Establishing New Zealand's LUCAS 2020 Land Use Map

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Establishing New Zealand's LUCAS 2020 Land Use Map

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Summary

Project and client

Underpinning New Zealand's reporting of greenhouse gas emissions is the Land Use and Carbon Analysis System (LUCAS) Land Use Map (LUM). This is a national digital temporal map of land use and land use change compiled for nominal dates beginning at 31 December 1989. This report describes the delivery of a new LUM, dated nominally at 31 December 2020.

Manaaki Whenua – Landcare Research (MWLR) (the Supplier) were contracted to deliver a new 2020 LUCAS Land Use Map (LUM 2020) for New Zealand to allow the Ministry for the Environment (MfE, the Client; and hereafter referred to as 'the Ministry') to calculate how greenhouse gas emissions are changing as a result of land use change. The four previous LUCAS digital land use maps (1989, 2007, 2012 and 2016) were procured from the Supplier. The Ministry requires the LUM 2020 to provide a consistent addition to the time series of land use change to underpin New Zealand's international greenhouse gas reporting under the United Nations Framework Convention on Climate Change and the Kyoto Protocol.

LUM 2020 is an update of the established 2016 Land Use Map (Newsome et al. 2018). It embodies land use change that occurred between nominal mapping dates of 31 December 2016 and 31 December 2020. These changes are identified using dated national satellite image mosaics based on Sentinel-2A (Sentinel-2B was launched in March 2017 and thus not available) imagery acquired in the summer (October–March) of 2016/17 and then based on Sentinel-2A and Sentinel-2B imagery acquired in the summer (October–March) 2020/21. Other afforestation and deforestation mapping provided to MWLR by the client is also to be incorporated into LUM 2020.

The contracted services included:

- a review of all areas currently mapped as forest in the 2016 LUM to improve the accuracy of forest mapping using deep learning techniques
- change detection between 2012 and 2016, in forest areas, to identify additional areas of deforestation and harvesting not previously mapped by the LUCAS programme
- incorporating mapping of areas of previously identified deforestation occurring during the 2016 – 2020 period into LUM 2020
- change detection between 2016 and 2020, to identify a range of non-forest change
- mapping new and updated areas of cropland, wetland and settlement into LUM
- undertaking targeted improvements to the 1990, 2008, 2012 and 2016 mapping data based on the Land Cover Data Base (LCDB5)
- Updates to grassland mapped based on methods developed for the 2016 LUM.

The Ministry required the services to be delivered in the form of both live edits to a geospatial feature service of LUM hosted by the Ministry and made accessible to the Supplier as well as bulk updates to an exported version of LUM provided by the Ministry.

Results and conclusions

- The LUM project comprised 16 mapping deliverables (listed in Appendix 1) with associated activities including: an updated 2016 LUM, the final 2020 LUM using both traditional and deep learning methods, and numerous intermediate products. All work was completed by 30 June 2023.
- Quality standards were adhered to (detailed within this report in tables 3-5 in section 4.5.).
- Image mosaics and control masks were delivered as specified by the Ministry.
- Interim spatial data was provided in an Esri file geodatabase format for provisional review by MfE. Final land use changes were edited directly into the Ministry's Esri web-feature service using ArcGIS Pro.
- We identified 5,581 ha areas of missed destocking. This resulted in a total of 256,536 Ha of destocking detected and mapped, across the 2017 to 2020 total time period, as at 31 December 2020 on mainland New Zealand.
- Of the 706,134 polygons in the improved and final version of LUM 2016 (Deliverable 7), 29,617 of these underwent land use change between 2016 and 2020. This included 9,596 attribute-only (tabular) changes where geometry (boundary) changes were not required.
- For the final LUM 2020 produced (Deliverable 14), 189,659 polygons (25%) had geometry updates applied, either because of land use change or polygon refinements to more accurately delineate land features. Attribute (tabular) changes occur as part of these edits to capture new land use classification as well as ensure the historic time-step details are accurate. This resulted in 733,867 polygons in the LUM 2020 final delivered version (Deliverable 14)[1].

Note: For results of the deep learning trial, please see section 4.2; full details of this are in a separate report (Martin et al. 2023).

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[1] Note that the first publicly released version of LUM 2020, scheduled for release in April 2024, will include further edits and enhancements completed by the Ministry.

1 Introduction

Increasing anthropogenic greenhouse gas emissions during the industrial era has led to atmospheric concentrations of carbon dioxide, methane and nitrous oxide that are at their highest level in at least the last 800,000 years. This, together with other anthropogenic drivers, is extremely likely to be the dominant cause of observed global warming since the mid-20th century (IPCC 2014).

The United Nations Framework Convention on Climate Change (UNFCCC) was instituted with the specific goal of stabilising greenhouse gas concentrations in the atmosphere at a level that would prevent dangerous anthropogenic interference with the climate system. New Zealand is a signatory to the UNFCC and the Paris Agreement. These agreements require New Zealand to submit an inventory of greenhouse gas emissions, annually and biennially, respectively.

Underpinning New Zealand's reporting of greenhouse gas emissions is the Land Use Carbon Analysis System (LUCAS) Land Use Map (LUM). This is a national digital temporal map of land use and land use change compiled for nominal dates beginning at 31 December 1989.

2 Project objective

The objective of the Manaaki Whenua – Landcare Research (MWLR) work described in this report is the delivery of a new 2020 LUCAS Land Use Map (LUM 2020) for New Zealand to allow the Ministry for the Environment (MfE, hereafter referred to as 'the Ministry') to calculate how greenhouse gas emissions are changing as a result of land use change.

Manaaki Whenua – Landcare Research has produced the four previous LUCAS land use maps (1989, 2007, 2012 and 2016), representing New Zealand land use at 31 December 1989, 2007, 2012, and 2016. The Ministry requires the LUM 2020 to provide a consistent time series of land use change to underpin New Zealand's international greenhouse gas reporting under the UNFCC and the Kyoto Protocol.

3 LUM mapping history 1989 – 2020

The LUCAS LUM is a key element of New Zealand's mechanism for calculating greenhouse gas emissions in the land-use, land-use change and forestry sector (LULUCF). This project required the production of a fifth time step – 2020 – to continue the regular time series from the 1989 benchmark.

The LUM covers all mainland New Zealand and offshore islands including the Chatham Islands, but not the more distant Kermadec, Auckland, Bounty, and Campbell Island groups, which are assumed to be in a steady state of land use. The map underpins New Zealand's international greenhouse gas reporting under the UNFCC and the Kyoto Protocol.

New Zealand's net emissions position, and the international credibility with which that position is established, depends on accurately determining the location and extent of land use and land use change between 1989 and 2007, between 2008 and 2012 (the first commitment period [CP1]), between 2013 and 2016, and then between 2017 and 2020 – particularly for change in the area of forested land. Determining the area of change accurately can be difficult when the area of a given land use activity undergoing change is commonly a small fraction of the total land area. Determining change with sufficient accuracy needs an emphasis on validating individual areas of change, rather than the usual approach of validating two land use data sets at adjacent dates and determining change by identifying their areas of difference.

Validation is usually based on multiple sources of evidence – combining information from satellite images, aerial photography, forest databases, statistical sampling, local knowledge, and field inspection. This is coupled to a methodology to resolve issues that arise when interpreting land use from observed land cover. The mapping process and final LUM 2020 products adhere to the Intergovernmental Panel on Climate Change Guidelines for National Greenhouse Gas Inventories (IPCC 2014).

The mapping specification, established during 2008 mapping has continued with minor updates through 2012, 2016 and 2020, and includes the following requirements.

- Mapping will be completed to a high standard such that there is 90% agreement per polygon class in the 2020 land use classification between the mapped class and a quality control assessment for a random set of sample points.
- Mapping for 2016–2020 land use change will be completed to a high standard such that there is 95% agreement per polygon class in the 2016 and 2020 land use classifications between the mapped class and a quality control assessment for a random set of sample points.

The mapping methodology has also remained consistent, or been improved, through LUM versions, and includes mapping on a region-by-region basis, with in-house quality control during processing and before delivery, including logic rules and topology checking.

The LUM 2020 now incorporates deep learning processes, semi-automation, and automated techniques in order to improve the efficiency and efficacy of the mapping processes.

This report details the activities and methods used in the production of LUM 2020. The LUM project deliverables, are listed in Appendix 1.

4 Activities and methods

LUM 2020 is an update of the established 2016 Land Use Map (Newsome et. al. 2018). It embodies land use change that occurred between nominal mapping dates of 31 December 2016 and 31 December 2020. These changes have been identified using dated national satellite image mosaics based on Sentinel-2 imagery acquired in the summers (October to March) of 2016/17 and 2020/21.

In preparation for the 2016–2020 change mapping, improvements were made to LUM 2016, including:

- deforestation corrections supplied from the Ministry (MfE)
- corrections to the mapping of the forest extent based on deep learning modelling and predictions of LUM 2016 imagery and data
- creating sub-classes for pre-1990 natural forest areas of 'Tall forest' and 'Shrubland' based on Land Cover Database version 5 (LCDB 5).

Each time step of the LUCAS LUM includes the entire time series of LUM since 1989 within the table of attributes. With each new data update corrections and improvements to historical time steps are also incorporated. This is the case particularly where new techniques or information can better inform the history of land use. This allows for the application of consistent methodologies for the entire LUCAS LUM time series, while allowing for the introduction of new techniques.

The remaining sections of this part of the report detail the methodologies that underpin key activities undertaken, to both finalise the LUCAS LUM 2016 time step data, and to produce the new LUCAS LUM 2020 time step. However, the emphasis is on new techniques applied during production of LUM 2020 that are not reported elsewhere. The deep learning methodologies as applied to LUM 2020 are covered in some detail here, but fully described in a separate report by Martin et al. 2023. Previous LUM reports (e.g. Dymond et al. 2012; Newsome et al. 2013, 2018) and related publications (e.g. Shepherd et al. 2017, 2020; Manderson et al. 2018,) can be considered supplementary reading and relevant background to the techniques discussed and evolution in methods used for LUM production.

4.1 Satellite image mosaic generation

Deliverables

Deliverable 1: National satellite image mosaics based on Sentinel-2 imagery of the North, South and Chatham Islands

Objective

The objective of Deliverable 1 was to produce seamless island image mosaics created from Sentinel-2 (S-2) satellite imagery acquired in the summer of 2021/22, using the most cloud-free S-2 orbital tracks acquired between October 2021 and March 2022.

Methods

These mosaics were created using the same methods we used to create the 2020/21 mosaics on which the LUM 2020 mapping will be based. These 2021/22 mosaics were used to provide an additional year of evidence to support decision making on the nature of land use change occurring at the end of 2020. For example, new planting is more evident in the 2021/22 mosaics than the 2020/21 mosaics.

These mosaics were atmospherically and spectrally corrected to provide a reflectance product suitable for computational analysis. The mosaics were also required to have minimal cloud via appropriate choice of component images.

For the New Zealand mainland North and South islands and the Chatham Islands, a mosaic was provided as both cloud-minimised and standardised reflectance in an ERDAS Imagine (*.img) format. We also provided a metadata raster showing which base image contributed to each pixel in the final mosaic. The cloud-minimised product is a mosaic of imagery corrected for atmospheric, view angle, and illumination effects, whereas the standardised reflectance mosaic is generated from imagery that includes additional processing for topographic correction (Dymond & Shepherd 2004).

The S-2 orbit tracks from which the cloud-free imagery was extracted are shown in Figure 1 for both the New Zealand mainland and the Chatham Islands.

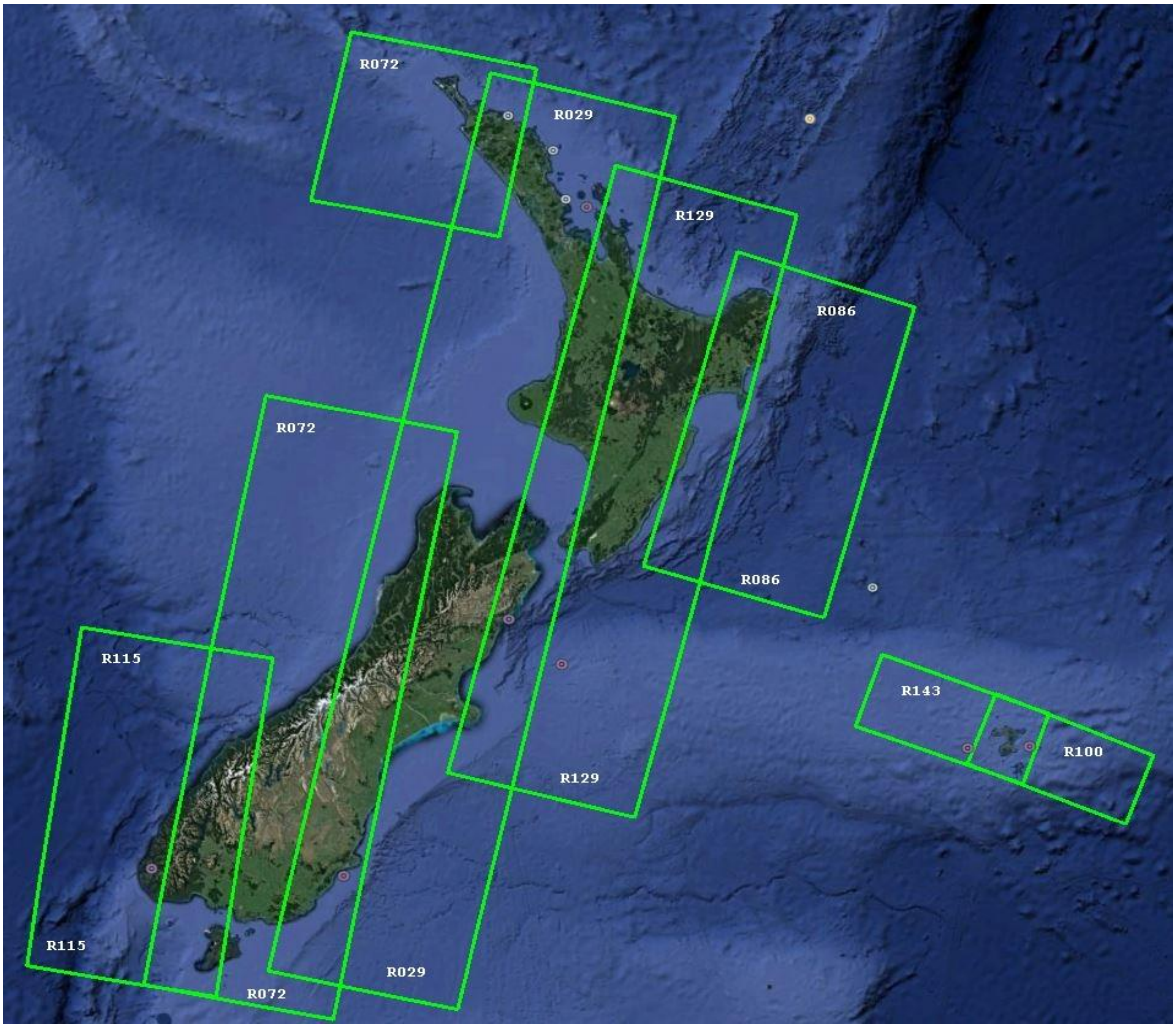
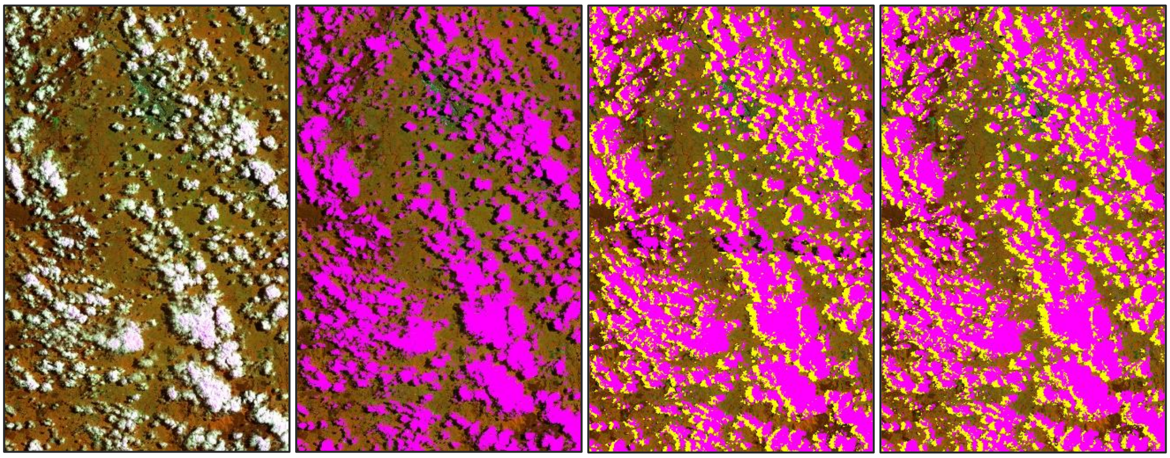


Figure 1. The Sentinel-2 orbit tracks (green) from which imagery was extracted to form the national mosaics.

Individual S-2 images were converted to surface reflectance by atmospheric and Bidirectional Reflectance Distribution Function (BRDF) correction methods (Dymond & Shepherd 2004; Newsome et al. 2013). With appropriate masking of cloud and cloud shadow, this correction process enabled automated mosaicking into a consistent image product that has calibrated reflectance values (Shepherd et al. 2020). The automated mosaicking of remotely-sensed imagery methods described in Shepherd et al. 2020, relies heavily on high-quality automated cloud and cloud-shadow detection using a combination of spectral, temporal, and object-based image analysis techniques. Figure 2 shows an example of the classification steps in the cloud-masking workflow.



Panel A Panel B Panel C Panel D

Figure 2. Example of the classification steps in the cloud-masking workflow: the original image (Panel A), the result of parallax cloud detection (Panel B), Fmask with parallax input to classify shadow (Panel C) and the Tmask result using temporal processing informed by the full record of single-date results (Panel D) (Shepherd et al. 2020).

