Evaluation of global land-cover data sets

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Summary

Project and client

The Ministry for the Environment contracted Manaaki Whenua – Landcare Research, a group of the Bioeconomy Science Institute, to investigate global land-cover data sets to determine their relevance to New Zealand mapping.

Objectives

- Evaluate the accuracy and utility of global land-cover data sets in the New Zealand context.
- Identify the limitations of global data sets for decision-making in environmental reporting and land-use modelling.
- Guide recommendations on using these data sets to support New Zealand's land management practices, ensuring they meet local requirements for resolution, taxonomy, and accuracy.
- Focus on three regions (Auckland, Manawatū-Whanganui, and Canterbury) for the purpose of assessing diverse land-cover configurations.
- Utilise the most recent data sets for comparison, while acknowledging potential discrepancies due to temporal misalignment.

Methods

We chose global data sets based on the following criteria:

- a global, classified land-cover map
- an adequate set of land-cover classes
- published methodology and validation results
- a suitable licence, free for research, and available online
- 10–30 m spatial resolution
- produced for multiple years since 2020.

Based on these criteria the following data sets were shortlisted:

- WorldCover: 10 m resolution, European Space Agency, validated with 75–76.7% accuracy, 11 classes.
- Dynamic World: 10 m resolution, Google, 73.8% accuracy, nine classes, only available via Google Earth Engine
- GLC_FCS30D: 30 m resolution, Chinese Academy of Sciences, 68.7–82.5% accuracy, 35 classes.

These were compared and analysed by:

- qualitative assessment of data set accessibility, alignment, and visualisation
- quantitative comparison within data sets (across time) and between data sets using Jaccard indices, confusion matrices, and Sankey diagrams
- absolute area estimates and the Jaccard index used for measuring similarity (analysis performed on pixel-level data reprojected to NZTM2000).

In terms of reproducibility:

- the methodology must be documented online and repeatable
- the code must be hosted publicly on GitHub under an MIT licence.

Results

- Dynamic World had the most anomalous classification, with particularly poor representation of forested areas. It also has a very simple taxonomy. However, it is extremely dynamic and can be used to easily obtain very recent land-cover maps.
- GLC_FCS30D also had major anomalies, this time due to processing artifacts. Despite the most comprehensive taxonomy, critical requirements for a New Zealand land-cover data set are missing. For example, it does not adequately distinguish grassland and cropland.
- WorldCover is the best candidate qualitatively and quantitatively, but it is taxonomically and temporally insufficient.

Conclusions

- None of the three data sets are well suited to any identified demand for land-cover information in New Zealand.
- WorldCover is the most consistent of the three, with baseline data sets and 10 m resolution, and is the only data set with no major anomalies. However, it is also the data set with the least temporality (only two sequential years) and with major methodological changes between these two years.

Recommendations

- Despite being unsuitable for the identified purposes, the data sets we considered may still be suitable for some other applications. There is value in the long-term temporal sequence of GLC_FCS30D, and in the rapid dynamic production of Dynamic World, but both these data sets should be used with care.
- Developments in global land-cover data sets should be monitored, as this is an active and competitive domain with room for future progress.
- In the short and medium term, validated land-cover data sets produced by New Zealand for New Zealand's needs (especially in terms of taxonomy and accuracy) are still necessary.

1 Introduction

The development of global land-cover data sets has significantly advanced recently and offers new opportunities to analyse and map land cover across regions with greater temporal and spatial resolution. However, these global data sets may not meet the specific requirements for land-cover analysis in New Zealand. This report aims to address this by critically evaluating three major land-cover maps generated from global data sets, with a focus on their applicability to New Zealand.

We considered the availability, price, timeliness, periodicity, and accuracy of these global land-cover data sets. Our analysis was driven by the need to determine the limitations they might present in decision-making processes related to land-cover applications within New Zealand. We employed both visual assessments, using maps and confusion diagrams, and quantitative measures such as the Jaccard index, to evaluate the degree of similarity and diversity among data sets, while remaining cognisant of the intrinsic errors and lack of consistent land-cover class definitions in existing maps.

2 Background

New Zealand's Land Cover Database (LCDB) serves as a valuable temporal record, but its relatively labour-intensive creation process results in limited update frequency. To maintain consistency with prior published versions, the LCDB is restricted to a 1:50,000 scale, with a minimum mapping unit of 1 hectare, and close attention must be paid to ensuring land-cover polygon boundary changes are real rather than artificial. In contrast, newly available global land-cover maps promise higher temporal and spatial resolutions.

3 Objectives

The primary objective of this study was to evaluate the accuracy and utility of global land-cover data sets in the New Zealand context. We also aimed to identify the limitations of these global data sets for supporting informed decision-making for environmental reporting, land-use modelling, and other key use cases. Ultimately, the findings will guide recommendations on the potential use of these data sets for supporting New Zealand's land management practices, ensuring they align with local requirements in terms of resolution, taxonomy, and accuracy.

We focused on three distinct regions in New Zealand: Auckland, Manawatū-Whanganui, and Canterbury. These areas were selected to ensure a comprehensive and representative evaluation of diverse land-cover types. We used the most recent data sets available to ensure the most accurate and relevant comparisons, and we also aligned them as closely as possible to a common date. However, it was not possible to achieve perfect temporal overlap across all candidate data sets, which is expected to confuse comparisons slightly.

4 Methods

Three data sets were shortlisted according to the following criteria:

- a global, classified land-cover map
- an adequate set of land-cover classes
- published methodology
- published validation results
- a suitable licence
- free (at least for research purposes)
- 10–30 m spatial resolution
- available online
- produced for more than one year from 2020.

The shortlisted data sets were ESA WorldCover, Dynamic World, and GLC_FCS30D. Information about them is presented in Table 1 below.

Table 1. Details of the three investigated global land cover data sets.

