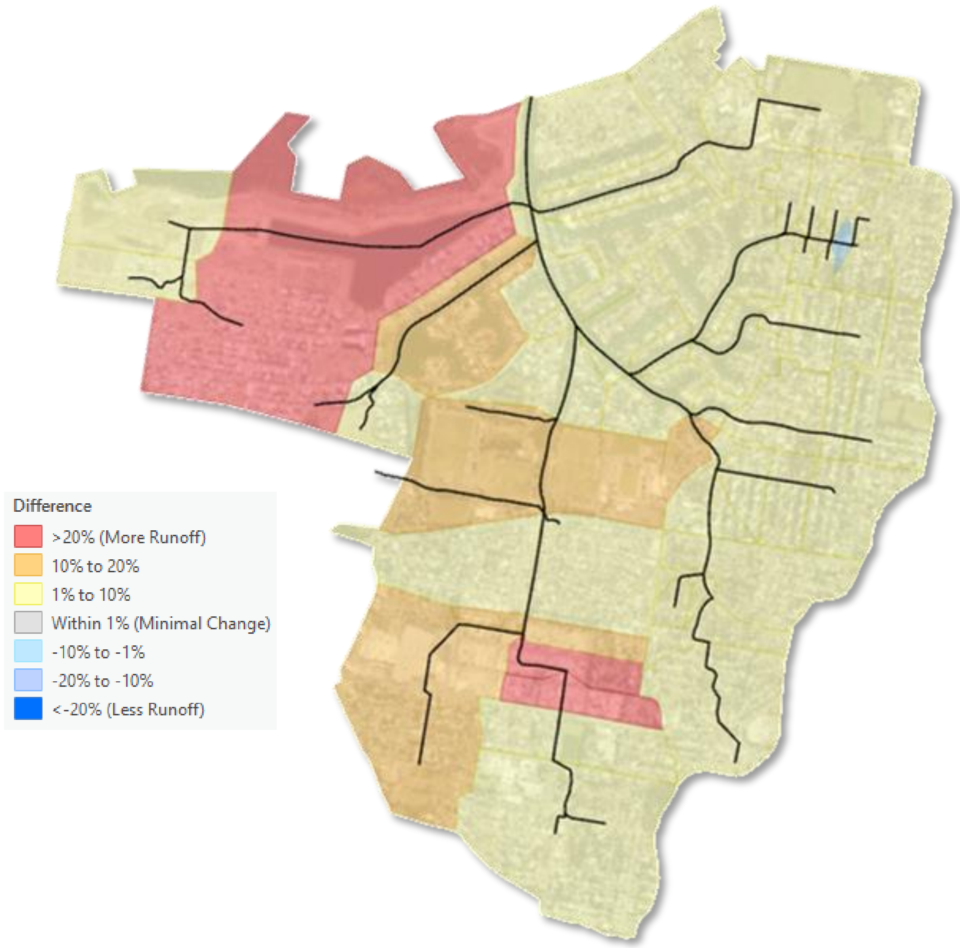

Figure 15 Walkers Creek (Redcliffe) catchment change in FI overview

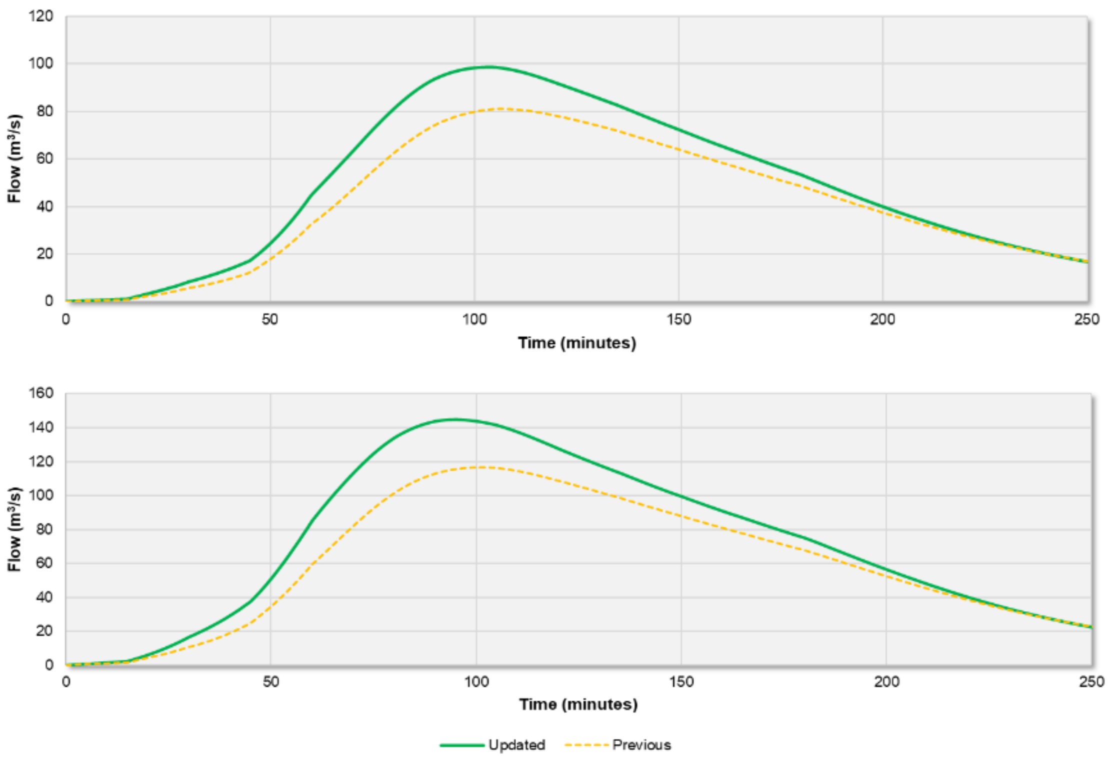

Figure 16 **5% AEP (top) and 1% AEP (bottom) ARR87 design events hydrographs**

Future Considerations

A persistent challenge exists within the industry regarding the engineering judgement applied in selecting an appropriate Manning's n roughness value for vegetation. When viewing vegetation from an aerial perspective, an engineer or AI program was often left to assume that a visually dense or high canopy correlates to a high hydraulic roughness value. Site visits have typically been used to verify and justify assumptions in critical locations, but time and budget constraints limit possible visits when points of interest are spread across an entire local government area.

The AI based methodology employed for this MBRC project offers the opportunity to greatly decrease potential inconsistencies in selection of Manning's n roughness values. The method allows quantification of understory density. Calibration of hydraulic models could hence eventually support correlation of Manning's n roughness values with AI determined understory density. The potential thus is to reduce reliance on engineering judgement of roughness based on a visual assessment of vegetation density at a few selected sites and move to numerically supported method consistent across an entire catchment or LGA.

Future MBRC projects will see the developed land use database and vegetation densities used to construct 2D material files of hydraulic roughness distributions for TUFLOW. MBRC expect differences in hydraulic calculations associated the new roughness layers and will use calibration to establish appropriate parameters for each class. Based on AECOM's experience in other locations throughout ANZ, it is expected calibration of the new roughness layers will allow for a closer match to historic flood events due to the increased precision and minimal human bias.

Regarding imperviousness, as demonstrated by the MBRC project, traditional approaches to estimated FI (especially those based on block-level planning information) cannot be expected to capture the local characteristics of significance within a catchment. Consequently, progress within the modelling industry calls for better methods to estimation of these crucial parameters to ensure models can be better understood, defended and utilised.

With the rise in high precision urban modelling and introduction of Quadtree and Sub-grid Sampling, there is a need to give some well-deserved TLC to hydraulic roughness and fraction impervious inputs. Based on our experience to date, a sustainable way forward can only be achieved by harnessing new technology (such as AI) and the value of raw data (such as LAS point clouds) to enhance how we model.

As Curtis Stone puts rightly, '*If you use quality ingredients, you don't need anything fancy to make food delicious*'.

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