The resulting pixels that remain of imagery for each strip (Panel D) are then assessed to prioritise each strip’s ability to contribute to a national mosaic.

For the 2021 national satellite image mosaic based on S-2 imagery, there were 226 candidate passes in total: 155 over mainland New Zealand and 71 over the Chatham Islands. After prioritisation by cloud-free contribution and sun angle, the actual number of passes that contributed to the final mosaic were: 84 for mainland New Zealand and 9 passes for the Chatham Islands. These strips were then mosaicked into North and South Island composites in New Zealand Transverse Mercator 2000 (NZTM2000) projection, and Chatham Island composites in Chatham Islands Transverse Mercator 2000 (CITM2000) projection.

4.2 Investigation of deep learning techniques for land use mapping

Deliverables:

Deliverable 2: LUM2016 Deep Learning map – NZ

Deliverable 3: LUM2016 Deep Learning corrections – NZ

Deliverable 4: LUM2020 Deep Learning map – NZ (edited feature service)

Deliverable 15: Deep learning review report

Objectives

The objective of Deliverable 2 and Deliverable 3 was to trial MWLR's deep learning (DL) classification, which uses an independent machine learning approach, to test the consistency of the mapping of land uses in the 2016 LUM on the New Zealand mainland. Data produced by DL was also used to highlight any significant errors in the 2016 land use map, in particular any areas of missed forest or deforestation.

The objective of Deliverable 4 was to use the same trained model developed in Deliverable 2 and trained further in Deliverable 3, to generate a 2020 LUM mapping prediction of the same land covers land uses using the same training data. We did this to quantify the ability of a DL model to be trained to automatically generate land use maps and land use change maps.

The objective of Deliverable 15 was to produce a report summarising the DL classification approach (Martin et al. 2023.). This included methodologies, results and recommendations for future generation of land use and land use change maps. This also required commentary on the accuracy of the 2016 LUM and any systematic errors, plus the suitability of the DL approach for identifying mappable land-use change.

The outputs from this work are listed below.

- LUM 2016 deep learning map – NZ: a raster map of land cover related to land use, generated automatically from a DL model (with training based on the existing 2016/17 LUM and a 2016/17 Sentinel-2 summer mosaic).
- LUM 2016 deep learning corrections – NZ: a polygon layer of suggested changes to the 2016 LUM forestry class, including both missed forestry and non-forest land incorrectly identified as forestry.
- LUM 2020 deep learning map – NZ: a raster map of land cover related to land use, generated automatically from a deep-learning model and a 2020/21 Sentinel-2 summer mosaic.
- A comprehensive report outlining the methods, results, and conclusions ((Martin et al. 2023.).

Methods

The DL method of semantic segmentation was applied to achieve the LUM deep learning mapping objectives. Semantic segmentation, a subset of deep learning, involves training a model to classify and label individual pixels within an image with specific classes. This process needs two primary data inputs: 1) labelled data; 2) image data. In the case of the LUM mapping, the labelled data was the 2016 LUM data reclassified into 10 land cover classes and the image data was the same 2016/17 S-2 summer mosaic used in the development of LUM 2016 and again in the assessment of land use change between 2016 and 2020 used to produce LUM 2020. The purpose of the labelled data was to provide context to the model during training to allow it to learn how to classify a mosaic into land use classes.

The LUM training data was generally mapped one-to-one with the following exceptions.

- The DL prototype combined LUM classes 71 – pre-1990 natural forest and 73 – post-1989 natural forest[2] to a single natural forest class.
- The DL prototype combined LUM classes 72 – pre-1990 planted forest and 73 – post-1989 planted forest to a single exotic forest class.
- The DL prototype combined LUM classes 75 – Grassland – high producing and 76 – Grassland – low producing to a single grassland class.

Where mappings were not one-to-one, this related to the amalgamation of classes that did not have a difference in visual semantics, such as pre-1990 and post-1989 forest classifications.

For training and testing, the S-2 mosaic and label data were divided into tiles. These image/label tiles were divided into 50% for training of the model, and 50% held back for validation of the trained model. The tiles were based on alternating LINZ topographic 1:50,000 map extents (i.e. all tiles contained within LINZ topographic image AT24 assigned to the training set, then all tiles contained within LINZ topographic image AT25 were assigned to the test set, and so on). For the LUM 2016 DL mapping objective, this data tiling technique allowed for the assessment of the model in recreating the 2016 LUM, in terms of both model fit and predictive ability.

A DL convolutional neural network U-Net model was trained on the training set image tile pairs for 400 epochs (a full cycle through the training data) of 300 steps, each processing two tile pairs, for a total of close to 240,000 model updates (i.e. each of the 8,520 training tiles was processed 28 times). This process was repeated twice to give two models, each trained on half of the S-2 raster as described above. The optimal number of epochs, steps and other model parameters were discovered via an extensive hyperparameter grid search.[3]

The resulting DL 2016 land cover raster layer was compared to the one derived from the 2016 LUM. The comparison revealed that, while the predicted layer did contain some errors, there were also significant examples where the prediction was more correct than the original LUM-based layer. On this basis, polygons were extracted for sufficiently large regions where the forestry class differed between the two maps, representing potential corrections. These polygons were then manually assessed to select those areas representing the most significant genuine corrections.

Then, we tested the ability to generate a whole new map by generating a 2020 land-use-based land cover map from a 2020/21 S-2 mosaic using the U-Net model trained on 2016/17 imagery and data.

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[2] The class of post-1989 forest was split into natural and planted forest using the mapped sub-class.

[3] A hyperparameter grid search is a technique in machine learning where model parameter values are systematically explored to find the combination that yields the best model performance.

Finally, we compared the 2016/17 and 2020/21 generated rasters to the 2016/17 LUM and a draft map of 2020/21 exotic forestry (provided by the Ministry) to assess how well the approach could detect new afforestation and deforestation activities.

This process involved the three steps that are outlined below.

1 Training a DL model based on LUM 2016 and/or related cover classes derived from LUM sub-classes and harvest mapping by:
   - generating a selection of training tiles from the 2016 S-2 image set and LUM vector layer
   - training a DL encoder/decoder model (e.g. of the U-Net family) to automatically generate the class tiles from the image set, performing a grid search over potential hyperparameter settings, including learning rate, training time and mini-batch sizes.
   - selecting the best model based on a combination of accuracy of the generated class masks and visual inspection of the differences (which might be errors in the LUM 2016 vector layer).

2 Generating LUM 2016 deep learning by:
   - running the model over the entire 2016 image set and generating LUM 2016 DL raster layer
   - generating a difference raster and visually inspecting this to classify the differences into prediction error versus potential map errors
   - refining of the training data, retraining of the model and regenerating of the LUM 2016 DL raster – if required
   - vectorising the LUM 2016 DL raster
   - generating and reviewing the difference raster
   - vectorising potential change areas for inclusion and LUM 2016 improvements.

3 Generating LUM 2020 by:
   - running the final DL model over the 2020 S-2 satellite mosaic to generate LUM 2020 raster
   - vectorising the LUM 2020 DL raster.

The workflow process for Deliverables 2–4 are outlined in Figure 3.

For more detailed information on the DL methods as applied to LUM 2020 refer to Martin et al. 2023.

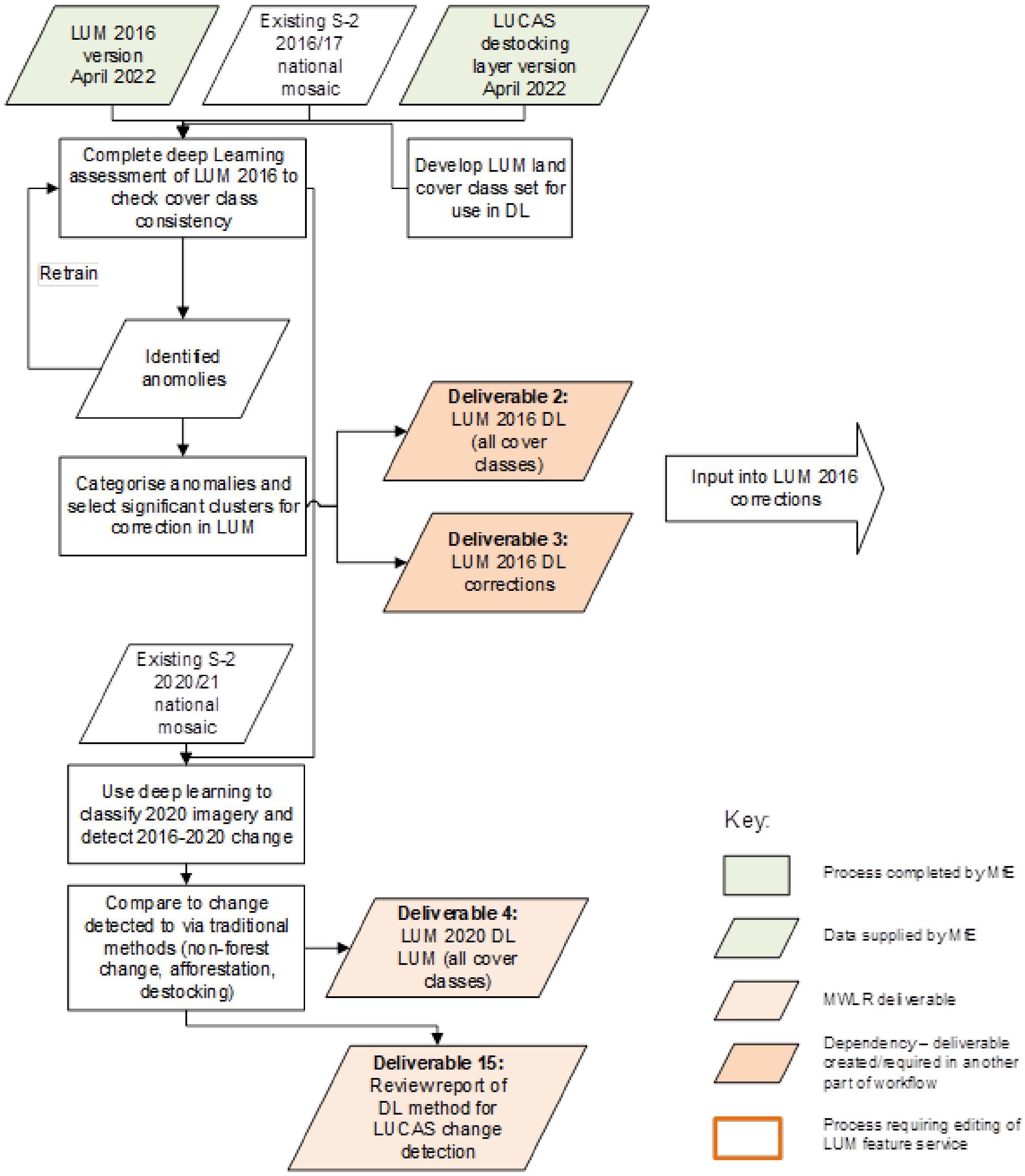


Figure 3. Deep learning workflow. LUCAS – Land Use and Carbon Analysis System; LUM – Land Use Map; MfE – Ministry for the Environment; MWLR – Manaaki Whenua – Landcare Research; S-2 Sentinel-2.

Results from these methods are discussed further in Section 4.2.

4.3 Improvements to LUM 2016

This section details the improvements made to LUM 2016 and related deliverables. These improvements focus on high-priority corrections to LUM 2016 so that they could be included in the 2022 carbon calculations for the 2021 greenhouse gas inventory. These corrections are a combination of known errors in the mapping of deforestation, improvements identified by the production of the deep learning LUM map, and improvements to the natural forest class.

4.3.1 Mapping known pre-2017 deforestation

Deliverable 5: LUM 2016 Update 1 – NZ

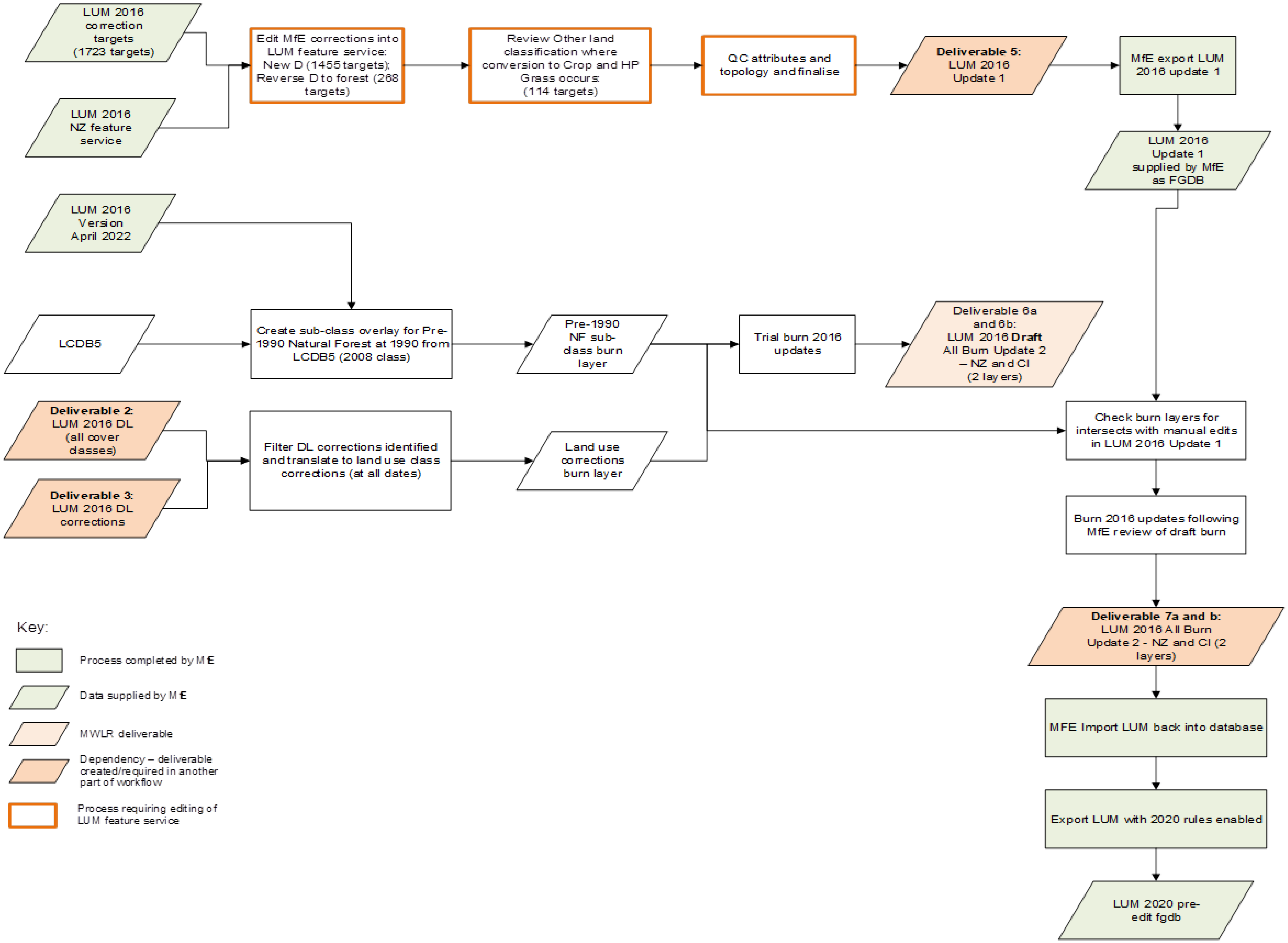
Objective

The objective of Deliverable 5 was to incorporate LUM 2016 deforestation corrections supplied by the Ministry. This required mapping of corrections directly into the Ministry's Esri ArcGIS LUCAS LUM NZ mainland feature service.

Methods

Edits of high-priority deforestation corrections for mainland New Zealand were incorporated into LUM 2016 so that they could be included in the 2022 carbon calculations for the 2021 Greenhouse Gas Inventory. These corrections were derived from known errors in the mapping of deforestation, supplied by The Ministry. These updating processes took care not to increase the total number of LUM polygons under 0.05 ha. The edits were made manually into the LUM feature service hosted by the Ministry, following the workflow in Figure 4.

Figure 4. LUM 2016 updates workflow. DL – Deep learning; LUCAS – Land Use and Carbon Analysis System; LUM – Land Use Map; MfE -Ministry for the Environment; MWLR – Manaaki Whenua – Landcare Research; S-2 Sentinel 2; HP – high producing; QC – quality control.



4.3.2 Adding new planted forest and sub-classing natural forests

Deliverable 6: LUM 2016 Draft All Burn Update 2 – NZ and CI and

Deliverable 7: LUM 2016 Final All Burn Update 2 – NZ and CI

Objectives

The objectives of Deliverable 6 and Deliverable 7 were to update both the New Zealand mainland and the Chatham Islands LUM 2016 mapping using automated techniques that integrated improvements and corrections to forest extent and forest sub-classification. The automated processes developed for this work included Python scripting to integrate spatial features and attribute tabular updates using sophisticated geospatial processing to enable these features to overwrite underlying data as well as manage the artefacts created by slivers and mismatched boundaries effectively. These techniques are referred to as 'burns' throughout the document.

The forest extent improvements involved rendering corrections to the mapping of forest extent based on DL modelling (see Section 3.2) and predictions of LUM 2016 imagery and data from Deliverable 3 and Deliverable 4. LUM 2016, like all maps, is a digital representation of the real world, affected by input sources and technology capability at the time of production. Deep learning modelling techniques were used to assess LUM 2016 to identify classification errors, legacy issues, and the potential for correction, with an emphasis on errors in forestry cover. We then applied the resulting corrections, identified with high confidence, to the final LUM 2016 data.