Data set	WorldCover	Dynamic World	GLC_FCS30D
Source	European Space Agency (ESA)	Google and the World Resources Institute	Aerospace Information Research Institute, Chinese Academy of Sciences
Resolution	10 m	10 m	30 m
Recurrence (ISO 8601)	R2/2020/P1Y	R/2015/P1D	R4/1985/P5Y, R/2000/P1Y
Licence	CC BY 4.0	CC BY 4.0	CC BY 4.0
Cost	Free	Free (requires Google Earth Engine and cloud storage; this is free for research, education, and non-profit use)	Free
Validation	Independently validated by Wageningen University (statistical accuracy) and IIASA (spatial accuracy). 75% (2020) 76.7% (2021)	Overall agreement between single-image Dynamic World model outputs and expert labels was 73.8%.	82.5% overall accuracy (2015) for the level-0 Land Cover Classification System (FAO LCCS) (9 basic land-cover types); 71.4% for the level-1 LCCS system; 68.7% for level-2.
Further information	https://github.com/ESA-WorldCover/esa-worldcover-datasets https://esa-worldcover.s3.eu-central-1.amazonaws.com/v200/2021/docs/WorldCover_PUM_V2.0.pdf	https://dynamicworld.app/about/	https://data.casearth.cn/thematic/glc_fcs30
Number of cover classes	11	9	35
Format	Earth Engine Asset; Cloud Optimised GeoTIFF (COG)	Earth Engine Asset; COG	Earth Engine Asset; COG
CRS/Projection	WGS 84 (EPSG:4326)	WGS 84 / UTM	WGS 84 (EPSG:4326)
Input data	Sentinel-1, Sentinel-2, plus several different auxiliary	Sentinel-2	Landsat (time series, encompassing Landsat 5 TM,

Data set	WorldCover	Dynamic World	GLC_FCS30D
	data sets (OpenStreetMap, Global Mangrove Watch, Global Human Settlement Layer, World Settlement Footprint, and the 2020 ESA WorldCover itself for the 2021 map).		Landsat 7 ETM+, Landsat 8 OLI and Landsat 9 OLI); ancillary elevation data set (ASTER DEM); MCD43A4 and CCI_LC (in training); GSPECLib (spectral library).
Associated publications	Zanaga.et al., 2022	Brown et al. 2022	Zhang et al. 2024
Download link	https://worldcover2020.esa.int/download https://worldcover2021.esa.int/download	https://dynamicworld.app/download	https://doi.org/10.5281/zenodo.8239305
GEE image collection	ESA/WorldCover/v100 ESA/WorldCover/v200	GOOGLE/DYNAMICWORLD/V1	projects/sat-io/open-datasets/GLC-FCS30D/annual projects/sat-io/open-datasets/GLC-FCS30D/five-years-map
Attribution	© ESA WorldCover project; contains modified Copernicus Sentinel data (2021) processed by ESA WorldCover consortium	Produced for the Dynamic World Project by Google in partnership with National Geographic Society and the World Resources Institute.	
Important notes	2020 and 2021 use different methodologies so temporal comparison is compromised.	Requires use of Google Earth Engine. Computed dynamically from imagery, so classification accuracy is expected to fluctuate spatially and temporally as a function of image quality.	Produced with a 'locally adaptive' model in 5° × 5° grids, which introduces boundary effects.

First, we considered the ease of obtaining, aligning, and visualising the land-cover information. We looked for obvious anomalies and critically assessed the published methodology and validation results.

Then we made a quantitative comparison between data sets (choosing data representing approximately the same time) and within data sets (across time) for three regions of New Zealand. Inter-data set comparisons are limited due to the use of incompatible (albeit similar) land-cover taxonomies, but confusion matrices, Sankey diagrams, and Jaccard indices were still used to demonstrate which classes tend to align. The Jaccard index is a statistic used to measure the similarity between two sample sets, defined as the size of the intersection divided by the size of the union of the sets. Its value ranges from 0 (no similarity) to 1 (identical sets). These three forms of comparison are all computed, in this case, on pixel-level information, after reprojecting data to the NZTM2000 projection and aligning all data to the same origin and using the same pixel size, clipped to the three study regions. Nearest-neighbour resampling is used where necessary. Comparisons are made between individual classes, though these do not necessarily have congruent meanings when made across different datasets. For Jaccard indices, classes are often combined to be more thematically similar (see Table 2).

Intra-data set comparisons (i.e. comparisons across time within the same thematic dataset) can reveal stability of methodology as well as each data set's estimate of real change. They are therefore less useful if there is methodological change, which is unfortunately the case between the v100 (2020) and v200 (2021) WorldCover data sets (the v200 methodology was apparently not applied backwards to produce a v200 map for 2020). We reported Jaccard indices for each of the candidate global data sets against LCDB v5 since it has a known accuracy for New Zealand.

The process (excluding data download, which was performed manually) is repeatable and documented online at https://github.com/manaakiwhenua/global-land-cover-comparison. This repository also includes QGIS style files for visualising each land-cover data set using the 'official' colours of each; these have been used consistently throughout this report in maps and other figures.

5 Results

5.1 Dynamic World

Producing the data set

Dynamic World images are available every 2–5 days depending on Sentinel-2 image acquisition in a particular location. They are produced using a deep learning model and are freely available and openly licensed. A distinguishing feature of Dynamic World is that it includes per-pixel probabilities to allow refinement of the classification for particular use cases or probabilistic tolerances.

Taxonomy

Taxonomically, it is difficult to interpret the difference between the 'Grass' and 'Crops' categories, particularly as they pertain to grass pasture (bold emphasis added to below summary). Dynamic World uses the following classes.

1 Water

2 Trees

   a Dense vegetation, typically with a closed canopy; taller and darker than surrounding vegetation (if present).

3 Grass

   a Natural meadows and fields

   b Urban parks and play fields

   c Pastures

4 Flooded vegetation

   a Any vegetation with obvious intermixing of water

   b Seasonally flooded areas

5 Crops

   a **Human planted**/plotted cereals, **grasses** and crops

6 Shrub and scrub

7 Built area

   a Includes nearby vegetative features clearly associated with built features

8 Bare ground

9 Snow and ice

Training and validation

The training of the deep-learning model underlying Dynamic World is described in detail in Brown et al. 2022. In brief, it involved both expert and non-expert validators, who were supplied with the classification taxonomy and corresponding definitions and tasked with drawing and labelling 'dense' polygons over image tiles. That is, the labels are applied to areas of relatively homogeneous land cover with similar colour and texture rather than being at the level of individual pixels.

The minimum mapping unit for human annotators was 5 × 5 pixels (50 × 50 m). Annotators had difficulty with the more heterogeneous classes (shrub and scrub, flooded vegetation) relative to those with more homogeneous appearance and regular shape (water, trees, crops, built area, etc.). Effort was made to ensure balance in training data sets; for example, by labelling tiles as low, medium or high occurrence for each land-cover category and then selecting approximately equal numbers of tiles with low, medium or high labels for each cover category.

The trained model is archived, with example code for running inference, on Zenodo at https://doi.org/10.5281/zenodo.5602141.