Creating the sub-classes of Pre-1990 natural forest areas based on LCDB 5 involved the use of automated techniques to alter the mapping of spatial extent as well as attribution of tabular data. This systematic update to LUM 2016 required the sub-classification of Pre-1990 natural forest into 'Tall forest' and 'Shrubland' areas informed by LCDB 5. The new sub-class for LUM 2016 was 'Tall forest,' where the 2008 LCDB time stamp class was either 'Indigenous forest' or 'Broadleaved indigenous hardwood'. All remaining polygons that are not consider Tall forest, needed to be sub-classified to Shrubland.

All burns had to be pre-approved by the Ministry before inclusion. In common with other deliverables, there was no increase in the number of polygons less than 0.05 ha resulting from this revision.

Methods

While the term 'burn' is used here and in the contract documents, the natural forest sub-classification process was essentially one of re-attributing the sub-class attribute of each LUM polygon based on the LCDB v5 classification. Sometimes polygons were split where indicated by the LCDB, provided the resulting components polygons still met a minimum size/shape constraint (1 ha). However, unlike the 'burn' process described in Section 3.4.3 there are no slivers created or needing to be cleaned up outside of the natural forest polygons given these were undertaken on sub-class features only.

4.4 Creating the LUCAS 2020 Land Use Map

4.4.1 Identifying areas of missed forest loss occurring between 2017 and 2020

Deliverable 8: Probable Missed Destocking 2017–2020 – NZ

Objective

Destocking of forests (clearing of forest as part of either harvesting or deforestation activity) which occurred during the years 2017 to 2020 had already been identified as part of previous contracts. However, it was expected that tracking change annually, or biennially, might have resulted in some missed destocking events that could have fallen under the size threshold when split between calendar years.

The objective of Deliverable 8 was to identify any areas that may have been missed due to the choice of forest mask used for previous annual destock work, or where destocking occurred progressively over multiple years and had been eliminated as it was considered undersized in each individual year of capture. This required considering the change across the total 2017–2020 time period, and cross-referencing to previously identified destocking as captured in previous individual contracts. Deliverable 8 needed to identify all areas deemed as missed destocking as at 31 December 2020 on mainland New Zealand.

Methods

For this work the main reference data sets were the 2016/2017 and 2020/2021 summer S-2 national mosaics. However, the nominal 2020 LUM mapping period is from 1 January 2017 to 31 December 2020.

The image-processing techniques were developed for the 2012 LUM mapping (Dymond et al. 2012) and further refined for the detection of 2013 to 2016 destocking (Newsome et al. 2018). These continuously improved techniques were used to identify areas of forest destocking greater than or equal to 1 ha in size, and at least 30 metres in width, on average. The forest change and destocking detection process followed methods described in Newsome et al. 2018. These methods included segmentation using the Shepherd iterative elimination algorithm (Clewley et al. 2014). It was a requirement of this that all destocking areas met the minimum size requirements consistent with the LUM scale. It was a requirement of this that all destocking areas met the minimum size requirements consistent with the LUM scale.

The objective of this deliverable was to identify only areas considered to have been missed during earlier destocking detection projects. However, for consistency and to ensure an accurate capture of forest estate changes for the LUM 2020 mapping, we undertook a comprehensive destocking detection and change analysis for 2017 to 2020. Our techniques also took account of the type of forest cover mapped and were calibrated accordingly. This included using the final LUM 2016 forests to apply a forest mask that appropriately accounted for the LUM 2016 final forest extent (‘All Burn’) produced in Deliverable 7.

All possible destocking areas were then manually checked using rapid semi-automated techniques to remove ‘false positives’ such as cloud or areas of image mis-registration which did not represent forest destocking. Areas of non-anthropogenic change were retained in the destocking layer and coded accordingly, where identified. Each remaining polygon was assigned the year in which the destocking event occurred (2017 to 2020) using annual S-2 national image mosaics. As a final step the polygon outlines were smoothed to remove raster edge artefacts. This methodology is summarised in Figure 5.

Previous destocking maps for 2017, 2018, 2019 and 2020 (produced by MWLR) were used to cross-reference the comprehensive 2017–2020 destocking detection, to identify areas deemed as ‘missed’ in the previous mapping of single-year destocking events.

Deliverable 8 – Probable missed destocking 2017–2020 – was supplied as a vector layer showing the extent of probable 2017–20 destocking attributed with: LUM forest class (71, 72, 73); the year of destocking; and if determined likely to be from natural events, coded as non-anthropogenic.

The quality standards for forest destocking were met. These are listed in the bullets below.

- At least 90% of the actual forest loss was identified at the 95% confidence level.
- ‘False positives’ (i.e. areas which had not actually been destocked) included in the deliverable did not exceed 5% of the polygons identified.
- The layers contained no overlaps.
- The layers contained no polygons less than 1 ha in size or less than 30 metres in width, on average.

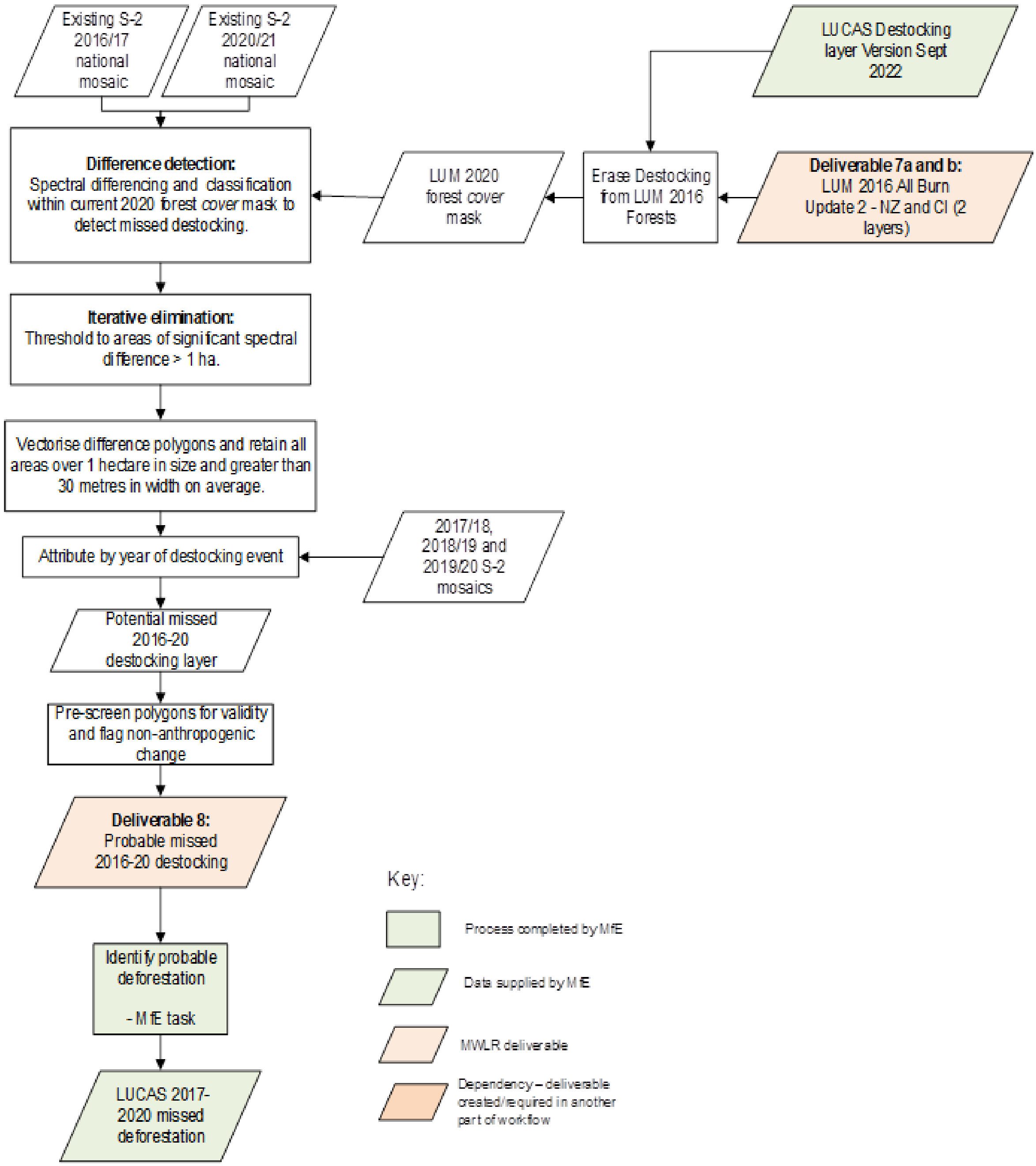


Figure 5. Missed destocking workflow for Deliverable 8. LUCAS – Land Use and Carbon Analysis System; LUM – Land Use Map; MfE – Ministry for the Environment; MWLR – Manaaki Whenua – Landcare Research; S-2 Sentinel-2.

4.4.2 Detecting and mapping change between 2016 and 2020

Deliverable 9: LUM2020 Aggregated Burn layer – NZ & CI

Deliverable 10: LUM2020 Aggregated Draw layer – NZ & CI

Deliverable 11: Updated Grassland layer – addition of the 2020 mapping date to mapping of low and high producing grassland at 2007, 2012, and 2016 with sub-classifications included (file geodatabase).

Deliverable 12: LUM2020 All Burn updates – NZ and CI

Deliverable 13: Draft LUM2020 - NZ and CI (file geodatabase)

Deliverable 14: Final LUM2020 – NZ and CI (edited feature service)

Objectives

The 2020 land use map is required to quantify areas of land use change for greenhouse gas reporting under the UNFCCC. LUM 2020 tracks all change occurring since 2016 by delineating areas of change into the 2016 LUM. LUM covers mainland New Zealand – i.e. the North Island, South Island, Stewart Island, and major offshore islands such as Great Barrier Island (Aotea Island), as well as the Chatham Islands. It does not include other, more remote offshore islands – the Kermadec, Bounty, Auckland, Campbell Island groups etc. as these are not considered to be subject to land use change.

We mapped land use changes according to the LUCAS land use classes and sub-classes (Appendix 4). In addition, there were some attributes to be updated (shown in Appendix 3).

Methods

In common with previous time steps of the LUM, the minimum mapping unit is 1 ha, and all polygons need to have an average width greater than or equal to 30 m. Over time, some polygons less than 1 ha have been included in LUM. However, the goal is to ensure that this number does not increase, and rather that it should decrease through improvement and corrections. Overall, the methodology we used to create the 2020 Land Use Map is broadly consistent with the approach we used to produce the 2012 and 2016 land use maps. However, we made several improvements to the methodology including, but not limited to, those listed in the bullets below.

- Incorporating changes that have originated from the deep learning experiment and ancillary data such as the LCDB 5 (2018) database, including forests and wetlands.
- Changes identified by rapid and semi-automated change detection routines, where assessed as appropriate (i.e. not requiring complex spatial boundary edits or research to understand changes through time) were automatically burnt into the 2020 layer using scripted geospatial processing. This saved time and increased the number of areas of change captured significantly, whilst retaining robust accuracy and quality assurance.
- Identifying cropland using temporal analysis of S-2 time series to identify crop rotation.
- Incorporating the national update of grassland subclasses for grazing and non-grazed grasses.

However, complex changes to land use polygons or areas requiring further investigation and research to understand changes over time were still hand drawn.

The bulk of the 2017–2020 land use change mapping was undertaken in a phase comprising spectral differencing and change detection followed by a succession of predominantly semi-automated manual visual analyses and digitising processes. These are illustrated in Figure 5 and described below.

Step 1: Spectral differencing and classification outside the improved LUM 2016 forest mask

The 2020/21 S-2 standardised-reflectance mosaics were segmented into homogeneous spectral units of at least 1 ha. An algorithm based on the EcoSat process (documented in Dymond et al. 2001; Shepherd & Dymond 2003; Dymond & Shepherd 2004) using a multi-temporal image stack was applied to detect areas where spectral characteristics are inconsistent with the land use mapped at 2016 and/or the 2016 standardised-reflectance imagery using a range of image processing techniques to identify these seven areas.

1 Afforestation not covered by MPI forestry schemes.

2 Grassland – Grassland with woody biomass (GWB) change.

3 Annual cropland change (using temporal analysis to analyse cultivation effects).

4 Perennial cropland change.

5 Gains and losses of open water (not including river realignment)

6 Wetland integration informed by LCDB 5.

7 Settlement expansion.

Step 2: Difference detection

A 2017–2020 raster potential change layer (at 10 m resolution) was created by thresholding the difference layer from Step 1 (10 m pixel resolution) to identify targeted changes. Areas less than 1 ha (which were classified as 'no change') and areas with an average width of less than 30 m were removed from this layer. Areas where 2020 satellite imagery was covered by cloud were also defaulted to 'no change'.

Step 3: Confirm change

In making an assessment of actual change, an operator simultaneously viewed each candidate polygon superimposed on imagery at several different dates in a pre-configured tool ('MapAccuracy'[4]), to make quick multi-choice decisions and code these candidate polygons for validity. The operator determined whether the change could be confirmed based on visual interpretation of satellite imagery from 1990, 1996, 2001, 2008, 2012, 2016 and 2020 (as well as 2021 to ensure changes had persisted) using guidance from the LUCAS Satellite Image Interpretation Guide, version 2 (Ministry for the Environment 2012). Where necessary, other evidence, such as ancillary data (i.e. LCDB 5)

[4] MapAccuracy is a very efficient in-house screening software that controls the panning/zooming and selection process across multiple screens of evidence and captures operator decisions and comments for onwards processing.

and available aerial photography were also used to determine the correct land use classification at each mapping date (1989, 2007, 2012, 2016 and 2020).

Step 4: Split change into areas to burn and manually draw

We used a second review using the 'MapAccuracy' pre-configured rapid assessment tool combined with a manual operator decision making process to confirm changes to split into two groups: 1) areas suitable to be automatically integrated (burnt) into the LUM; 2) areas that required manual editing because the updates were too complex or would require significant work to integrate into LUM data.

For those areas deemed 'burn-ready', a third review was undertaken using 'MapAccuracy' pre-configured rapid assessment tool to assign LUM 2020 classifications and sub-classes where appropriate. This third rapid assessment was also used to ensure the quality of decision making was consistent and appropriate for all change areas to be burnt into LUM 2020, including previous time-steps where relevant.

All areas of land use change incorporated into LUM 2020 underwent at least three reviews to ensure accuracy of the spatial boundary as well as attribute information was correct. This included the land use classes and the year of change recorded.

Afforestation mapping

We added areas of afforestation as defined in the Ministry for Primary Industries (MPI) Afforestation layer. MPI administers most of New Zealand's afforestation incentive schemes (notably the Emissions Trading Scheme, Afforestation Grants Scheme, Permanent Forest Sinks Initiative, and Erosion Control Funding Programme). Information from this mapping, supplemented with other sources of information, enabled the Ministry to compile afforestation target layers for 2017–2020.

There were instances when not all of these afforestation target areas included a planting date, or where image evidence contradicted the date nominated. This meant that some of these target areas needed to be classified as forest at dates prior to 2020 and required updates to previous time step classification, to ensure mapping was accurate at all time steps for LUM. In all cases, we carried out checks to corroborate or otherwise estimate the approximate year of planting, mostly by checking the imagery sequence (particularly aerial images when available) and inferring the planting date based on the fact that forests may take several years to become visible in multispectral imagery. Where planting was too recent to be informed by aerial and satellite imagery, we used the identified date that was supplied to us by MfE.

The resulting afforestation polygons were split into those suitable for burning and those that needed to be manually edited into the LUM. For both draw and burn polygons, the area of afforestation was 'cut' into existing polygons by digitising its periphery (or tracing the target polygon if it was good enough) and the land use change assigned from the planting date recorded in the target layer, confirmed by reference to the MPI layer and visual inspection of imagery.

Deforestation mapping

This activity included updating the LUM with all deforestation which occurred during 2017–2020. Polygon targets for this activity were supplied by the Ministry and also incorporated the 'Probable Missed Destocking' (Deliverable 8) detailed in Section 3.4.1 The original detection of forest destocking was performed by MWLR, and then processed by the Ministry to define whether the destocking event was considered permanent deforestation. Again, these target areas were split into targets suitable for burning and those that required manual editing owing to the complexity of the change and the spatial polygon edits required to represent this in LUM. Whilst the Ministry had identified the land use class with which these deforested areas were going to (i.e. LUM 2020 classification), these were also checked by operators to ensure this was a correct reflection of what the land use was at 2020.

These targets were incorporated into the LUM by either the burn or draw processes (described later in this section). For manual editing, target polygons were combined with underlying photography and satellite imagery and ancillary layers (notably the Ministry's (i.e. MfE's) deforestation tracking layer). In every case, as well as recording the land use change, attributes identifying the deforestation event and the year of deforestation were maintained unless there was strong evidence that contradicted this advice.

Once all the foregoing edits were complete, regional LUM maps were checked for quality by MWLR before returning regional versions of LUM 2020 to the Ministry for final quality control checking and acceptance.

In all, this 2020 land use change phase delivered mapping as 16 regions covering the North and South Islands of New Zealand and one further deliverable covering the Chatham Islands. Mapping and quality control measures were in place for data editing, based on the LUM 2020 schema (see Appendix 3).

Wetland updates

The LUM wetlands were updated and augmented from the wetland mapping in LCDB 5. This included both updates to the mapped extent of wetlands (wetland boundary) at all dates and the mapping of change in wetland extent. Where wetland changes were noted in LCDB 5 but the wetlands were not present in the LUM, we added them. The 2016/17 national S-2 mosaic was also used in this process to determine whether these changes occurred before or after the 2016 LUM and therefore whether they should be mapped into previous LUM time steps and 2020 maps, or just the 2020 map. Many of the wetlands informed by LCDB 5 required extensive changes to the LUM time steps and we note that many of these wetlands had not previously been identified in LUM.

The LUCAS Land Use Map (LUM) maps vegetated wetlands based on the definition included in New Zealand annual Greenhouse Gas Inventory. This definition includes 'trees of any stature', recognising that wetlands can contain tree species and sometimes contain tree weeds (such as grey willows). Because of this definition, LCDB 5 wetlands not yet represented in LUM required additional scrutiny and a logic-based assessment on LUM class definitions.

The Ministry supplied us with guidance on the mapping of wetlands dominated by tree species, to enable a decision making process for when wetlands would and would not be incorporated into LUM. The rationale for including "trees of any stature" in the LUM vegetated wetland definition is that these trees are essentially in a "wetland land use" rather than a forestry land use and that control of tree weeds in a wetland context, (which does not lead to a land use change), should not be considered to be deforestation for the purposes of greenhouse gas reporting (which would occur if they were mapped as a natural forest to vegetated wetland change).

To date, the LUM has not included areas that are entirely made up of forest cover in the vegetated wetland class (apart from some mangrove areas). One reason for this is that it is hard to detect wet ground under forest canopy in satellite imagery.

For LUM 2020 mapping, LCDB 5 detection and delineations of wetlands were incorporated when they satisfied the logic-based rules set by the Ministry and adapted by MWLR's geospatial digitising team. Polygons larger than 1 ha, and classified in LCDB 5 as an LCDB class that converts to either wetland class in LUM (class 79/80), but had not yet been included in LUM 2016, were reviewed manually. The operator analysed these areas using aerial photography and additional data to determine their fit with the LUM classification.

This assessment also included wetlands currently captured in LUM but with a greater extent in LCDB 5. For these wetlands, a choice was made between simply using the target polygon itself, or using the larger 'parent' LCDB 5 polygon. In the latter case, some of the LCDB wetland area would have already been classified as wetland in the LUM, and therefore the target was considered to be an extension to the existing LUM wetland boundary, as opposed to a new wetland. However, taken as a whole, the parent LCDB polygon better represented the wetland. (Note that a LCDB parent polygon could replace several targets and sometimes included areas around the original LUM wetland polygon that had fallen below the 1 ha threshold.) The resulting wetlands identified, along with their spatial extents, were split into those suitable for burning and those that needed to be manually edited into the LUM.

Open water detection

The detection for new open water follows the same process as other classes, namely we segmented a multi-date (2017 and 2020) set of S-2 Red, Near infrared and short-wave infrared bands to a minimum size of 1 ha (i.e. 100 units of 10 m ×10 m pixels). Importantly, this only occurred in areas deemed not currently water in LUM. In addition to spectral information for both dates for each segment, we also added mean Sentinel-1 (S-1) Synthetic Aperture Radar (SAR) backscatter information to the raster attribute table.

Synthetic Aperture Radar (SAR) images from Sentinel-1 have been widely used for water surface detection (Huang et al. 2017; Bioresita et al. 2018). The S-1 SAR data we used is a temporal per-pixel median of imagery taken over the final date range (summer of 2020/21); this minimises noise or 'speckle' in the mosaic. The units of this mosaic are decibels, and the polarisations are vertical send – vertical receive (VV) and vertical send - horizontal receive (VH). To choose a segment as being likely to be water (and subsequently forwarded for manual confirmation) we applied the following thresholds: the sum of NIR and SWIR final reflectances is less than 12%, VV is less than -17 dB and VH less than -25 dB (i.e. low reflectance in infrared and very low backscatter in both polarisations). It is the combining of these techniques that enable the detection of new open water in the landscape.

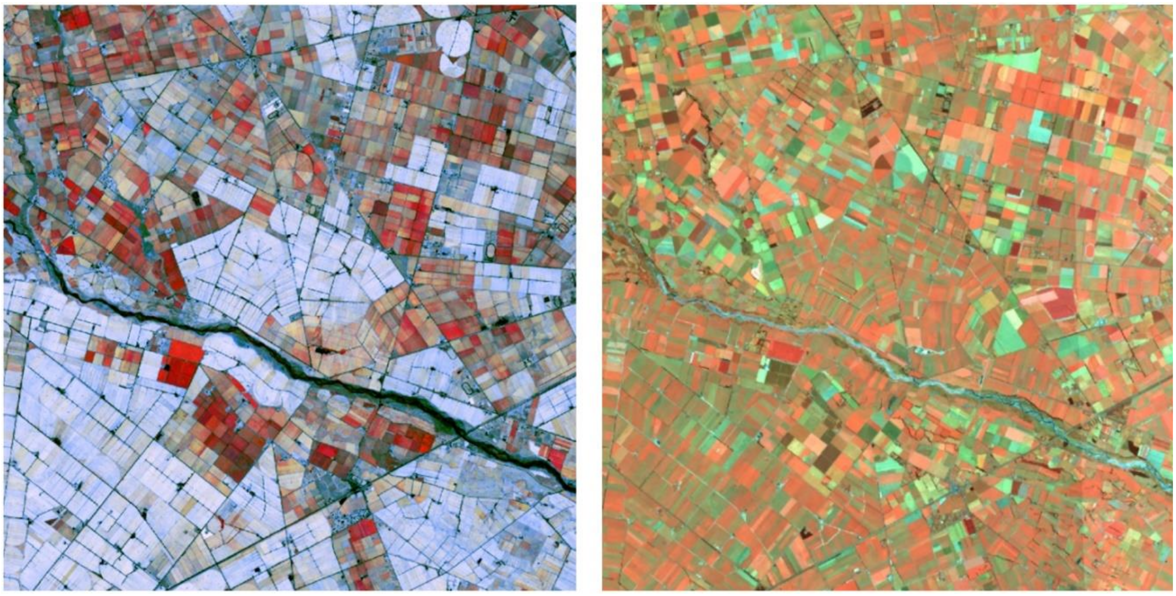
New settlement detection

We followed a similar process to the open water detection, but we looked for different physical properties to select segments that were likely to be urban expansion. Specifically, we were looking for areas that were bright in S-2 bands (Red > 5%, NIR > 12%, 13% < SWIR < 23%) and which had relatively high backscatter in S-1 VV polarisation (VV > -8.6 dB). Segments which met these spectral and SAR backscatter criteria and whose majority were within 1 km of current settlements were extracted and forwarded for manual confirmation.

Cropland (and grassland) updates

We used Normalised Difference Vegetation Index (NDVI) temporal analysis to identify areas of continual greening (constant spectral signature i.e. grassland or forest versus intermittent spectral signature consistent with cultivation effects of cropping) to assess the effects of cultivation and compare this to the steady state of grass cover. This offered a new technique to enable cropland updates to LUM 2020. Underpinned by the time series now available through S-2 national mosaics, we used a temporal analysis over the time period for LUM 2020 change mapping to assess the effects of cultivation at a paddock scale. The ratio of the number of vegetated observations of a pixel compared to the total number of observations of that same pixel were calculated for the time series of Sentinel-2 images (Amies et al. 2021).

Amies et al. 2021 details all relevant methods used in this section and in particular, the wording and details presented below.



A B

Figure 6. Cropland and pasture updates. A) Map of Canterbury highlighting vegetation patterns indicative of rotational cropping (red) and permanent pasture (blue) using ratios of positive NDVI image on the left; B) Topographically flattened summer mosaic of the same area.

This technique highlights areas where short-rotation crops are planted (showing as red in Figure 6A above), because these areas have varying NDVI levels over time, and in some instances have negative NDVI values which are ignored for the calculation of vegetated median NDVI (Amies et al. 2021). These areas are in contrast to areas showing as blue in Figure 6A that have mostly identical NDVI time series and therefore have similar red and green band values (Amies et al. 2021). Distinguishing these areas of cropland as opposed to permanent pasture using single images or mosaics can be comparatively difficult, depending on the date of image acquisition and planted crop (Amies et al. 2021). However, this objective method can be used to identify areas in the LUM where, although land is classed as annual cropland, the multitemporal spectral response of those areas' pixels indicate that the land cover is in continuous grassland cover – or vice versa (Amies et al. 2021). These discrepancies were used to correct and update the mapping of annual cropland in LUM 2020.

Grassland updates and sub-classification

Manderson et al. 2018 described the grassland improvement mapping using Innovative Data Analysis (IDA) techniques that was used to classify (as high-producing or low-producing) and also sub-classify grasslands at the 2016 and earlier time steps. Since undertaking the extensive modelling of grassland land uses for IDA, only two input data sets have been updated: valuation land use (potential and actual) and protected areas parcels. Because of this, we deemed that developing a solution informed by the updated data sets would be more cost effective than re-running the fuzzy logic and decision-making process that the IDA techniques had used.

In addition to potentially modifying class and sub-class attributes of grassland polygons, we made corrections to polygons previously changed from cropland to grassland as detailed in the section 0 above. This is as valuation data indicated these areas should have been retained as cropland rather than being reclassified as grassland. This formed an additional cross-checking mechanism dependent on the time valuation was undertaken.

Polygons from LUM 2020 classified as high- or low-producing grassland were updated for correct class and sub-class using the property valuation data and a set of rules (as tabulated in Appendix 2). These rules were based on the following criteria.

- Existing class/sub-class at 2016 and 2020.
- Land use at 2016 and 2022 from valuation data sets.
- Protected natural area status – this was used to determine which areas should be assigned to Low-producing grassland with the sub-class 'Ungrazed'. Twenty-four areas of protected land were found that had not been captured as 'Ungrazed grassland' in the 2016 LUM. It is important to note that protection status does not imply an area is ungrazed. Research into the protection status of land was undertaken and ultimately assessed, and areas with high confidence due to conservation or exclusion of activities were considered ungrazed.

Grassland sub-classification changes informed by property valuation were based on actual valuation closest to 2020. The 2016 valuation data was compared to valuation data at or near the 2020 date, with detailed analysis and logic applied where these differed. The logic rules used to classify land uses into LUM grassland subclasses was developed in conjunction with the Ministry. This was to ensure as much detail about all possible change was considered, in order to inform a grassland sub-class for all grasslands in LUM 2020 and previous time steps (see Appendix 2).

4.4.3 Processes for burn and draw methods

Four distinct polygon burns were carried out in the construction of the LUM 2020 version. Two of these, the DL and the Deliverable 10 (D10) burns focused on corrections to the LUM 2016 version from other sources of information, while the remaining two focused on updating the map for the new LUM 2020 time step.

- DL burn – exotic polygons identified by deep learning method.
- D10 burn – a combination of four data sets, 'MPI_afforest_1720_agg_burn', 'LUCAS_forest_deforestation_burn', 'MWLR_grassland_burn', 'MWLR_grasswoodybiomass_burn_v2'.
- Crop & wetland burn – from remote sensing temporal analysis and LCDB v5 wetland information.
- Grasslands burn – based on new valuation data, protected natural area information, and a rule set.

All confirmed land use change polygons and areas of improvement that had been identified as requiring updates (as described throughout this report) were split into those polygons suitable for burning (burn polygons) and those that would need to be manually edited into the LUM (draw polygons). This included LUM 2020 changes as well as changes to previous LUM time steps, as appropriate. This also included the required sub-classing where necessary as well as inclusion of a land use change date for some LUM classes such as afforestation.

Burn methods

Burning polygons into an existing map such as the LUM involves first overlaying the new polygons. Inevitably, this creates ‘sliver’ polygons which are undesirable artefacts due to their being too small, too narrow, or otherwise insignificant at the mapping scale. Apart from size and shape, the selection of sliver polygons can be dependent on other factors such as their class, or if the remaining proportion is significant with respect to the original polygon from which it came. For example, if after inserting a new burn polygon of new cleared grassland, a small pond remains at 90% of its original size, then that should be retained. However, a similar sized polygon of forest, that is just a few percent of an original harvested forest and largely overwritten by the burn polygon, should be removed as a sliver.

We eliminated the slivers by merging them into a neighbouring polygon. Exactly how this is done depends on the nature of the polygon set being burnt. Generally, the new burn polygon boundaries are considered more authoritative and therefore slivers should merge with non-burn polygons. However, we considered the original LUM boundaries more reliable – being hand drawn by an operator using imagery at some point – than the cropland burns from remote sensing NDVI temporal analysis.

Figure 7 shows the basic burn steps and illustrates how slivers sometimes need to be split in order to merge with neighbours without creating artefacts when more than one non-burn neighbour is present. It is important to note that these techniques were also automated to expedite, replicate, and replace the work previously done by manual operators.

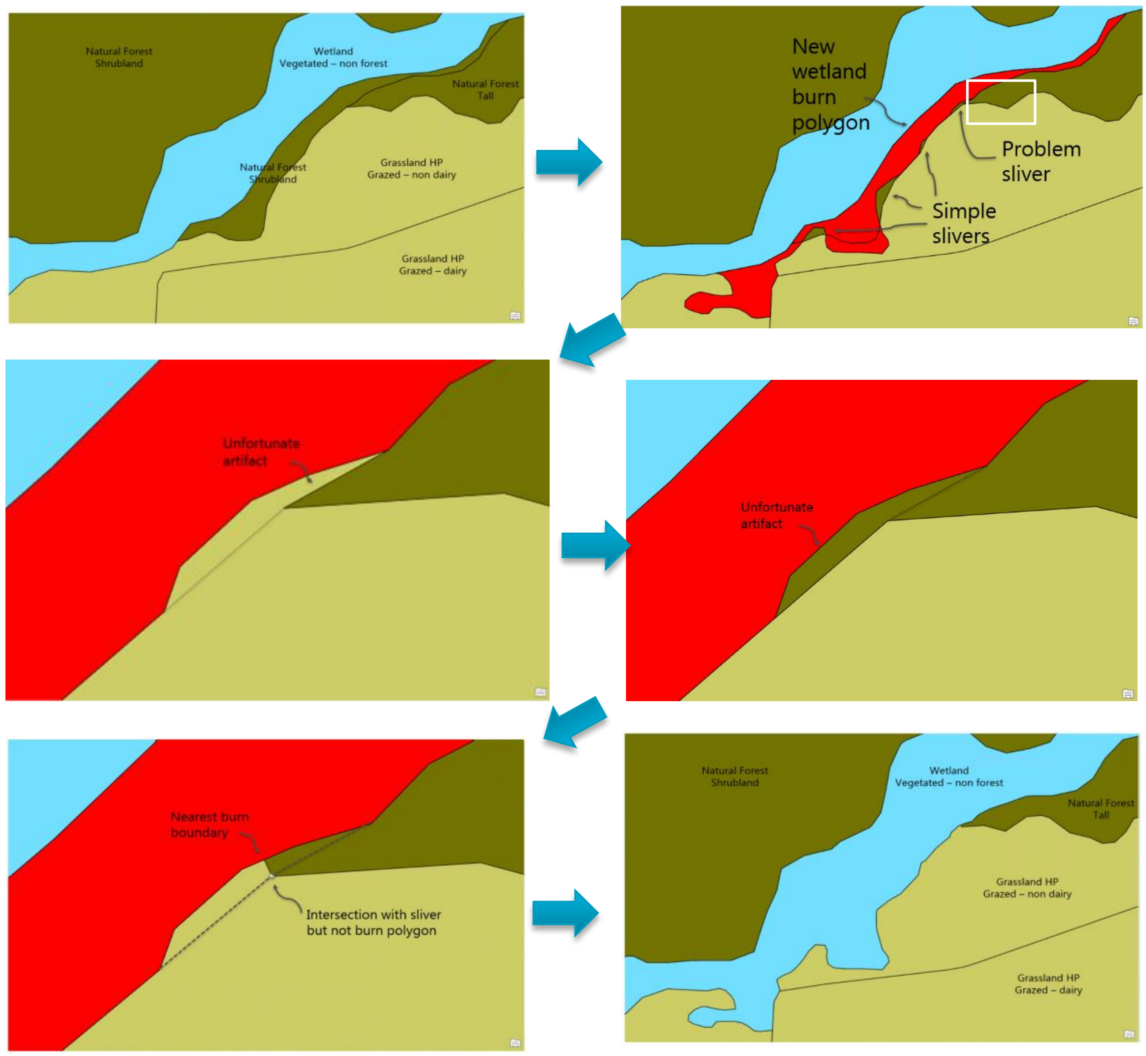


Figure 7. An example of 'burning' an LCDB vegetated wetland polygon. The image at the top left is the original LUM layer and the image at the bottom right shows this layer with the new areas of wetland burnt in and the adjacent polygons tidied up. Blue arrows indicate the sequence of successive steps from the start to the finish of this process. Further details of the basic steps are presented in below:

- Starting state (top left).
- New red polygon burns over underlying LUM boundaries (top right). This new polygon represents a wetland to be included in LUM 2020.
- Remaining slivers are defined in a variety of ways (or combinations of ways) i.e. by size, shape, proportion of original polygon, and class.
- Rather than eliminating across the longest boundary, we normally eliminated to the adjacent non-burn polygon, as the new burn boundary was usually (but not always) considered more 'authoritative'.

- Problems arose if there was more than one adjacent non-burn polygon (see problem sliver above in the top left image). The middle row above demonstrates how eliminating into either non-burn neighbour creates an unwanted artefact (middle left and middle right images).
- The solution is to split the sliver and eliminate the parts independently to their adjacent non-burn polygons (bottom left image).

After each burn, all burn layers were collated and merged into a single data set with the LUM 2020 data schema and tabular format. All unnecessary boundaries were dissolved out and slivers under 1 ha eliminated from the result.

While using the burn process a variety of other attributes were updated for the modified parts of the LUM. These are listed in the bullets below.

- Unique Identifier (FEATURE_ID) – retained original where possible, and otherwise a new GUID is generated. Note, existing unique identifiers can be inherited by the largest polygon that would intersect with the original.
- Modified By (MOD_ORG) – set to 0 - Manaaki Whenua – Landcare Research.
- MOD_USER – set to 'BURN'.
- Mapping Method (LUM_METH_ID) –
  - 38 – for exotic polygons from DL
  - xx – for D10 burns it came from input data, i.e.: 5 (MPI Afforest), 33(LUCAS deforestation), 39(grassland & GWB)
  - 40 – for Wetland from LCDB
  - 41 – for Cropland from LCDB
  - 42 – for the grassland burn (including any reversals of crop->grass, or modification of the crop->grass date).
- MOD_DATE = 29/07/2022 – for exotic polygons from DL.
- MOD_DATE = 01/02/2023 – for the D10 burn layers ('MPI_afforest_1720_agg_burn', 'LUCAS_forest_deforestation_burn', 'MWLR_grassland_burn', 'MWLR_grasswoodybiomass_burn_v2').
- MOD_DATE = 01/03/2023 – for the Crop & wetland burn.
- MOD_DATE = 30/06/2023 – for the Grasslands burn.
- AREA_HA – set to new actual area.