Validation of the model was assessed against a validation set of 409 image tiles withheld from model training. These tiles were independently validated by three expert annotators and one non-expert annotator, yielding 1,636 tile annotations, which were assessed for expert/non-expert agreement, inter-expert consistency, and agreement between machine labelling and different forms of expert consensus. Overall agreement between the model outputs and the expert labels was **73.8%**, nearly as high as the 77.8% agreement between the non-expert and expert labels, or between annotators in general. The grass category had especially poor performance in the model vs expert validation: 49.6% recall/producer's accuracy (indicating many false negatives), and 34.9% precision/user's accuracy (indicating many false positives). Of note for New Zealand is that the validation set of 409 tiles included two in New Zealand, one from each of the North and South Islands, making a total area of 52 km^2.

Assessment

Dynamic World is distinct from the other candidate land-cover maps in that it is generated dynamically and is accessible primarily using the Google Earth engine. There is no product to assess *per se*; it is intended to be used as an intermediate data product to which users can add further classification rules and assign final class values, producing derivative land cover maps. The default taxonomy was designed to be close to the IPCC[1] good practice guidance to ensure application of the data for estimating carbon stocks and greenhouse gas emissions.

We assessed the Dynamic World classification with the default taxonomy and highest probability class for each pixel as given. Code was written to produce a summer land-cover map for the 5-month period from 1 November to 1 April in each year. This 5-month period was used because the modal-classified value was taken for each pixel, and a wide period was necessary to attempt to avoid including cloud artifacts in the output. Even so, some remained. It may be that using Sentinel-2 cloud masks directly in conjunction with the Dynamic World image could improve this.

An immediate assessment of Dynamic World shows a few obvious artifacts in each of the years for which data were obtained. Most of these appear to be cloud related. Frustratingly, the areas that exhibit these errors are coded 0, the value used for legitimate water classification. This creates several large, phantom lakes. These could perhaps be distinguished with further processing with reference to an authoritative data set of permanent water bodies.

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[1] Intergovernmental Panel on Climate Change.

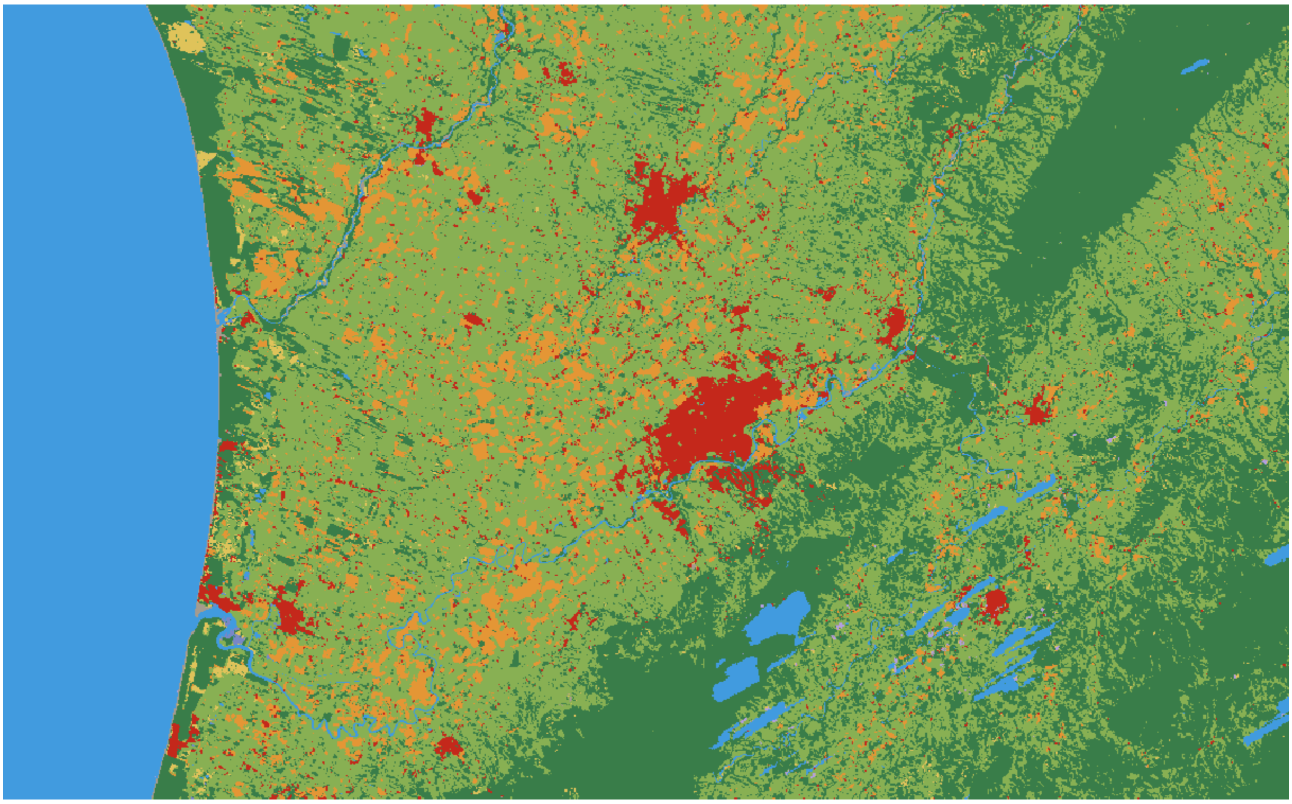

Figure 1. Dynamic World 2024/25 subset of the Manawatū-Whanganui region, showing large, non-existent lakes in the Tararua and Ruahine Ranges near Pahiatua (lower-right quadrant of image). Similar artifacts occur on the summit of Mt Taranaki, and in Te Urewera. In other years Northland is affected by the same anomaly. In this image, as in others, the officially supplied colour palette is used: water is blue, trees are dark green, grass is light green, crops are ochre, shrub and scrub are yellow, and built-up areas are red.

The other major discrepancy in Dynamic World is an extreme over-prediction of trees. This is most common in pastoral hill country, suggesting there is difficulty discriminating between shadow and forest. This effect is stable across time within Dynamic World, implying it is a systematic error.