Finally, topology checks were performed on the updated LUM and the Ministry's LUM validation tool was run.

Draw methods

We deemed approximately 15% of the overall land use change targets to be too complex in spatial extent, and/or impacted a complicated area in the existing LUM (i.e. crossed many boundaries of existing LUM polygons), and/or required detailed research in order to be burnt into LUM. Hese were thus hand drawn. All digitising of spatial edits and/or tabular attribute updates or changes, took place in the Ministry's web feature service using

ArcGIS Pro. For this work, draw targets were overlayed with the improved LUM data (resulting from automated burns), to manually digitise in polygon areas of land use change. In the GIS software, imagery at all dates available was also used (see imagery list below), alongside ancillary data sets (such as LCDB 5), aerial imagery and time series imagery to confirm changes and/or identify the year of change where required. This also provided an opportunity to review areas burnt in where an operator was looking at the same area to assess the editing requirements for a draw polygon target.

For the Ministry's web feature service editing, all user controls and version management was administered by the Ministry. MWLR staff were set up with guest accounts to use the Ministry's ArcGIS Enterprise platform. This approach also ensured that pre-coded business logic constraints were active during all LUM editing work.

To help avoid MWLR staff creating conflicts within the multi-editor web service, definition queries by region were used to geographically isolate edits within a version. Satellite imagery accessed via the Ministry's (MfE's) ArcGIS Enterprise platform was used to confirm and check change. This included:

- MfE Sentinel2 2021 NIR SWIR R Mainland NZ
- MfE Sentinel2 2020 NIR SWIR R Mainland NZ
- MfE Sentinel2 2019 NIR SWIR R Mainland NZ
- MfE Orthophotos Latest R G B Mainland NZ
- MfE Sentinel2 2018 NIR SWIR R Mainland NZ
- MfE Sentinel2 2017 NIR SWIR R Mainland NZ
- MfE Sentinel2 2016 NIR SWIR R Mainland NZ
- MfE Landsat8 2016 NIR SWIR R Mainland NZ
- MfE Landsat8 2015 NIR SWIR R Mainland NZ
- MfE Landsat8 2014 NIR SWIR R Mainland NZ
- MfE SPOTMaps 2014 R G B Mainland NZ
- MfE Landsat7 2013 NIR SWIR R Mainland NZ
- MfE SPOTS 2013 NIR SWIR R Mainland NZ
- MfE Landsat7 2012 NIR SWIR R Mainland NZ
- MfE SPOTS 2011 NIR SWIR R Mainland NZ
- MfE DMC 2010 G R NIR Mainland NZ
- MfE SPOTMaps 2009 R G B Mainland NZ
- MfE SPOTS 2008 NIR SWIR R Mainland NZ
- MfE Landsat7 2008 NIR R G Mainland NZ
- MfE Landsat7 2001 NIR SWIR R Mainland NZ
- MfE SPOT3 1997 NIR R G Mainland NZ
- MfE Landsat4 1990 NIR SWIR R Mainland NZ
- MfE SPOT1 1990 NIR R G Mainland NZ.

as well as ancillary aerial imagery, OpenStreetMap (https://www.openstreetmap.org/#map=2/-41.2/-6.6) and Retrolens (historic aerial imagery; https://retrolens.co.nz/).

MfE set the methodology for data editing and required us to use their web feature service for all live editing of land use change data (Deliverable 13 and 14). Their methodology included specific instructions for how to work with polygon selection and deselection, updating attributes, saving edits and other critical set up requirements or restrictions for both ArcGIS Enterprise and ArcGIS Pro. This allowed for the mitigation of known bugs and data editing challenges editing web feature services. The development of this knowledge and/or set up of the system was ongoing throughout editing work and required trouble-shooting as challenges arose.

Version management involved these six broad steps.

1 Signing into the Ministry's ArcGIS Enterprise.
2 Loading the LUM feature service into ArcGIS Pro.
3 Loading the Ministry's imagery into ArcGIS Pro.
4 Creating and connecting to a version of the LUM web feature service.
5 Applying a definition query to constrain edits to a geographical area (region).
6 Requesting the Ministry reassign ownership of the version to the next designated MWLR staff member.

Regional ArcGIS Pro templates were created to reduce the risk of set-up errors leading to editing conflicts. A master spreadsheet was used to track and project progress, manage version assignment and stage editing by the digitising team.

Regional versions were assessed for quality and accuracy at completion of all class-based edits and changes by region. Reconciliation and validation steps were undertaken by MWLR, and involved the four broad steps listed below.

1 Reconciling the child version with the parent (brought in updates from other regions, if the Ministry had posted them to the parent).
2 Exploring version changes to validate individual editing work and validity of the change (QC/QA step-change checking).
3 Undertaking topology checks – any errors found were resolved as appropriate.
4 Once confirmed, handing over finalised versions the Ministry for final quality checks/corrections before they were accepted and posted.

Figure 8 provides a visual overview of the broad workflow undertaken to incorporate LUM 2020 changes and editing using both the 'burn' and 'draw' polygon changes split. This figure does not detail individual methods used at each stage. However, it does show the general data and information workflow that informed the staged updates applied to LUM 2020. This includes how data was generated, the split between draw and burn targets, and the stages required to administer changes using multiple techniques.

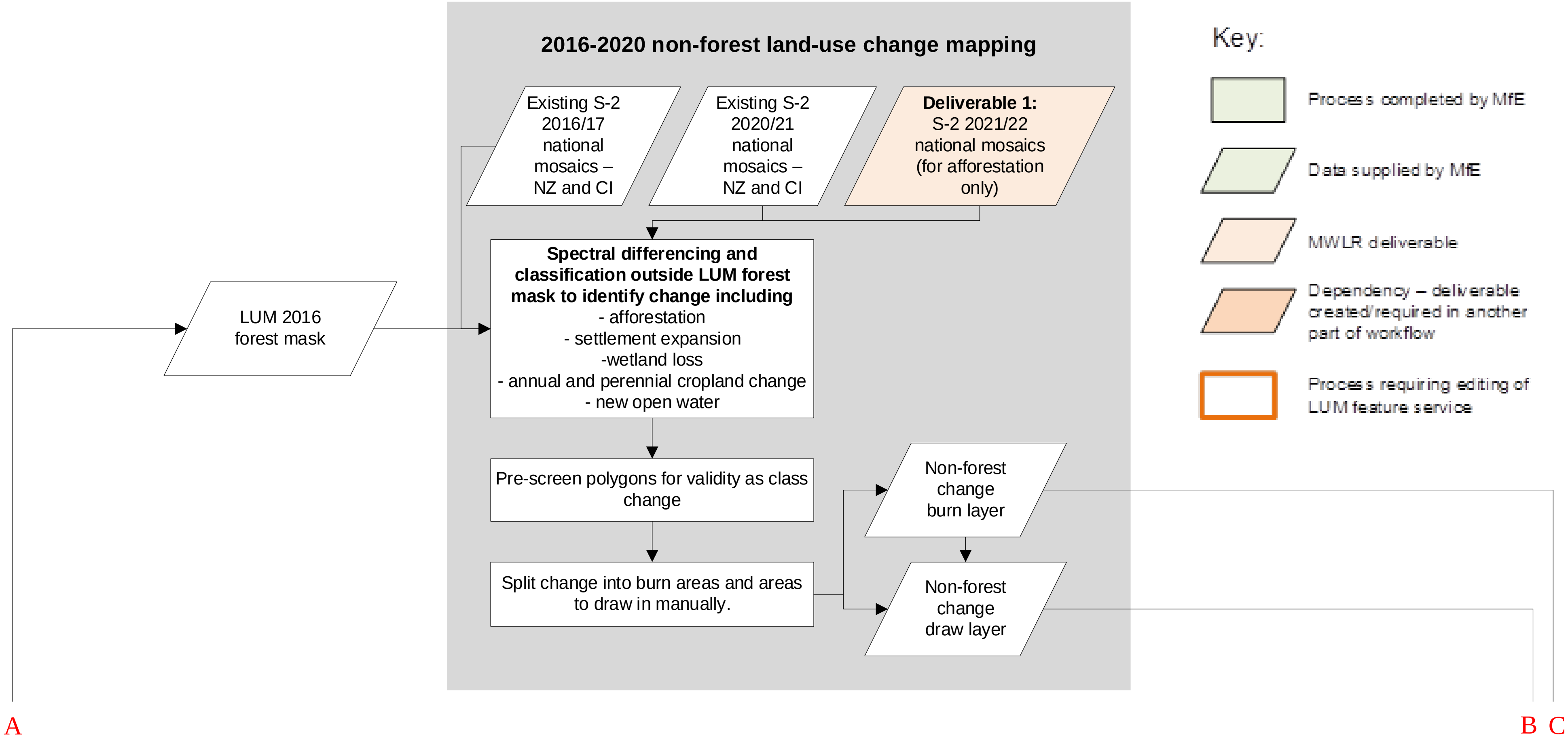


Figure 8. LUM 2020 mapping workflow. CI – Chatham Islands; IDA –Innovative Data Analysis; LCDB 5 – Land Cover Database; LUM – Land Use Map; MfE – Ministry for the Environment; MPI – Ministry for Primary Industries. MWLR – Manaaki Whenua – Landcare Research; LINZ -Land Information New Zealand; NZLRI - New Zealand Land Resource Inventory– ; PANZ – Protected Areas of New Zealand; I S-2 Sentinel-2.

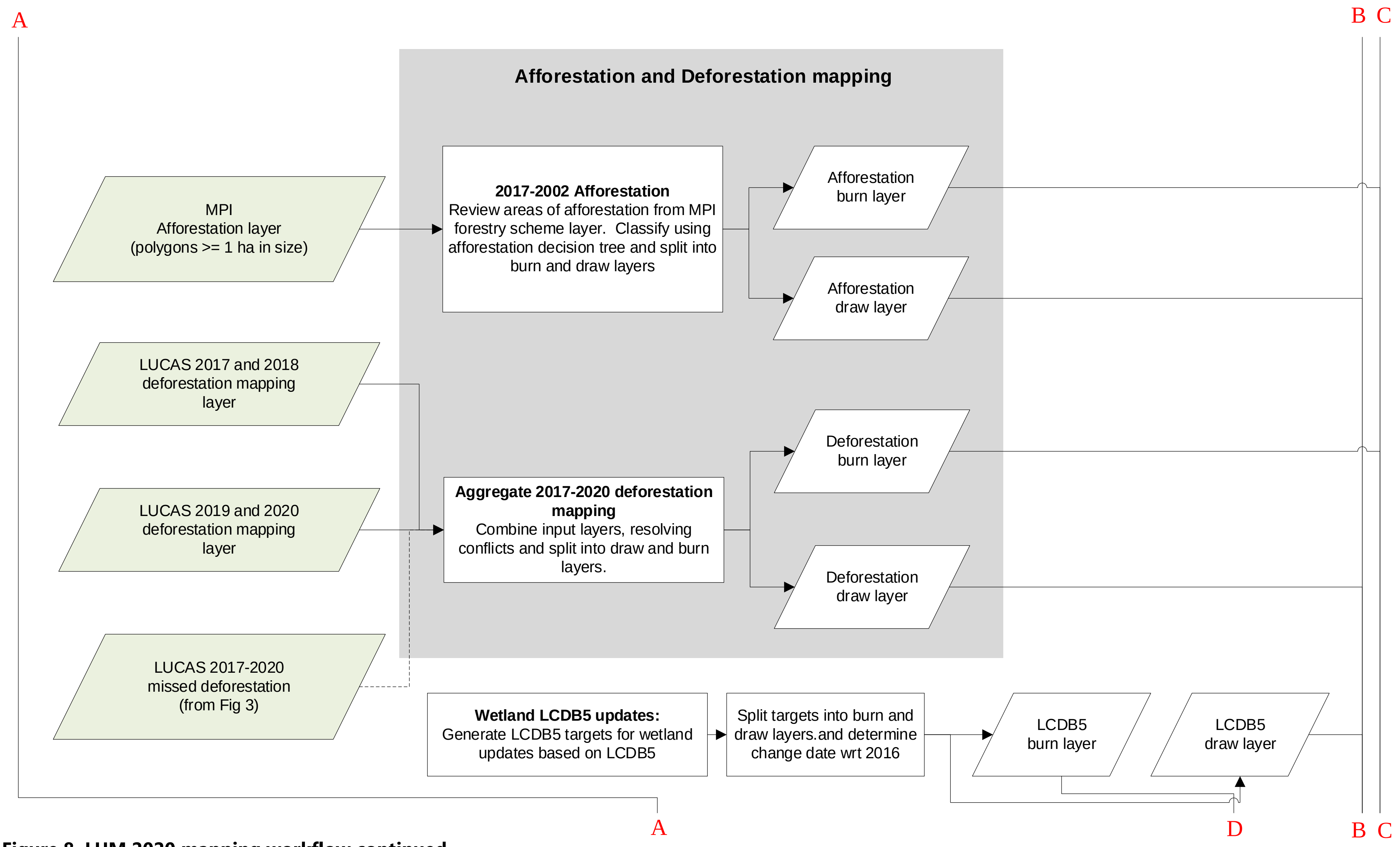


Figure 8. LUM 2020 mapping workflow continued.

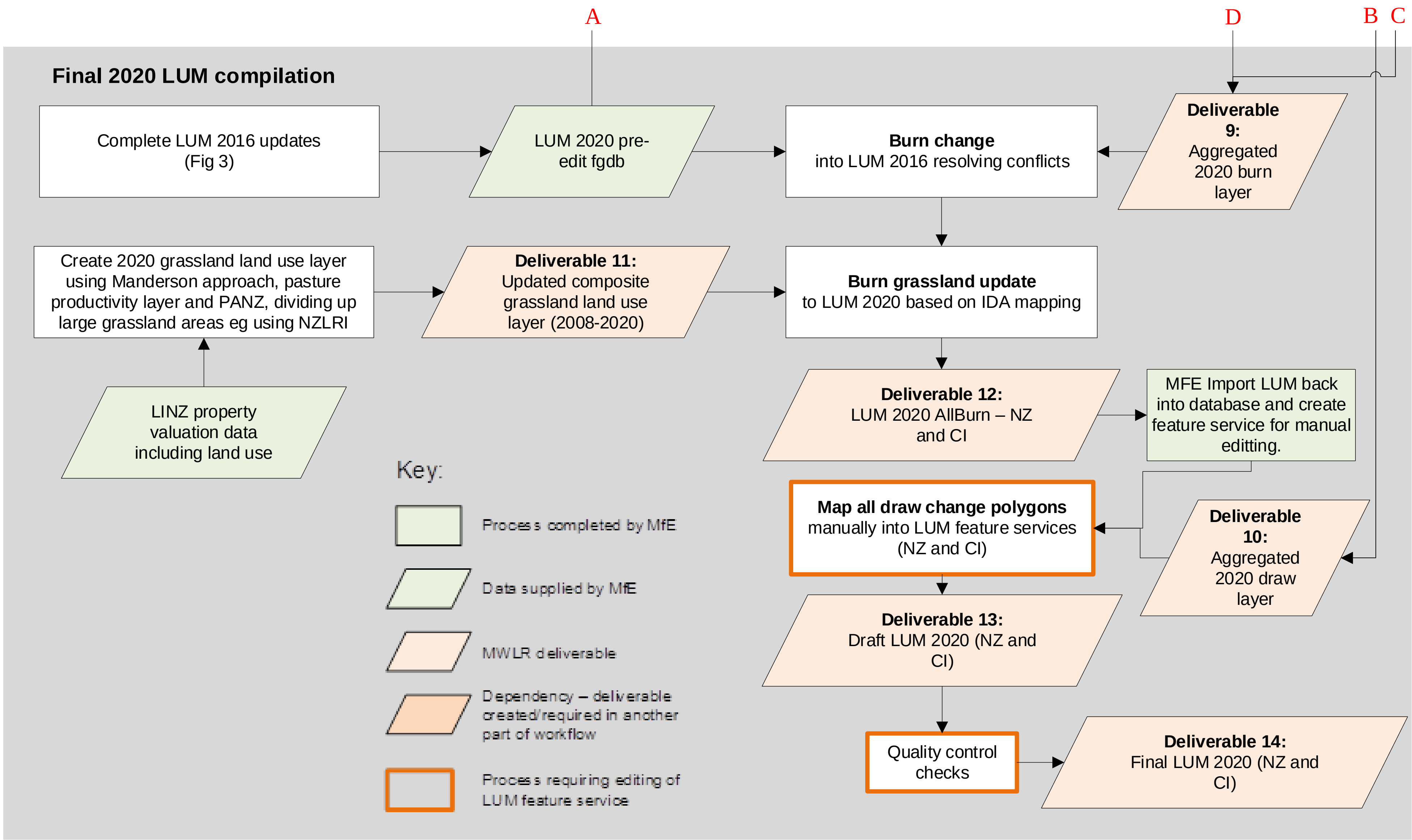


Figure 8. LUM 2020 mapping workflow continued.

5 Results

5.1 Deliverable 1: National mosaics

Seamless island image mosaics were created from Sentinel-2 (S-2) satellite imagery acquired in the summer of 2021/22, using the most cloud-free S-2 orbital tracks acquired between October 2021 and March 2022.

LUM 2020 change detection techniques used seamless image mosaics created for and purchased by MfE previously. We also used the 2021/22 summer mosaic in the LUM assessments to ensure that land use change persisted in the year following LUM 2020.

Th 2021/22 national mosaics are shown below (Figure 9).

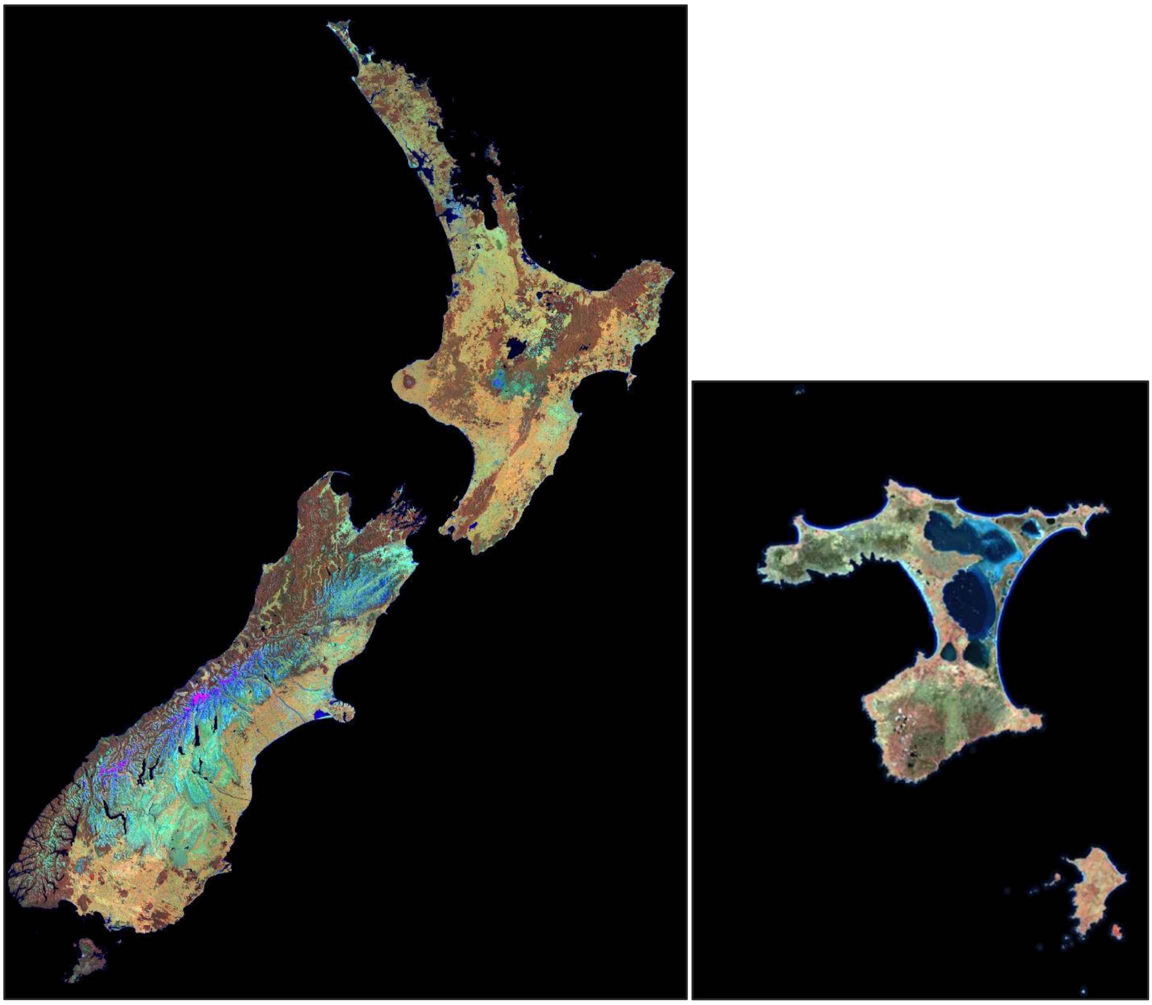


Figure 9. Sentinel-2 mainland New Zealand image mosaic for 2021/2022 and Sentinel 2 Chatham Islands, New Zealand, image mosaic for 2021/2022. Images are shown in false colours where pasture is orange; bare and semi-bare ground is pale blue; forest is brown.

5.2 Deliverables 2–4: Deep learning products, corrections and improvements to LUM 2016

Initial DL prototypes

This section provides an overview of the results of the DL objectives as part of LUM 2020. For a more detailed discussion of result refer to Martin et al. 2023.

The resulting LUM-DL v001 land use map comprised four data sets in geolocated PNG raster format, as listed below.

- LUM_DL_2016_predicted: LUM-based land cover raster (10 land cover classes) predicted from a S-2 2016 10-band raster using a DL model trained on an alternate subset of the raster and the 2016 LUCAS LUM v008 (updated 19 June 2020).
- LUM_DL_2016_model_fit: LUM-based land cover raster (10 land cover classes) generated from a S-2 2016 10-band raster using a deep learning model trained on the same raster imagery and the 2016 LUCAS LUM v008 (updated 19 June 2020).
- LUM_DL_2016_predicted_visual: RGB visualisation of the LUM_DL_2016_predicted raster.
- LUM_DL_2016_model_fit_visual: RGB visualisation of the LUM_DL_2016_model_fit raster.

Generating the entire LUCAS LUM classes directly and automatically was/is not practicable because some class definitions include non-visual semantics such as pre-/post-1989 forest. Instead, we sought to generate a land-use-based landcover map that can be used to inform the LUM. We generated a new layer, 'LUM – Land Cover' (LUM-LC), and used this layer for subsequent training and testing.

Our results include (but are not limited to) the following.

- A DL model trained on a 50% subset of the 2016 LUM-LC was able to reproduce the rest of the map with 89% overall pixel accuracy. Recall for each of the 10 classes ranged from 95.8% for grassland to 26.0% for annual crops, with a median of 74.1%.
- The model was able to detect errors in the classification of forestry. Manual inspection of 5,698 candidate error polygons (equal to 89,473ha) resulted in 744 (8,607 ha) being chosen for corrections to the 2016 LUM. This was not all possible candidates and focused on significant areas with extremely high confidence to prioritise works. The remaining areas were considered as needing further work and investigation which was out of scope for this project. Many had low confidence, were errors in the model output or were too small to be considered significant. Using the model's confidence to rank the candidates may reduce the number of candidates to be checked by up to 50%.
- A model trained on 2016 imagery was able to generate a 2020 LUM-LC with similar accuracy to the 2016 prediction, and high agreement with the 2016 prediction (94% agreement), demonstrating a high degree of transferability to new imagery.
- Aggregating the total area of each class for the predicted 2016 and 2020 layers produced totals that generally had high agreement with the actual totals (± 0.5%),

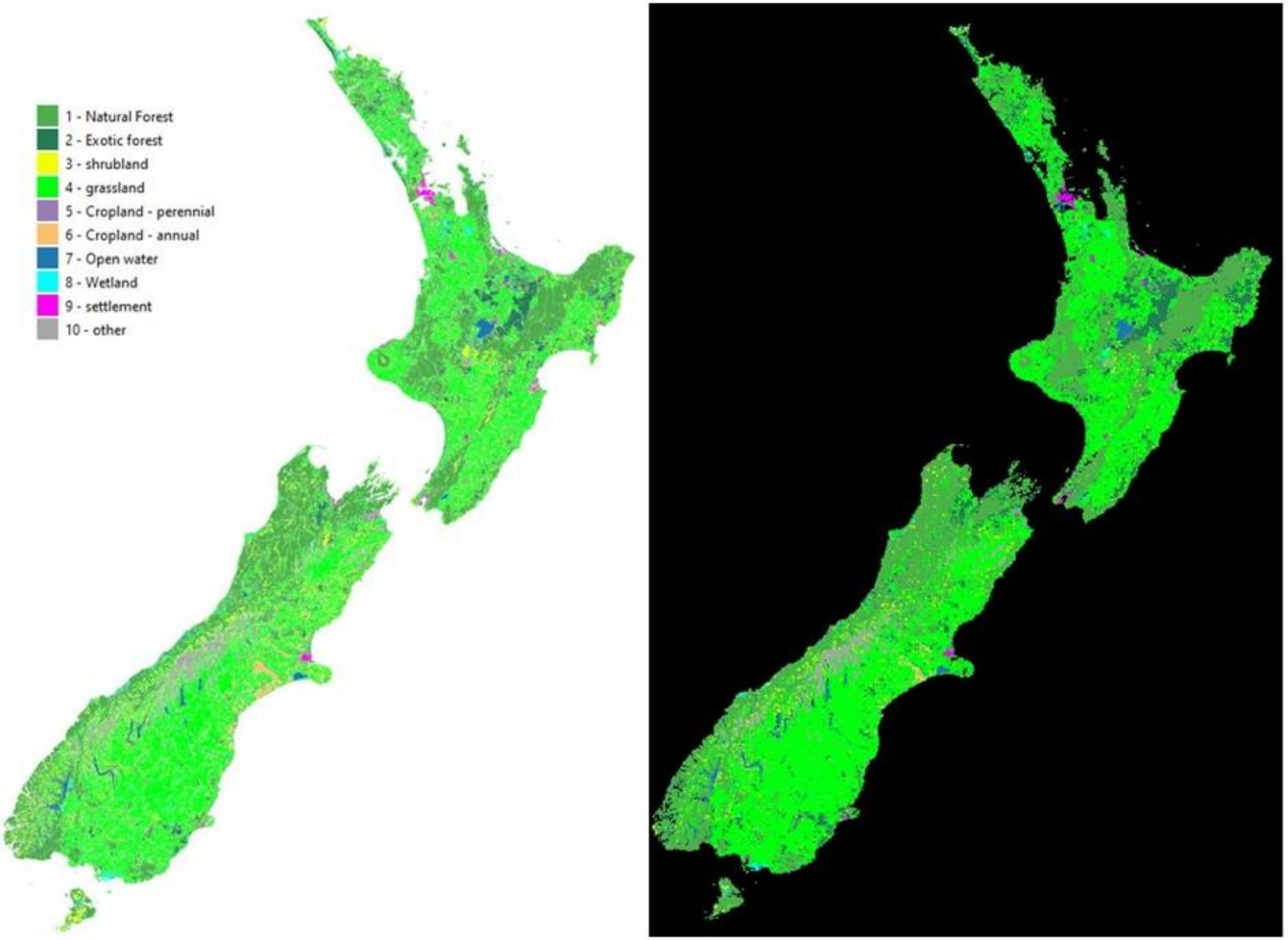
with the exception of the grassland class, which was over-represented by around 3% of total land area, and the shrubland class, which, was under-represented by around 2% of total land area. The aggregate totals had higher accuracy than the pixel accuracy for each land cover class because some errors cancel out (e.g. native forest misclassified as grassland can be cancelled out by grassland – or any other class – being misclassified as native forest).

- Using the layers directly for change detection produced mixed results. While differences in some classes, including urban settlement, appeared to be well represented, the error rates in the grassland, shrubland, and forestry classes were higher than the amount of change during the 2016–2020 period. Further, when known afforestation and deforestation areas were compared to the two LUM-LC layers, only around half of deforestation was detected (and less than one-third of afforestation) owing to the changes in land use not being immediately visible.

At the completion of the DL trials that ran alongside the LUM 2016 and LUM 2020 mapping undertaken in this body of work, we reached the following conclusions. (For more detail, please refer to Martin et al. 2023).

- We successfully trained models to automatically generate a land-use-based landcover map from S-2 imagery with acceptable accuracy that met or exceeded the performance metrics agreed with the Ministry.
- The map generated is sufficiently accurate to give a broad estimate of the total coverage of the landcover classes.
- The model shows promise as a means of detecting errors in exotic forest cover, and potentially in other classes.
- The model shows similar accuracy when used to predict a different year, and a high degree of stability, demonstrating its potential usefulness for generating periodic maps from a time series of summer mosaics (assuming the mosaics are all prepared in the same way).
- We demonstrated only partial success in detecting the changes in deforestation (50%) and afforestation (30%) occurring between 2016 and 2020; we also note that the amount of actual change during this period is smaller than the error in the predictions for the forest classes.
- Overall, the approach shows promise, and has the potential to make the map process more efficient to allow more frequent updates and assist with change detection.

Samples of these prototype results are shown in Figure 10 and Figure 11.



A **B**

Figure 10. National-scale prototype LUM-based land cover map. A) Training layer; B) Predicted layer.

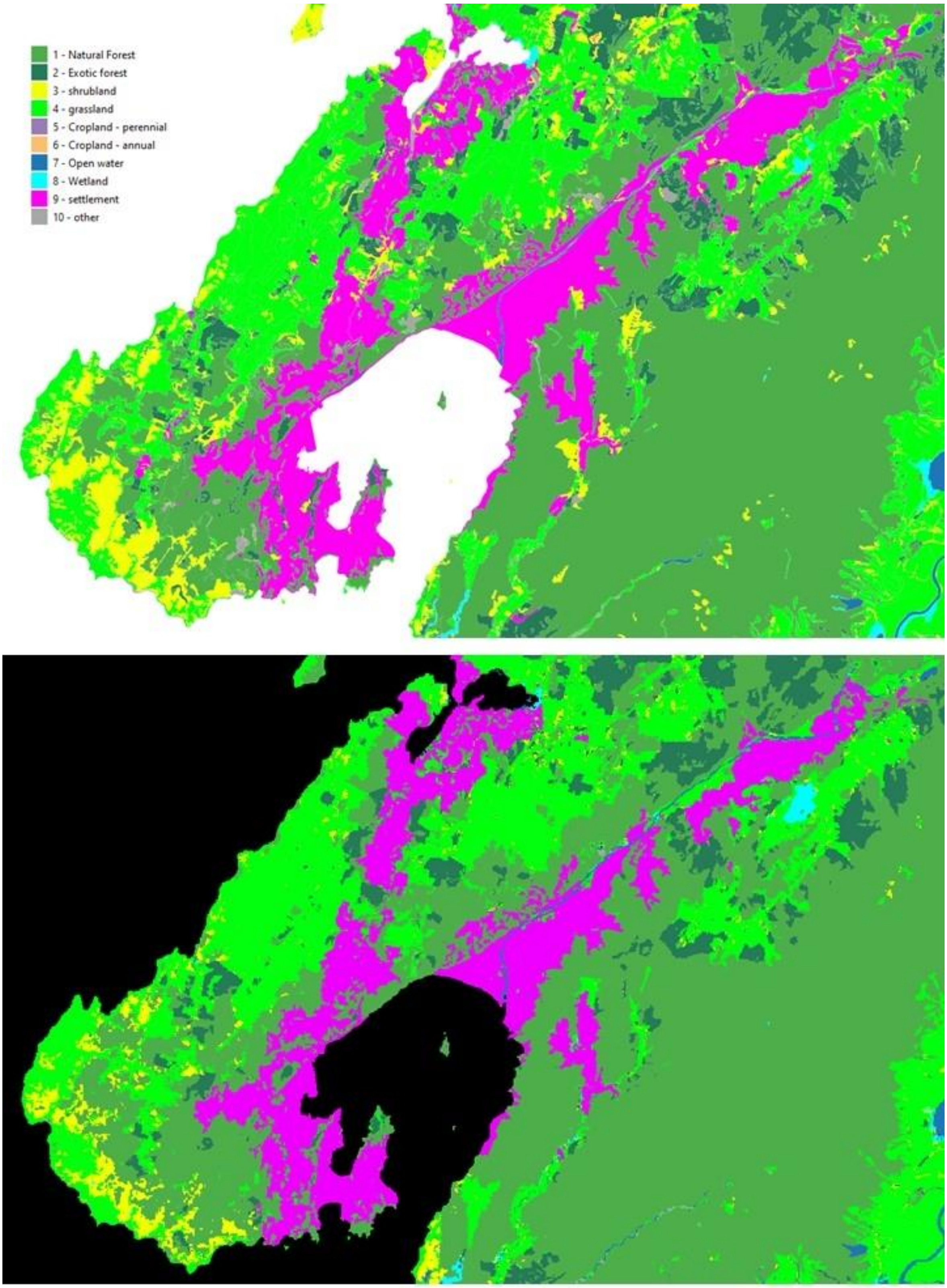


Figure 11. Subscene of Wellington from the national-scale prototype LUM-based land cover map. Top) Training layer. Bottom) predicted layer.

These prototypes, generated to assess the feasibility of using DL to infer land use/landcover classes from imagery, revealed several issues that needed to be resolved in subsequent iterations. These issues are listed in the bullets below.

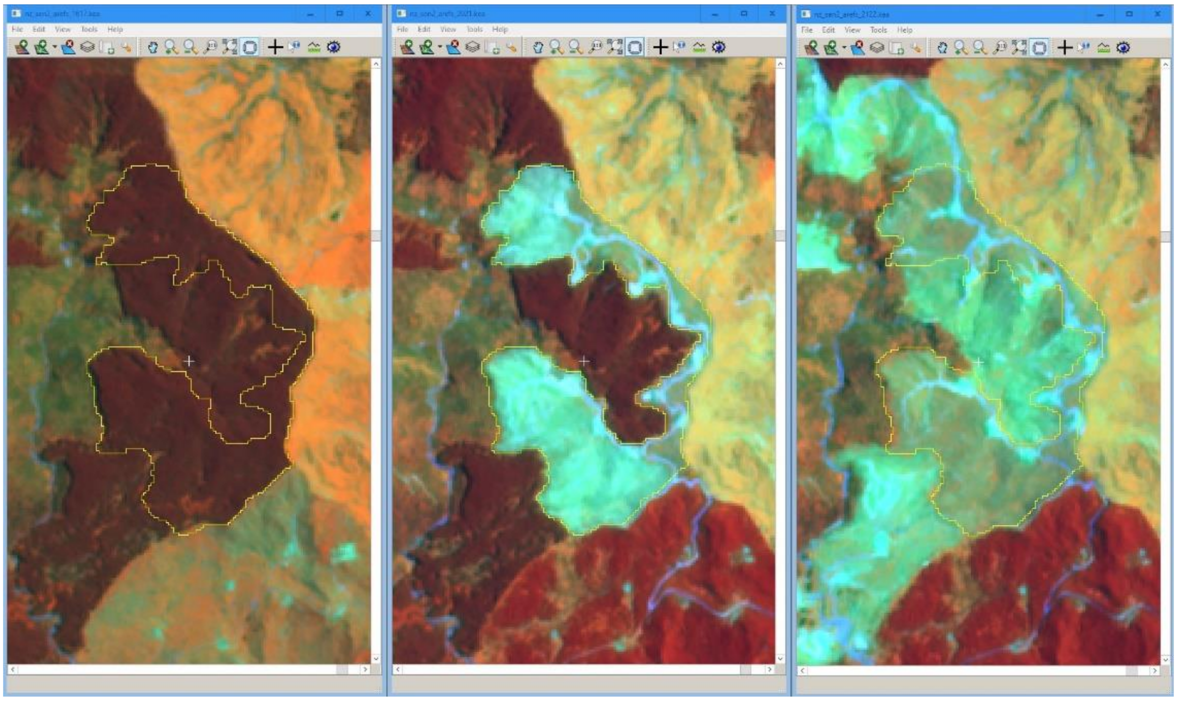
- Edge discontinuities introduced by the 512 × 512 non-overlapping raster tiles when the raster mosaics was assembled. Subsequent mosaics to employ overlapping image tiles.
- Band-by-band image normalisation processes appeared to be lowering prediction accuracies and exacerbating edge discontinuities.
- Images excluded from the training sets due to processing errors.
- Not including Stewart Island in the initial training.