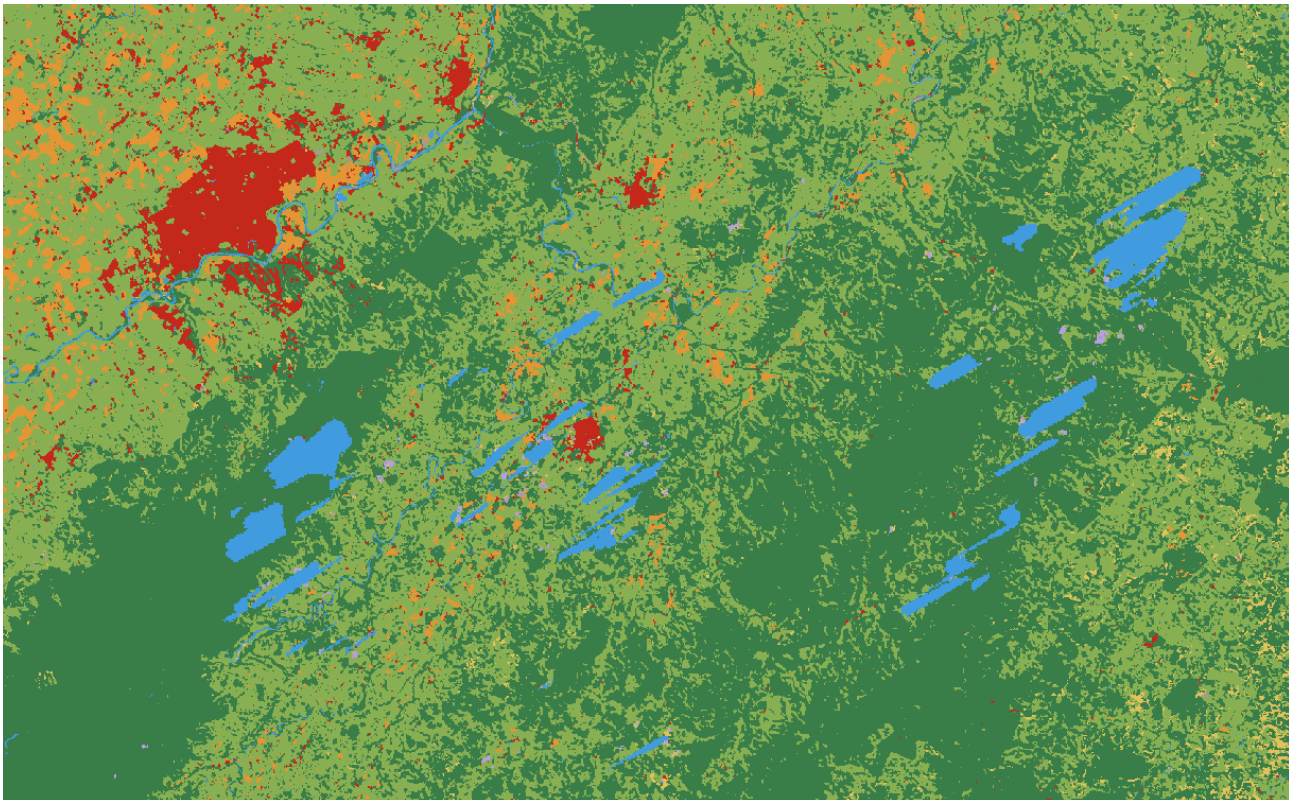

Figure 2. Dynamic World, subset of the Manawatū-Whanganui region, roughly corresponding to the lower right quadrant of Figure 1, showing over-prediction of trees, as well as a closer inspection of anomalous water features.

Figure 3. Aerial image equivalent of Figure 2, shown for reference.

When we took the entire Manawatū-Whanganui district as a region of interest and produced a Sankey diagram to investigate class correspondences between Dynamic World and the other candidates, Dynamic World had a clear, extreme over-prediction of the trees class. This is almost entirely attributable to under-classification of grass. Relative to the corresponding classes in WorldCover and GLC_FCS30D, Dynamic World predicts roughly twice as much trees area within this region. The same pattern is true in Auckland and Canterbury, although somewhat muted because this appears to be a specific difficultly with hill-country pastoral land (which is more prevalent in Manawatū-Whanganui).

With respect to the crops class, Dynamic World appears reasonable within the Canterbury Plains, labelling an equivalent and largely consistent area of land as cropland, as does WorldCover (allowing for the inherent dynamism of the concept). However, in general the built areas class is more thoroughly represented, including within the plains area, which the alternative cover maps over-represent as crops and grassland (see Figure 6).

Table 2 quantifies these findings by presenting the absolute area of the class assignment across the three regions, as well as the Jaccard index when compared against the LCDB 5 and the 2018/19 'Woody layer' (Manaaki Whenua – Landcare Research's unpublished layer of unspecified woody vegetation at 10 m resolution, identified using Sentinel-2 imagery; comparable thematically to the EcoSat Woody layer at 15 m resolution, see Dymond & Shepherd 2004). The Jaccard index between the 'Woody layer' and LCDB v5 is given as helpful context for interpreting disagreement in forested classes, because much of it can be ascribed to differences in spatial resolution. Note that the table presents results for Dynamic World as well as the other global land-cover data sets.

Figures 4 and 5 show comparisons of these three global landcover datasets.

Table 2. Area of trees, by region, as estimated by the three global land-cover products, in comparison with LCDB and the Manaaki Whenua –Landcare Research 'Woody layer'.

Land-cover product	Region	Estimated area of trees	Grasslands	Crops
Dynamic World (2024-11-01 – 2025-03-31) **Tree classes: [1]** **Grasslands: [2]** **Crops: [4]**	AKL	233.4 kha J1: 0.482 J2: 0.719	165.6 kha J1: 0.604	10.67 kha J1: 0.255
	MWT	1,314 kha J1: 0.485 J2: 0.625	729.3 kha J1: 0.521	48.83 kha J1: 0.104
	CAN	1,263 kha J1: 0.348 J2: 0.553	1,499 kha J1: 0.462	455.5 kha J1: 0.266
WorldCover **Tree classes: [10]** **Grasslands: [30]** **Crops: [40]**	AKL	237.4 kha J1: 0.494 J2: 0.745	204.8 kha J1: 0.681	7.916 kha J1: 0.230
	MWT	914.9 kha J1: 0.682 J2: 0.799	1,244 kha J1: 0.799	31.32 kha J1: 0.117
	CAN	868.8 kha J1: 0.483 J2: 0.681	2,585 kha J1: 0.695	379.2 kha J1: 0.290
GLC_FCS30D **Tree classes: [51,52,61,62,71,72,81,82,91,92]** **Grasslands: [130]** **Crops: [10,11,12,20]**	AKL	125.2 kha J1: 0.569 J2: 0.483	18.758 kha J1: 0.025	241.902 J1: 0.020
	MWT	655.1 kha J1: 0.696 J2: 0.623	79.89 kha J1: 0.033	1,241 kha J1: 0.013
	CAN	447.7 kha J1: 0.598 J2: 0.483	1,807 kha J1: 0.460	1,439 kha J1: 0.157
LCDB v5 **Tree classes: [54,68,69,79]** **Grasslands: [15,40,41,43,44]** **Crops: [30]**	AKL	127.1 kha	233.2 kha	8.972 kha
	MWT	673.8 kha	1,312 kha	17.15 kha
	CAN	479.8 kha	2,762 kha	247.9 kha
Woody layer (2018/19)	AKL	225.7 J1: 0.534	NA	NA
	MWT	904.2 J1: 0.704	NA	NA
	CAN	811.0 J1: 0.526	NA	NA

Notes: Classes are collapsed where necessary to produce more comparable estimates (lists of collapsed classes are presented in square brackets). The Jaccard index is indicated beneath each area figure. The Jaccard index is a statistic used to determine the similarity or diversity of sample sets, defined as the ratio of the intersection size divided by the union size. A value of 0 would indicate no pixels in common, and a value of 1 would indicate that the two sets are exactly equal; higher values indicate more consistent classification. The comparison in each case is between the candidate global land-cover map and LCDB v5 (J1); for the area of trees, comparison is also made with the 'Woody layer' (J2). Fair comparisons are sometimes difficult to make (e.g. Dynamic World 'trees' is inclusive of shrubs).

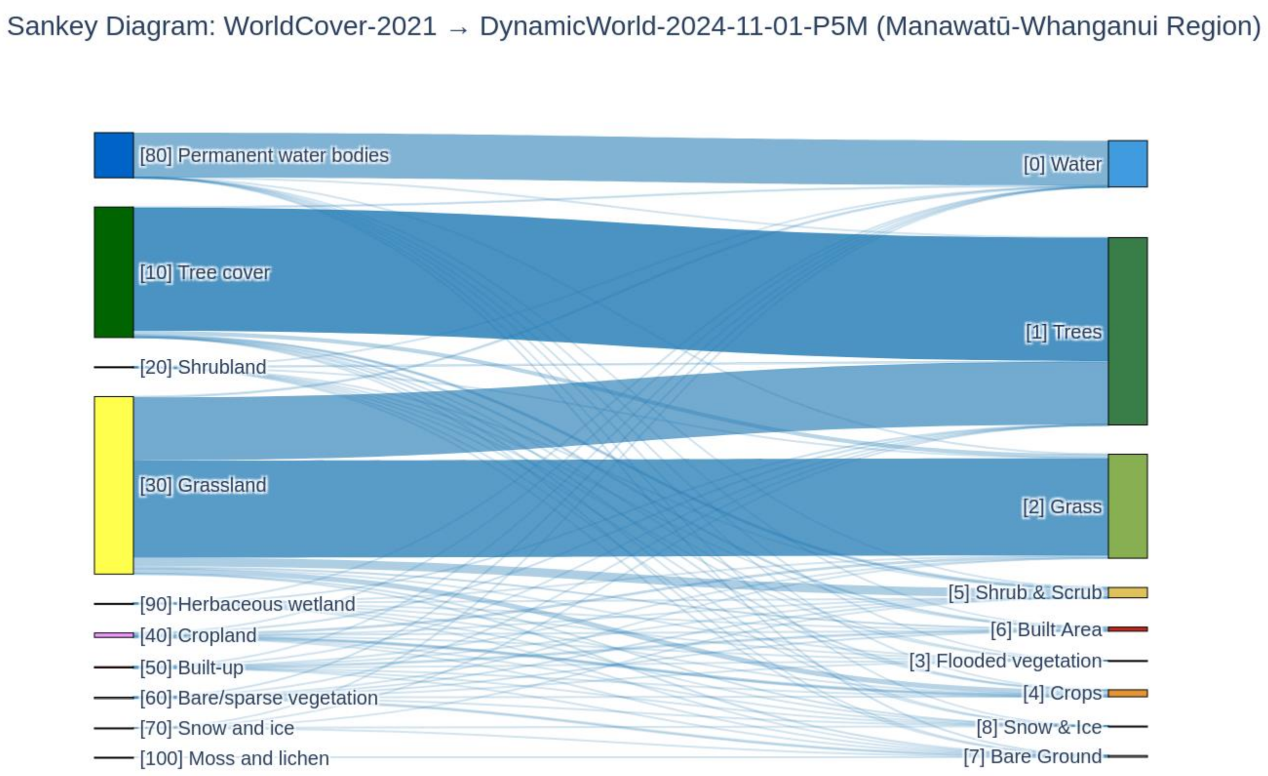

Figure 4. Sankey diagram comparing WorldCover v200 (left) against Dynamic World (right), for Manawatū-Whanganui.

Notes: Note especially the large disagreement in tree cover. Table 2 shows that LCDB indicates considerably less tree cover again (673.8 kha) than WorldCover (919.4 kha). Dynamic World predicts 1,314 kha, more than twice as much for this region as LCDB, with a Jaccard index of 0.485.