5.3 Deliverable 8: Probable missed destocking 2017–2020

We identified 5,581 ha (259 polygon) areas of missed destocking. These had been missed in previous analysis due to the choice of forest mask used for previous annual destock work, or where destocking occurred progressively over multiple years and had been eliminated as it was considered undersized in each individual year of capture.

This resulted in a total of 256,536 Ha (1,676 polygons) of destocking detected and mapped, across the 2017 to 2020 total time period, as at 31 December 2020 on mainland New Zealand.

Figure 12 shows screenshots of an example of correctly detected deforestation.



A B C

Figure 12. An example of valid deforestation. Exotic forest has been destocked between: A) 2016/17; and B) 2020/21; C) the 2021/22 imagery confirms the destocking. In these false colour images, forest is brown/red-brown, pastures are orange, and bare areas are pale blue.

5.4 Deliverables 9 and 10: Aggregated burn and draw layers

Of the 706,134 polygons in the LUM 2016 improved and final version (Deliverable 7), 29,617 underwent land use change between 2016 and 2020. This included 9,596 attribute-only (tabular) changes where geometry (boundary) changes were not required.

For the final LUM 2020, 189,659 polygons (25%) underwent geometry updates, either because of land use change or polygon refinements to more accurately delineate land features. This resulted in 733,867 polygons in the LUM 2020 final version (Deliverable 14)*.

The aggregated burn layer (Deliverable 9) resulted in 20,550 areas of land use change (target polygons) that were validated and considered 'burn-ready'.

The aggregated draw layer (Deliverable 10) resulted in 5,873 areas of land use change (target polygons) that were considered to be valid change but required additional editing and/or research due to the complexity of the land use change over time. These were digitised by manual editors.

Summary statistics of land use and land use change from all mapping are summarised in Table 1. Final statistics will be compiled by the Ministry as part of New Zealand's national reporting obligations.

Of particular note is that the area of new forest planting over the period was not based on the 2020 LUM techniques described in this report but modelled from other data sources (afforestation). This is because not all new planting is visible in the satellite imagery used to create the 2020 LUM.

*Note also that these land use change areas are provisional and will undergo further refinement before being used to calculate emissions and removals from land use for the 2017–2020 period.

Table 1: Summary area statistics from the 2020 LUCAS Land Use Map, totalled for New Zealand mainland. LUCAS land use class numbers shown above/next to their names. (For full class details see Appendix 4).

2016-2020 Change Matrix			2020												
			71	**72**	**73**	**74**	**75**	**76**	**77**	**78**	**79**	**80**	**81**	**82**	
(Unit = Hectare)			**Natural forest**	**Pre-1990 planted forest**	**Post-1989 forest**	**Grassland - with woody biomass**	**Grassland - high producing**	**Grassland - low producing**	**Cropland - perennial**	**Cropland - annual**	**Wetland - open water**	**Wetland - vegetated non forest**	**Settlements**	**Other**	**Grand total**
2016	**71**	**Natural forest**	7,731,502	287		693	401	714	2		12		27	137	7,733,775
	72	**Pre-1990 planted forest**		1,436,919		1,714	4,223	2,938	71	18	1	7	30	74	1,445,995
	73	**Post-1989 forest**			687,592	2,825	8,173	5,920	7	44	2	8	14	88	704,673
	74	**Grassland - with woody biomass**		288	3,340	1,263,589	2,614	7,208	3	220	96	20	120	303	1,277,801
	75	**Grassland - high producing**		208	15,302	227	6,782,148	1,358	52	65,216	458	36	2,617	58	6,867,679
	76	**Grassland - low producing**		469	19,721	638	11,815	6,366,512		862	118	9	95	78	6,400,315
	77	**Cropland - perennial**							104,818		6		117		104,941
	78	**Cropland - annual**			77	5	29,855	6	567	302,492	92	29	308		333,429
	79	**Wetland - open water**				2	6				514,559	2	*	21	514,590
	80	**Wetland - vegetated non forest**				4	1	21			122	236,148	2	4	236,301
	81	**Settlements**			*	3	6	1			3		237,552	1	237,565
	82	**Other**		*		3					478		21	894,890	895,392
		Grand total	7,731,502	1,438,170	726,031	1,269,702	6,839,241	6,384,677	105,519	368,852	515,946	236,258	240,905	895,654	26,752,458

* Denotes a minor change however this has been rounded down to 0 hectares.

5.5 Project management and quality control

The project team consisted of remote sensing senior scientists, deep learning experts, image processing scientists, geographic information system (GIS) specialists, and image analysts experienced in land-use and land-use change mapping from satellite imagery. The core of this team has successfully delivered four dates of LUCAS land-use mapping (LUM) and three dates of New Zealand landcover database mapping (LCDB), and has conducted developmental research to prototype methods and processes in support of such work. The technical lead of the project team is also a project manager with successful experience in large mapping and IT projects both in New Zealand and overseas. Workflows required the use of proven or prototyped processes on the same or similar data types as before, so resourcing and throughput could be estimated with reasonable confidence.

Progress against timelines was managed using conventional project management tools, using both electronic monitoring and spreadsheet-based progress tracking that was visible to all the team. Mapping decision making and problem solving was both collaborative and collective so that standards and decisions were consistent across all tasks related to deliverables.

Regular reports were also provided to the Ministry (monthly progress) along with weekly and fortnightly meetings depending on relevance to deliverables. Teleconferences were conducted via online meetings (MS Teams) between project managers from MWLR and the Ministry, with technical staff included, as appropriate. All quality standards were met: Tables 2–5 display required quality standards for each task(s) related to Deliverables where they were required.

Table 2. Quality standards associated with Deliverable 1

QA1	All mosaics, with the exception of the Chatham Islands mosaics, will be provided in the New Zealand Transverse Mercator (NZTM2000) projection system. The Chatham Islands data will be provided in Chatham Islands Transverse Mercator (CITM2000) projection.
QA2	All cloud-minimised image mosaics will have a minimum cloud content based on available imagery with the target being less than 10% cloud cover.
QA3	Cloud masking will be generalised to avoid high frequency ‘noise’ in the resulting mosaics. Each distinct ‘patch’ in the control mask should be no smaller than 100 hectares in size, unless adherence to this rule creates a hole in the mosaic.
QA4	Cloud masking in all standardised-reflectance image mosaics should cover at least 95% of the cloud and cloud shadow present in each mosaic by area.

Table 3. Quality standards associated with Deliverable 2–4 and 15

QA5	A minimum of 90% agreement between 2016 LUM-derived classes for all of New Zealand and DL model predictions for the same area, repeated at least three times.
QA6	At Least 85% accuracy between 2016 LUM model trained on 50% of the land area and tested on the other 50% in a chequerboard pattern, repeated twice
QA7	A minimum of 85% agreement between predicted 2020 LUM classes and 2016 training data.
QA8	Report is reviewed at draft stage by the Ministry and is judged to be a clear and concise record of the methods and findings.
QA9	Vector layers will contain no overlaps or undersized polygons (less than 0.1 ha).

Table 4. Quality standards associated with Deliverable 5

QA10	The feature service will pass all attribute rules and topology checks included in the service.
QA11	The total number of polygons less than 0.05 ha in size does not increase as a result of mapping activity.

Table 5. Quality standards associated with Deliverable 6 and 7

QA12	All spatial data, with the exception of the Chatham Islands data, will be provided in the New Zealand Transverse Mercator (NZTM2000) projection system. The Chatham Islands data will be provided in Chatham Islands Transverse Mercator (CITM2000) projection.
QA13	All mapping data which is supplied by the Ministry in LUM geodatabases will be delivered back to the Ministry in the same form. Integrity of the file geodatabases will be maintained such that they can be successfully imported back into the LUM production database.
QA14	All mapping deliverables pass all the topology checks included in the file geodatabase as supplied by the Ministry.
QA15	All LUM mapping deliverables will have attributes updated in accordance with the Schema update rules provided in Schedule 3 and will pass all attribute checks supplied by the Ministry.
QA16	The number of polygons less than 0.05 ha in size in each LUM layer. does not increase as a result of mapping activity.
QA17	Vector layers will contain no overlaps.

6 Acknowledgement

We acknowledge the contribution that Simon Planzer (MWLR) made to this report and to the Ministry for the Environment's Carbon Sequestration team (previously known as the LUCAS team) for the collaborative approach to LUM data production and techniques.

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Appendix 1 – Project deliverables

The LUM project comprised 16 mapping deliverables completed 30 June 2023.

1. 2021/22 National satellite image mosaics based on Sentinel-2 imagery of the North and South Islands (NZ), and the Chatham Islands (CI)
2. LUM 2016 Deep Learning map – NZ
3. LUM 2016 Deep Learning corrections - NZ
4. LUM 2020 Deep Learning map – NZ (edited feature service)
5. LUM 2016 Update 1 – NZ
6. LUM 2016 Draft All Burn Update 2 – NZ and CI (file geodatabase)
7. LUM 2016 Final All Burn Update 2 – NZ and CI (file geodatabase)
8. Probable Missed Destocking 2017-2020 – NZ (file geodatabase)
9. LUM 2020 Aggregated Burn layer – NZ and CI
10. LUM 2020 Aggregated Draw layer – NZ and CI
11. Updated Grassland layer – addition of the 2020 mapping date to mapping of low and high producing grassland at 2008, 2012, and 2016 with sub-classifications included (file geodatabase)
12. LUM 2020 All Burn updates – NZ and CI
13. Draft LUM 2020 – NZ and CI (file geodatabase)
14. Final LUM 2020 – NZ and CI (edited feature service)
15. Deep Learning review report
16. Final LUM 2020 mapping report.

Appendix 2 – Grassland class/sub-class updating rules

These rules were designed to integrate valuation land use information that may have changed since the 2016 LUM where IDA modelling was used to determine grassland class/sub-class. Some additional rules were designed to correct inconsistencies or reduce the ‘Unknown’ sub-class. Rules were checked in the order shown and the first rule found to fit the criteria applied. Subsequent rules meeting the criteria were reported so that checks could be made for any inconsistencies. Where:

Rule1LU2020 = ['Arable farming', 'Multi-use within rural industry', 'Single-unit', 'Specialist livestock', 'Stock finishing', 'Store livestock', 'Vacant']

Rule2LU2020 = ['Market gardens and orchards', 'Multi-unit', 'Single-unit excluding bach']

Rule	Source data values						Changed attributes for final LUM classification				Reason
	LUCID_2016	SUBID_2016	LUCID_2020	SUBID_2020	LUse_2016	LUse_2022	LUCID_2016	SUBID_2016	LUCID_2020	SUBID_2020	
Rules applied without additional constraints											
35	78	<Any>	75	<Any>	<Any>	Arable farming			78		Grassland -> Cropland reversion
36	78	<Any>	75	<Any>	Dairy	Dairy	75	Grazed - dairy		Grazed - dairy	Grassland -> Cropland date shift
37	78	<Any>	75	<Any>	Market gardens and orchards	Market gardens and orchards	77		77		Grassland -> Perennial crop revert from 2016
38	78	<Any>	75	<Any>	<Not> Market gardens and orchards	Market gardens and orchards			77		Grassland -> Perennial crop revert (2020)
39		<Any>	<Any>	<Any>	<Any>	PNA				Ungrazed	Protected natural areas

Rule	Source data values						Changed attributes for final LUM classification				Reason
	LUCID_2016	**SUBID_2016**	**LUCID_2020**	**SUBID_2020**	**LUse_2016**	**LUse_2022**	**LUCID_2016**	**SUBID_2016**	**LUCID_2020**	**SUBID_2020**	
Rules applied if valuation land use has changed, that is LUse_2016 != LUse_2020											
21	[72, 73, 74]	<Any>	76	Unknown	<Any>	Dairy			75	Grazed - dairy	Upgrade to 75 for Dairy areas
1	76	Grazed - dairy	76	Grazed - dairy	Dairy	<in> Rule1LU2020		Grazed - non-dairy		Grazed - non-dairy	Generally low DOT; probably incorrectly classed as Dairy at 2016
2	76	Grazed - dairy	76	Grazed - dairy	Dairy	<in> Rule2LU2020	75		75	Grazed - non-dairy	Higher DoT so 75 but transitioning to non-dairy
3	76	Grazed - non-dairy	76	Grazed - non-dairy	Multi-use within rural industry	Dairy			75	Grazed - dairy	Likely intensification in Bay of Plenty (BOP) Waikato (WAI) and Northland (NTH)
4	76	Grazed - non-dairy	76	Grazed - non-dairy	Forestry	Dairy			75	Grazed - dairy	Likely intensification in BOP WAI and NTH
5	76	Unknown	76	Unknown	Stock finishing	Dairy		Grazed - non-dairy	75	Grazed - dairy	Even though low DoT, part of dairy conversion in Tasman (TAS) – Westland (WST)

Rule	Source data values						Changed attributes for final LUM classification				Reason
	LUCID_2016	SUBID_2016	LUCID_2020	SUBID_2020	LUse_2016	LUse_2022	LUCID_2016	SUBID_2016	LUCID_2020	SUBID_2020	
6	76	Grazed - non-dairy	76	Grazed - non-dairy	Stock finishing	Dairy			75	Grazed - dairy	Even though low DoT, generally part of dairy operation and both 2016 and 2020 values indicate intensive use developing
7	76	Grazed - dairy	76	Grazed - dairy	<Any>	Dairy	75		75		Correct inconsistent class of low producing (LP) grass with Dairy
8	75	Grazed – non-dairy	75	Grazed – non-dairy	<Any>	Dairy				Grazed - dairy	Change subclassing to dairy where indicated
9	75	Grazed – dairy	75	Grazed – dairy	Forestry	Store livestock				Grazed – non-dairy	No longer dairy
10	75	Grazed – dairy	75	Grazed – dairy	Water supply	Dairy		Grazed – non-dairy		Grazed – non-dairy	Single polygon correction
11	75	Grazed – dairy	75	Grazed – dairy	Dairy	<Not> Dairy				Grazed – non-dairy	no longer dairy at 2020
12	75	Grazed – non-dairy	76	Grazed – non-dairy	<Any>				75		no justification for changing class from 75 to 76 at 2020

Rule	Source data values						Changed attributes for final LUM classification				Reason
	LUCID_2016	SUBID_2016	LUCID_2020	SUBID_2020	LUse_2016	LUse_2022	LUCID_2016	SUBID_2016	LUCID_2020	SUBID_2020	
13	76	Ungrazed	76	Ungrazed	<Any>	Dairy			75	Grazed - dairy	Examples of marginal strips not grazed. Enough justification to remove from ungrazed
14	72	Unknown	76	Grazed – non-dairy	Forestry	Dairy			75	Grazed - dairy	BOP dairy conversion
15	[71,72,73,74]	Unknown	76	Unknown	<Any>	<Any>				Grazed - non-dairy	Replace all these unknowns with default "Grazed - non-dairy"
16	[72,73,74,78]	<Any>	75	<Any>	<Any>	Dairy				Grazed - dairy	Add 'Grazed - dairy' subclass at 2020 for changes to grassland where valuation is Dairy
18	[71,72,73,74, 78]	Unknown	75	Unknown	<Any>	<Not> Dairy				Grazed - non-dairy	
Rules applied where SUBID_2020 = 'Unknown'											
19	71	Unknown	75	Unknown	Vacant	Stock finishing		Tall forest		Grazed - non-dairy	Class 71 (LCDB = Broadleaved Indig hardwood) at 2016 set to

Rule	Source data values						Changed attributes for final LUM classification				Reason
	LUCID_2016	SUBID_2016	LUCID_2020	SUBID_2020	LUse_2016	LUse_2022	LUCID_2016	SUBID_2016	LUCID_2020	SUBID_2020	
											non-dairy grazing at 2020
20	71	Unknown	76	Unknown	Stock finishing	Stock finishing	72		75	Grazed - non-dairy	Additional Destock found by MWLR but actually 72 not 71
22	[72, 73, 74]	<Any>	76	Unknown	<Any>	<Not> Dairy				Grazed – non-dairy	Default to non-dairy
23	[72, 73, 74, 78]	<Any>	75	Unknown	<Any>	Dairy				Grazed - dairy	Add 'Grazed - dairy' subclass at 2020 for changes to grassland where valuation is Dairy
24	[72, 73, 74, 78]	<Any>	75	Unknown	<Any>	<Not> Dairy				Grazed - non-dairy	Add 'Grazed - non-dairy' subclass at 2020 for changes to grassland where valuation is NOT Dairy and a subclass has not been added manually by editors
25	75	Unknown	75	Unknown	<Any>	Dairy		Grazed - non-dairy		Grazed - dairy	