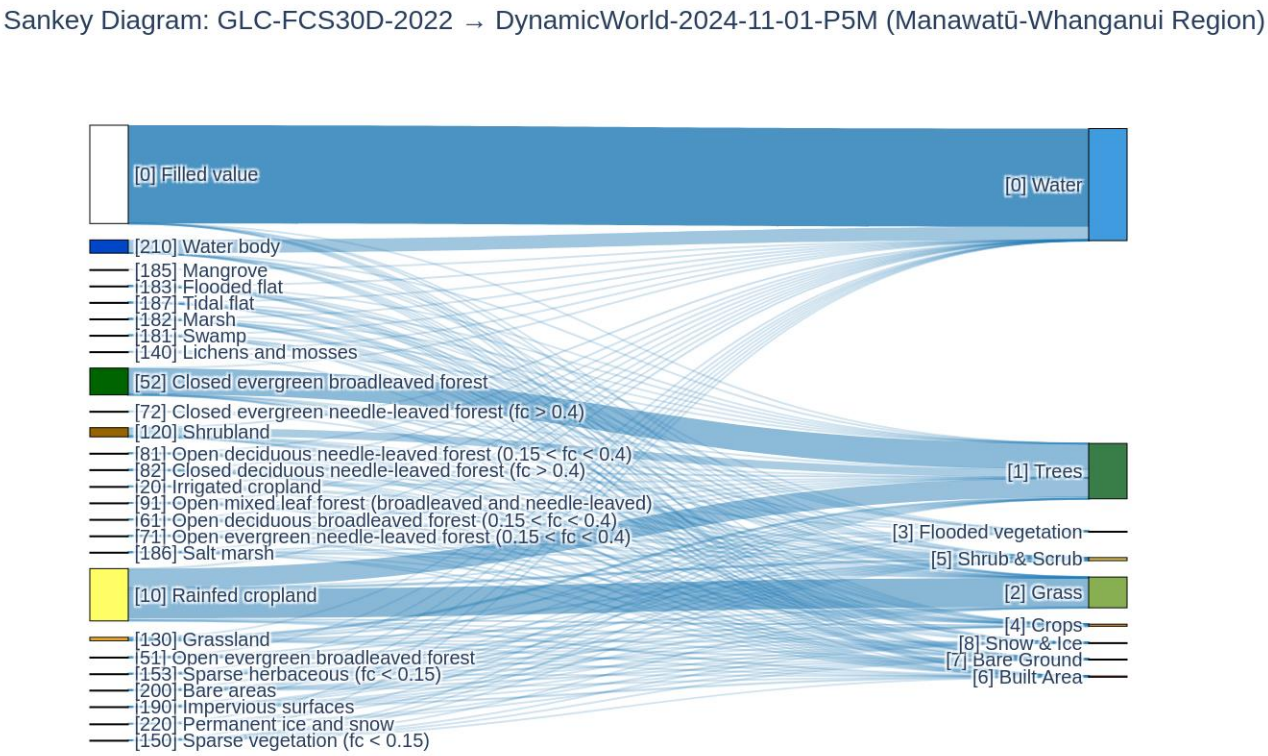

Figure 5. Sankey diagram, as for Figure 4 but comparing Dynamic World (right) against GLC_FCS30D (left). Limited to the Manawatū-Whanganui region.

Note: Once again this visually demonstrates the extent of Dynamic World's over-prediction of tree cover, particularly on grassland.

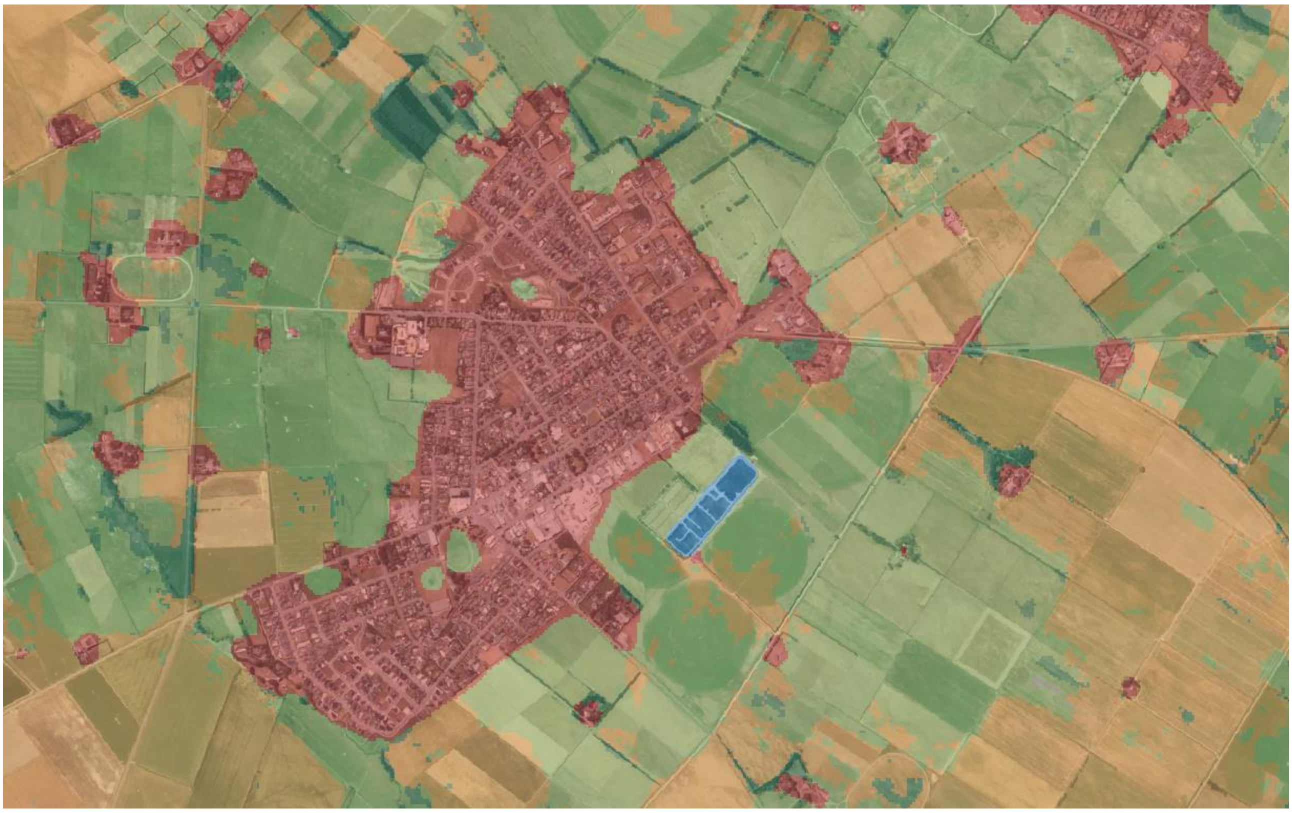

Figure 6. Dynamic World extract shown semi-transparently over an aerial image of the Canterbury Plains. Red represents built area labels.

Notes: This demonstrates Dynamic World's inclusion of considerable details missing from alternative cover maps within this class. It also indicates, perhaps, the deep-learning model's learning of a human annotator's tendency to draw training polygons smoothly around built area features; this reduces noise at the limits of such features compared to pixel-based approaches.

5.2 WorldCover

Producing the data set

WorldCover production consists of the following stages

1 Pre-processing

   a Cloud masking, speckle filtering, filling missing values, etc.

   b Feature extraction, including auxiliary (non-Sentinel) data features, including information from digital elevation models (DEMs) and yearly meteorological information.

2 Classification and prediction

   a Gradient Boosting Decision Tree algorithm (CatBoost) was employed to create three models: one using all features, one excluding Sentinel-1 features, and one excluding Sentinel-2 features.

   b The three models were combined into a final land-cover map, applying different expert rules. Some of these rules use further auxiliary data sets, including OpenStreetMap, as well as published data for mangroves, human settlements, and the v100 ESA WorldCover itself (for v200). This is used to improve classification accuracy when distinguishing between bare areas and urban areas, and between mangroves and trees, especially where there is a low-quality input due to cloud cover or spectral mixing.

Taxonomy

The European Space Agency (ESA) WorldCover data set employs a land-cover taxonomy defined according to the United Nations Land Cover Classification System (LCCS; Di Gregorio 2005), with concordances detailed in the *Product User Manual* (Van De Kerchove 2022). The LCCS was designed hierarchically and with the intention of allowing adjustments to its thematic organisation to account for the information available. Concordances between the WorldCover taxonomy and the LCCS are provided in the *Product User Manual*. This makes WorldCover particularly interoperable and well documented with respect to its taxonomy, however it still consists of a small number of high-level classes.

Following is the WorldCover taxonomy, with notes.

1 Tree cover

2 Shrubland

    a Evergreen or deciduous

3 Grassland

    a Areas ‘dominated by natural herbaceous plants … (grasslands, prairies, steppes, savannahs, pastures) with a cover of 10% or more. May contain uncultivated cropland areas without harvest or a bare soil period in the reference year’.

4 Cropland

    a Annual cropland ‘sowed/planted and harvestable at least once within the 12 months after the sowing/planting date’.

    b Perennial woody crops will be classified as the appropriate tree cover or shrub land cover type.

    c Greenhouses are considered built-up.

5 Built-up

    a Excludes urban greenspaces.

6 Bare/sparse vegetation

7 Snow and ice

8 Permanent water bodies

9 Herbaceous wetland

10 Mangroves

11 Moss and lichen

Validation

For validation, the data set relies on the independently developed Global Land Cover Validation data set developed for the Copernicus Global Land Service-Land Cover (CGLS-LC) validation. This comprises over 21,000 sampling units, each with a hundred 10 × 10 m reference pixels, with abundant sampling in New Zealand as part of the 'Australia and Oceania' continental division. The reference land cover used for validation was made by 30 remote, regional experts, all of whom have experience in satellite-based land-cover analysis or image interpretation. Their interpretations were then reviewed and improved, where necessary, as part of quality assurance.

For the 2021 WorldCover data set, validation showed:

- overall accuracy: 76.7% ± 0.5%.
- Australia and Oceania: 72.5% ± 1.3% (noted as the lowest-performing continent, attributed to difficulty classifying shrublands, grasslands and trees in open woodlands of Australia)
- grassland class performance: 75.9% (producer's accuracy) and 83.2% (user's accuracy)
- shrubland: particularly poorly performing, with an accuracy of 38.2% (producer) and 47.1% (user).

Stated limitations from the validation report and *Product User Manual* are as follows.

- There is an overestimation of trees, particularly in the temperate regions of Eurasia and Europe.
- Cloud artifacts might persist in areas of high cloud cover.
- Glaciers and mountain shadows may be misclassified as water bodies.
- Irrigated agriculture and herbaceous wetland have a high spectral similarity and can be confused.

It was not possible to directly compare v100 (2020) and v200 (2021) because there was methodological change between the two. Additionally, the method's reliance on independently produced, auxiliary data sets suggests that a dynamic annual version may be unlikely.

Assessment

Following are our qualitative observations on the WorldCover data set.

- Viticulture around Martinborough in Wairarapa appears to be systematically misidentified as grassland, sometimes cropland. We would have expected classification to shrub or tree more likely according to their taxonomy, and we did find considerably more tree labels for viticulture in the area surrounding Hastings, Hawke's Bay.
- Irrigated pastures are often labelled as cropland, especially around Ngatea (Hauraki Plains, see Figure 7 and 8).
- Roofs of large industrial buildings are often classed as bare/sparse vegetation.
- Urban parks are often classed as grassland or cropland.
- There is some confusion of mountain shadow and snow with water bodies, but considerably less than in both Dynamic World and GLC_FCS30D.

- Lakes in the Volcanic Plateau of the North Island are well defined, whereas both Dynamic World and GLC_FCS30D have gross errors here due to shadow and snow.

Overall, we did not note any extreme, systematic anomalies.