Rule	Source data values						Changed attributes for final LUM classification				Reason
	LUCID_2016	SUBID_2016	LUCID_2020	SUBID_2020	LUse_2016	LUse_2022	LUCID_2016	SUBID_2016	LUCID_2020	SUBID_2020	
26	75	Unknown	75	Unknown	<Any>	<Not> Dairy		Grazed - non-dairy		Grazed - non-dairy	
27	76	Unknown	[75, 76]	Unknown	<Any>	Dairy		Grazed - non-dairy	75	Grazed - dairy	
28	76	Unknown	[75, 76]	Unknown	<Any>	<Not> Dairy		Grazed - non-dairy		Grazed – non-dairy	
29	71	<Not> Unknown	75	Unknown	<Any>	Dairy				Grazed - dairy	Same as rule 23 but handled separately because of rule 19
30	71	<Not> Unknown	75	Unknown	<Any>	<Not> Dairy				Grazed – non-dairy	Same as rule 24 but handled separately because of rule 19
31	71	<Not> Unknown	76	Unknown	<Any>	Dairy			75	Grazed – dairy	Same as rule 21 but handled separately because of rule 20
32	71	<Not> Unknown	76	Unknown	<Any>	<Not> Dairy				Grazed – non-dairy	Same as rule 22 but handled separately because of rule 20
33	79	Unknown	75	Unknown	Dairy	Dairy				Grazed - dairy	
34	[75, 76]	<Not> Unknown	[75, 76]	Unknown	<Any>	<Any>				Grazed - non-dairy	

Appendix 3 – Schedule 3: LUM schema and domains

LUM 2020 Schema (greyed out attributes do not require editing)

	Field	Alias	Domain	Comment
	OBJECTID		-	System managed
	Shape		-	System managed
Land Use Attributes	**LUCID_FUTR**	FUTURE_LAND_USE	LUC	Future land use update beyond the last map (otherwise <NULL>)
	SUBID_FUTR	FUTURE_SUB_CLASS	SUB_LUC	Future subclassified land use
	START_FUTR	FUTURE_START_YEAR	-	Year the LUCID_FUTR land use commenced (change year)
	LUCID_2020	2020_LAND_USE	LUC	Land use at 31 December 2020
	SUBID_2020	2020_SUB_CLASS	SUB_LUC	Subclassified land use at 31 December 2020
	START_2020	2020_START_YEAR	-	Year the LUCID_2020 land use commenced (change year)
	LUCID_2016	2016_LAND_USE	LUC	Land use at 31 December 2016
	SUBID_2016	2016_SUB_CLASS	SUB_LUC	Subclassified land use at 31 December 2016
	START_2016	2016_START_YEAR	-	Year the LUCID_2016 land use commenced (change year)
	LUCID_2012	2012_LAND_USE	LUC	Land use at 31 December 2012
	SUBID_2012	2012_SUB_CLASS	SUB_LUC	Subclassified land use at 31 December 2012
	START_2012	2012_START_YEAR	-	Year the LUCID_2012 land use commenced (change year)
	LUCID_2007	2007_LAND_USE	LUC	Land use at 31 December 2007
	SUBID_2007	2007_SUB_CLASS	SUB_LUC	Subclassified land use at 31 December 2007
	START_2007	2007_START_YEAR	-	Year the LUCID_2007 land use commenced (change year)
	LUCID_1989	1989_LAND_USE	LUC	Land use at 31 December 1989
	SUBID_1989	1989_SUB_CLASS	SUB_LUC	Subclassified land use at 31 December 1989
	START_1989	1989_START_YEAR	-	Year the LUCID_1989 land use commenced (change year)

	Field	Alias	Domain	Comment
Original Mapping Attributes	**MAP_YEAR**	MAP_YEAR	-	Latest nominal mapping year
	MAP_METHID	MAPPING_METHOD	LUM_METHOD	Method used to map latest nominal map
	MAP_ORG_ID	MAPPING_ORGANISATION	ORGANISATION	Organisation that mapped latest nominal map
	MAP_USER	MAPPING_USER	-	Portal username of latest nominal map editor
Change Tracking Attributes	**MOD_ORG_ID**	MODIFIED_ORGANISATION	ORGANISATION	Organisation last to modify
	MOD_USER	MODIFIED_USER	-	Portal username of latest editor
	MOD_DATE	MODIFIED_DATE	-	Date last modified
	MAP_YEAR	MAP_YEAR	-	Latest nominal mapping year
Deforestation Attribute	**DEFORESTED**	DEFORESTED	BOOLEAN	Post-2007 deforestation flag
Carbon Equivalent Forest Attributes	**CEF_CLASS**	CARBON_EQUIVALENT_FOREST_CLASS	CEF	Carbon Equivalent Forest classification
	CEF_YEAR	CARBON_EQUIVALENT_FOREST_CHANGE_YEAR	-	Carbon Equivalent Forest change year
	CEF_ID	CARBON_EQUIVALENT_FOREST_ID	-	Carbon Equivalent Forest ID
Location Attributes	**ISLAND_ID**	ISLAND	LUM_ISLAND	Island ("North" vs "South" for CRA batch processing only)
	LUM_REG_ID	LUM_REGION	LUM_REGION	Adapted from Statistics New Zealand detailed 12 mile region boundaries (coastline differs)
	AREA_HA	AREA_HECTARES	-	Shape area in hectares
	GlobalID	GlobalID	-	System managed
	created_user	created_user	-	System managed
	created_date	created_date	-	System managed
	last_edited_user	last_edited_user	-	System managed
	last_edited_date	last_edited_date	-	System managed
	Shape_Length		-	System managed
	Shape_Area		-	System managed
	ID	ID	-	Copy of GlobalID (applicable to exports only)

Attribute domains

Domain	Type	Value	
BOOLEAN	Coded Value	0	0 - no
		1	1 - yes
CEF	Coded Value	1	1 - NE
		2	2 - HC
LUC	Coded Value	71	71 - Natural Forest
		72	72 - Planted Forest - Pre 1990
		73	73 - Post 1989 Forest
		74	74 - Grassland - With woody biomass
		75	75 - Grassland - High producing
		76	76 - Grassland - Low producing
		77	77 - Cropland - Orchards and vineyards (perennial)
		78	78 - Cropland - Annual
		79	79 - Wetland - Open water
		80	80 - Wetland - Vegetated non forest
		81	81 - Settlements or built-up area
		82	82 - Other
LUM_ISLAND	Coded Value	1	1 - North Island
		2	2 - South Island
LUM_METHOD	Coded Value	1	1 - EcoSat Process
		2	2 - EcoSat Harvested
		3	3 - 1990 Planted Forest Review
		4	4 - 2012 Ecosat Process
		5	5 - MPI Forestry Scheme Mapping
		6	6 - 2008-2011 Mapping improvement programme
		7	7 - 2012 Mapping Improvement programme
		10	10 - LRI High Producing
		11	11 - LRI Low Producing
		12	12 - LRI Undetermined
		20	20 - LCDB1 version 2 data
		21	21 - LCDB2 data
		22	22 - LCDB3 data
		30	30 - LINZ NZMS260 hydro data
		31	31 - 2016 EcoSat Process
		32	32 - 2017 IDA Grassland
		33	33 - MfE Deforestation Mapping
		34	34 - LCDB4 data
		35	35 - LCR Regional Cropland Mapping
		36	36 - Manual Image Interpretation
		37	37 - WONI data
ORGANISATION	Coded Value	0	0 - Manaaki Whenua - Landcare Research
		1	1 - Ministry for the Environment

Domain	Type	Value	
SUB_LUC	Coded Value	0	0 - Unknown
		101	101 - Coastal forest
		102	102 - Kauri
		103	103 - Podocarp forest
		104	104 - Podocarp-broadleaved forest
		105	105 - Beech forest
		106	106 - Broadleaved forest
		107	107 - Podocarp-broadleaved / Beech forest
		108	108 - Beech / Broadleaved forest
		109	109 - Beech / Podocarp-broadleaved forest
		110	110 - Subalpine scrub
		111	111 - Other
		120	120 - Shrubland
		121	121 - Tall Forest
		122	122 - Wilding trees
		201	201 - Pinus radiata
		202	202 - Douglas fir
		203	203 - Unspecified exotic species
		204	204 - Regenerating natural species
		501	501 - Winter forage
		502	502 - Grazed - dairy
		503	503 - Grazed - non-dairy
		504	504 - Ungrazed
		901	901 - Naturally occurring
		902	902 - Human induced
		1001	1001 - Peat mine

Appendix 4 – Schedule 4: LUCAS land use classes and sub-classes

LUCAS Land Use Class Definitions

(greyed out sub-classes are valid but not required for this contract)

Land Use Class	Definition	Sub-classes
71 - Pre-1990 natural forest	Areas that, on 1 January 1990, were and presently include: • tall indigenous forest • self-sown exotic trees, such as wilding pines and grey willows, established before 1 January 1990 • broadleaved hardwood shrubland, mānuka–kānuka (*Leptospermum scoparium–Kunzea ericoides*) shrubland and other woody shrubland (≥30 per cent cover, with potential to reach ≥5 metres at maturity *in situ* under current land management within 30–40 years) • areas of bare ground of any size that were previously forested but, due to natural disturbances (e.g., erosion, storms, fire), have temporarily lost vegetation cover • areas that were planted forest at 1990 but are subsequently managed to regenerate with natural species that will meet the forest definition • roads and tracks less than 30 metres in width and other temporarily unstocked areas associated with a forest land use.	0 - Unknown 120 - Shrubland 121 - Tall Forest 122 - Wilding trees
72 - Pre-1990 planted forest	Areas that, on 1 January 1990, were and presently include: • radiata pine (*Pinus radiata*), Douglas fir (*Pseudotsuga menziesii*), eucalypts (*Eucalyptus* spp.) or other planted species (with potential to reach ≥5 metre height at maturity *in situ*) established before 1 January 1990 or replanted on land that was forest land as at 31 December 1989 • exotic forest species that were planted after 31 December 1989 on land that was natural forest • riparian or erosion control plantings that meet the forest definition and that were planted before 1 January 1990 • harvested areas within pre-1990 planted forest (assumes these will be replanted, unless deforestation is later detected) • roads, tracks, skid sites and other temporarily unstocked areas less than 30 metres in width associated with a forest land use • areas of bare ground of any size that were previously forested at 31 December 1989 but, due to natural disturbances (e.g., erosion, storms, fire), have lost vegetation cover.	0 - Unknown 201 - Pinus radiata 202 - Douglas fir 203 - Unspecified exotic species 204 - Regenerating natural species
73 - Post-1989 forest	Includes post-1989 planted forest, which consists of: • exotic forest (with the potential to reach ≥5 metre height at maturity *in situ*) planted or established on land that was non-forest land as at 31 December 1989 (e.g. radiata pine, Douglas fir, eucalypts or other planted species) • riparian or erosion control plantings that meet the forest definition and that were planted after 31 December 1989	0 - Unknown 122 - Wilding trees 201 - Pinus radiata 202 - Douglas fir 203 - Unspecified exotic species

Land Use Class	Definition	Sub-classes
	• harvested areas within post-1989 forest land (assuming these will be replanted, unless deforestation is later detected). • Includes post-1989 natural forest, which consists of: • forests arising from natural regeneration of indigenous tree species as a result of management change after 31 December 1989 • self-sown exotic trees, such as wilding conifers or grey willows, established after 31 December 1989. • Includes areas within post-1989 natural forest or post-1989 planted forest that are: • roads, tracks, skid sites and other temporarily unstocked areas associated with a forest land use • areas of bare ground of any size that were previously forested (established after 31 December 1989) but, due to natural disturbances (e.g. erosion, storms, fire), have lost vegetation cover.	204 - Regenerated natural species
74 - Grassland with woody biomass	Includes: • grassland with matagouri (*Discaria toumatou*) and sweet briar (*Rosa rubiginosa*), broadleaved hardwood shrubland (e.g., māhoe – *Melicytus ramiflorus*), wineberry (*Aristotelia serrata*), *Pseudopanax* spp., *Pittosporum* spp.), mānuka–kānuka (*Leptospermum scoparium–Kunzea ericoides*) shrubland, coastal and other woody shrubland (<5 metres tall and any per cent cover) where, under current management or environmental conditions (climate and/or soil), it is expected that the forest criteria will not be met over a 30- to 40-year period • above-timberline shrubland vegetation intermixed with montane herb fields (does not have the potential to reach >5 metres in height *in situ*) • grassland with tall tree species (<30 per cent cover), such as golf courses in rural areas (except where the Land Cover Database has classified these as settlements) • grassland with riparian or erosion control plantings (<30 per cent cover) • linear shelterbelts that are >1 hectare in area and <30 metres in mean width • areas of bare ground of any size that previously contained grassland with woody biomass but, due to natural disturbances (e.g. erosion, fire), have lost vegetation cover.	0 - Unknown
75 - High producing grassland	Includes: • grassland with high-quality pasture species • linear shelterbelts that are <1 hectare in area or <30 metres in mean width (larger shelterbelts are mapped separately as grassland – with woody biomass) • areas of bare ground of any size that were previously grassland but, due to natural disturbances (e.g. erosion), have lost vegetation cover.	0 - Unknown 501 - Winter forage 502 - Grazed - dairy 503 - Grazed - non-dairy 504 - Ungrazed

Land Use Class	Definition	Sub-classes
76 - Low producing grassland	Includes: • low-fertility grassland and tussock grasslands (e.g. *Chionochloa* and *Festuca* spp.) • mostly hill country • montane herb fields either at an altitude higher than above-timberline vegetation or where the herb fields are not mixed up with woody vegetation • linear shelter belts that are <1 hectare in area or <30 metres in mean width (larger shelter belts are mapped separately as grassland – with woody biomass) • other areas of limited vegetation cover and significant bare soil, including erosion and coastal herbaceous sand-dune vegetation.	0 - Unknown 501 - Winter forage 502 - Grazed - dairy 503 - Grazed - non-dairy 504 - Ungrazed
77 - Perennial cropland	Includes: • all orchards and vineyards • linear shelterbelts associated with perennial cropland.	0 - Unknown
78 - Annual cropland	Includes: • all annual crops • all cultivated bare ground • linear shelterbelts associated with annual cropland.	0 - Unknown
79 - Open water	Includes: • lakes, rivers, dams and reservoirs • estuarine–tidal areas including mangroves.	0 - Unknown 901 - Naturally occurring 902 - Human induced
80 - Vegetated wetland	Includes: • herbaceous and/or non-forest woody vegetation that may be periodically flooded. Includes scattered patches of tall tree-like vegetation in the wetland environment where cover reaches <30 per cent • estuarine–tidal areas including mangroves.	0 - Unknown
81 - Settlements	Includes: • built-up areas and impervious surfaces • grassland within 'settlements' including recreational areas, urban parklands and open spaces that do not meet the forest definition • major roading infrastructure • airports and runways • dam infrastructure • urban subdivisions under construction.	0 - Unknown
82 - Other land	Includes: • montane rock and/or scree • river gravels, rocky outcrops, sand dunes and beaches, coastal cliffs, mines (including spoil), quarries • permanent ice and/or snow and glaciers • any other remaining land that does not fall into any of the other land use categories.	0 - Unknown

LUCAS Sub-class Definitions

Sub-class	Definition	Land Use Classes
0 - Unknown	Default sub-class: • not specified • not known	71 - Natural Forest 72 - Planted Forest - Pre 1990 74 - Grassland - With woody biomass 75 - Grassland - High producing 76 - Grassland - Low producing 77 - Cropland - Perennial 78 - Cropland - Annual 79 - Wetland - Open water 80 - Wetland - Vegetated non forest 81 - Settlements or built-up area 82 - Other
120 - Shrubland	Areas of natural forest that: • consist mainly of shrub-like species at the given mapping date and, • have potential to reach forest definition within 30-40 years	71 - Natural Forest
121 - Tall Forest	Areas of natural forest that: • meet the forest definition at the given mapping date	71 - Natural Forest
122 - Wilding Trees	Areas of exotic forest that: • have established from self-seeding	71 - Natural Forest 73 - Post 1989 Forest
201 - Pinus radiata	Areas of intentionally planted forest that: • consist mainly of *Pinus radiata* (radiata pine)	72 - Planted Forest - Pre 1990 73 - Post 1989 Forest
202 - Douglas fir	Areas of intentionally planted forest that: • consist mainly of *Pseudotsuga menziesii* (Douglas fir)	72 - Planted Forest - Pre 1990 73 - Post 1989 Forest
203 - Unspecified exotic species	Areas of planted forest: • that consist of a mix of exotic species • or that consist of a known species other than *Pinus radiata* or *Pseudotsuga menziesii* • or where the signature is exotic, but the specific species is unknown	72 - Planted Forest - Pre 1990 73 - Post 1989 Forest
204 - Regenerated natural species	Areas of woody vegetation that: • were not in a forest land use at 1 January 1990 • and are now reverting to natural forest as evidenced by other mapping (e.g. MPI forestry schemes) or context (e.g. fence line or other barrier to grazing which encourages regeneration)	73 - Post 1989 Forest
501 - Winter forage	Areas of grassland that: • are planted in a leafy crop for livestock grazing	75 - Grassland - High producing 76 - Grassland - Low producing
502 – Grazed - dairy	Areas of grassland that: • are used for grazing of dairy cattle	75 - Grassland - High producing 76 - Grassland - Low producing
503 – Grazed – non-dairy	Areas of grassland that: • are used for grazing non-dairy livestock	75 - Grassland - High producing 76 - Grassland - Low producing

Sub-class	Definition	Land Use Classes
504 – Ungrazed	Areas of grassland that: • are not grazed.	75 - Grassland - High producing 76 - Grassland - Low producing
901 - Naturally occurring	Areas of open water that: • formed and are contained naturally at the given mapping date	79 - Wetland - Open water
902 - Human induced	Areas of open water that: • were formed by or are now contained by direct human intervention(s) (e.g. sewage or irrigation pond; hydroelectric dam, intentionally dammed valley)	79 - Wetland - Open water
1001 – Peat mine	Areas of vegetated wetland mined for peat	80 - Wetland - Vegetated non forest