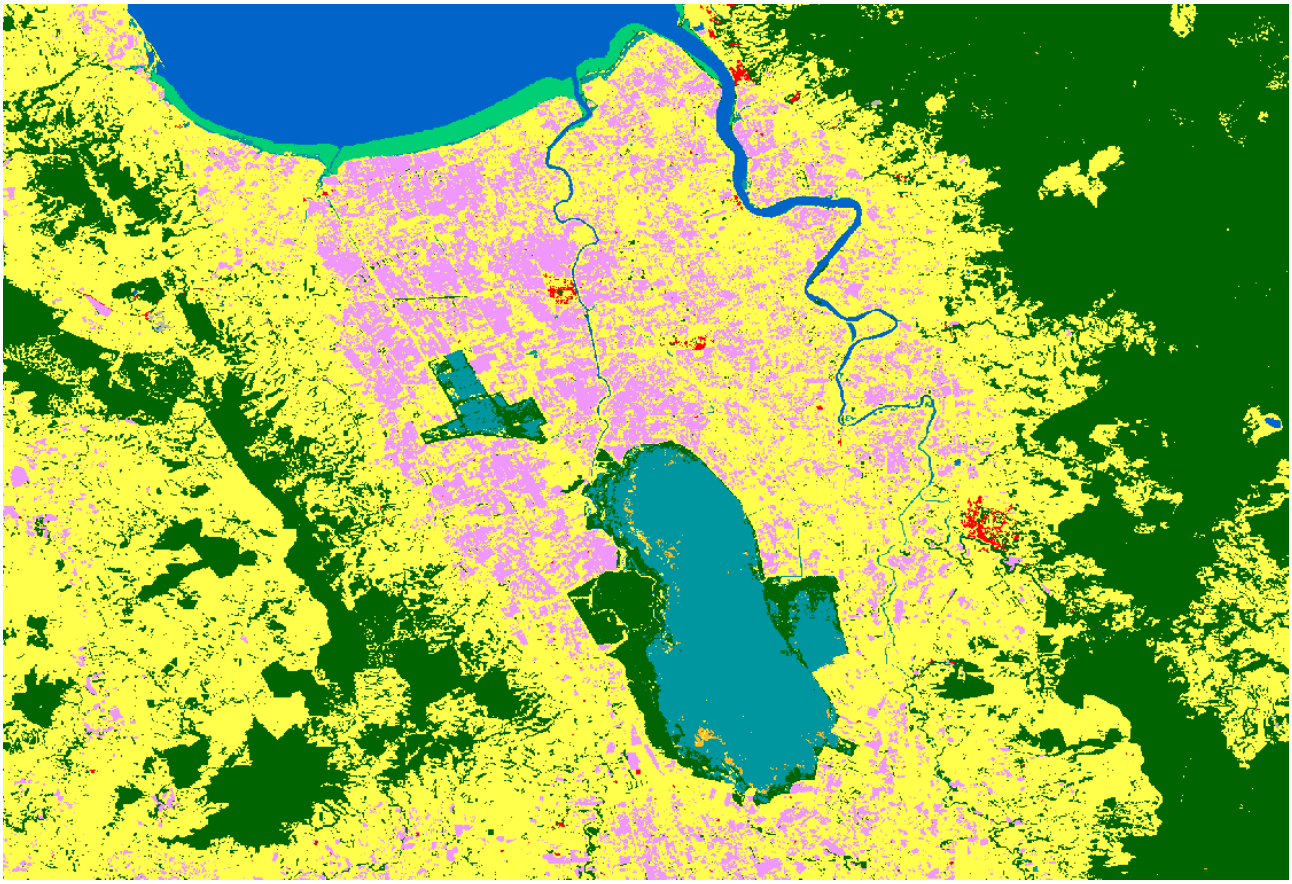

Figure 7. WorldCover v200 over the Hauraki Plains, showing large areas of cropland. Here cropland is pink; forest is dark green; pasture is yellow; water is blue; wetland is teal; built-up areas are red; and mangrove is light green.

Figure 8. Aerial image equivalent of Figure 7, for reference.

5.3 GLC_FCS30D

Producing the data set

The GLC_FCS30 (global land-cover product with a fine classification system) data set is a 30 m resolution global land-cover map designed to provide a 'fine' classification of land use using a hierarchical system of the UN LCSS classes (up to 30 categories at level 2) with a time series component (annually from 2000).

The creation of GLC_FCS30 involves the use of the full time-series of Landsat imagery. Automatic sample extraction procedures were used to draw training samples from existing, high-quality land-cover products and data sets, as follows.

- The ESA's Climate Change Initiative Global Land Cover (CCI_LC): this is used as a primary reference for determining land-cover types and their spatial distribution and is used for extracting representative training samples.
- MODIS Nadir Bidirectional Reflectance Distribution Function-Adjusted Reflectance, MCD43A4): this allows for the refinement of spectral characteristics in the training samples, ensuring that only samples with high spectral fidelity are included in the training set.

Production of this data set used a locally adaptive random forest classification model, applied to geographic tiles of 5° × 5°, allowing the model to account for regional differences in land-cover characteristics. The model was trained using derived spectral and temporal metrics from Landsat data, seeking spectral signatures of different land-cover types.

Taxonomy

The GLC_FCS30 taxonomy is as follows.

1 Rain-fed cropland

2 Herbaceous cover

3 Tree or shrub cover (Orchard)

4 Irrigated cropland (note: this does not seem to be applied in New Zealand)

5 Broadleaved forest

- a Evergreen
  - i Open (15% < fractional cover < 40%)
  - ii Closed (fractional cover > 40%)
- b Deciduous
  - i Open
  - ii Closed

6 Needle-leaved forest

- a Evergreen
  - i Open
  - ii Closed
- b Deciduous
  - i Open
  - ii Closed

7 Mixed leaf forest (broadleaved and needle-leaved)

- a Open
- b Closed

8 Shrubland

- a Evergreen
- b Deciduous

9 Grassland

10 Lichens and mosses

11 Sparse vegetation (fractional cover < 15%)

- a Shrubland
- b Herbaceous

12 Wetlands
  a Swamp
  b Marsh
  c Flooded flat
  d Saline
  e Mangrove
  f Salt marsh
  g Tidal flat
13 Impervious surfaces
14 Bare areas
  a Consolidated
  b Unconsolidated
15 Water body
16 Permanent ice and snow

Validation

Validation of GLC_FCS30 uses a set of over 44,000 validation samples with a global distribution, including an adequate inclusion of sites in New Zealand. The samples were selected with a stratified random sampling method to ensure a balanced representation of different land-cover types. High-resolution satellite imagery was used as a reference, in conjunction with recent land-cover products with expert assessment to measure producer's and user's accuracy.

Taxonomically, the GLC_FCS30 is organised into three hierarchical levels. Notably, six of the level 2 cover types (closed/open deciduous/evergreen forests; broadleaved/needleleaved forests) were removed from consideration in validation by folding them back to level 1 types because the producers were not confident in these classes within the validation data sets. Relative to the other candidate land-cover data sets, the means of validating GLC_FCS30 is unclear, particularly in terms of why the baseline land-cover data sets were themselves considered to be reliable. Therefore, the stated accuracy results for GLC_FCS30 should be treated with considerable caution.

Nevertheless, the stated validation process revealed that the GLC_FCS30 data set achieved an overall accuracy of **82.5%** for the basic classification system of nine major land-cover types. For the more detailed level 2 system, which includes 24 land-cover categories (i.e. excluding the six forest types mentioned above), the data set achieved an accuracy of **68.7%**.

The authors of GLC_FCS30 noted the following challenges.

- Spectral similarity between certain land-cover types in heterogeneous landscapes (particularly within and at the edge of built areas) is pronounced due to its 30 m cell resolution.
- Reliance on Landsat imagery means that areas with frequent cloud cover or missing data are expected to have lower accuracy.

Some detailed land-cover types are difficult to classify consistently at a global scale due to regional variations in vegetation. The locally adapted model is intended to ameliorate this but comes with the penalty of introducing methodological differences at certain arbitrary latitudes and longitudes (i.e. the zones for local adaptation are not based on biomes or any other meaningful quality).

Assessment

Our visual inspection of the GLC_FCS30 data relating to New Zealand for the period 2020–2022 revealed two major anomalies.

First there was a gross error in Northland (Figure 9). At –35.123° latitude there is a sharp boundary where grassland (north of this line) becomes labelled rainfed cropland (to the south). This demarcation persists over time, so it is, perhaps, evidence of the locally adaptive random forest model used for each 5° × 5° geographic tile, and there is presumably a break at this latitude.

Taxonomically, pasture belongs to the croplands category in GLC_FCS30D, so the erroneous part of the map with respect to the Northland anomaly is on the northern side of the boundary. In practice in the New Zealand context, grassland in the context of GLC_FCS30D appears to generally correspond to low-producing pasture and tundra, so is more abundant in the South Island.

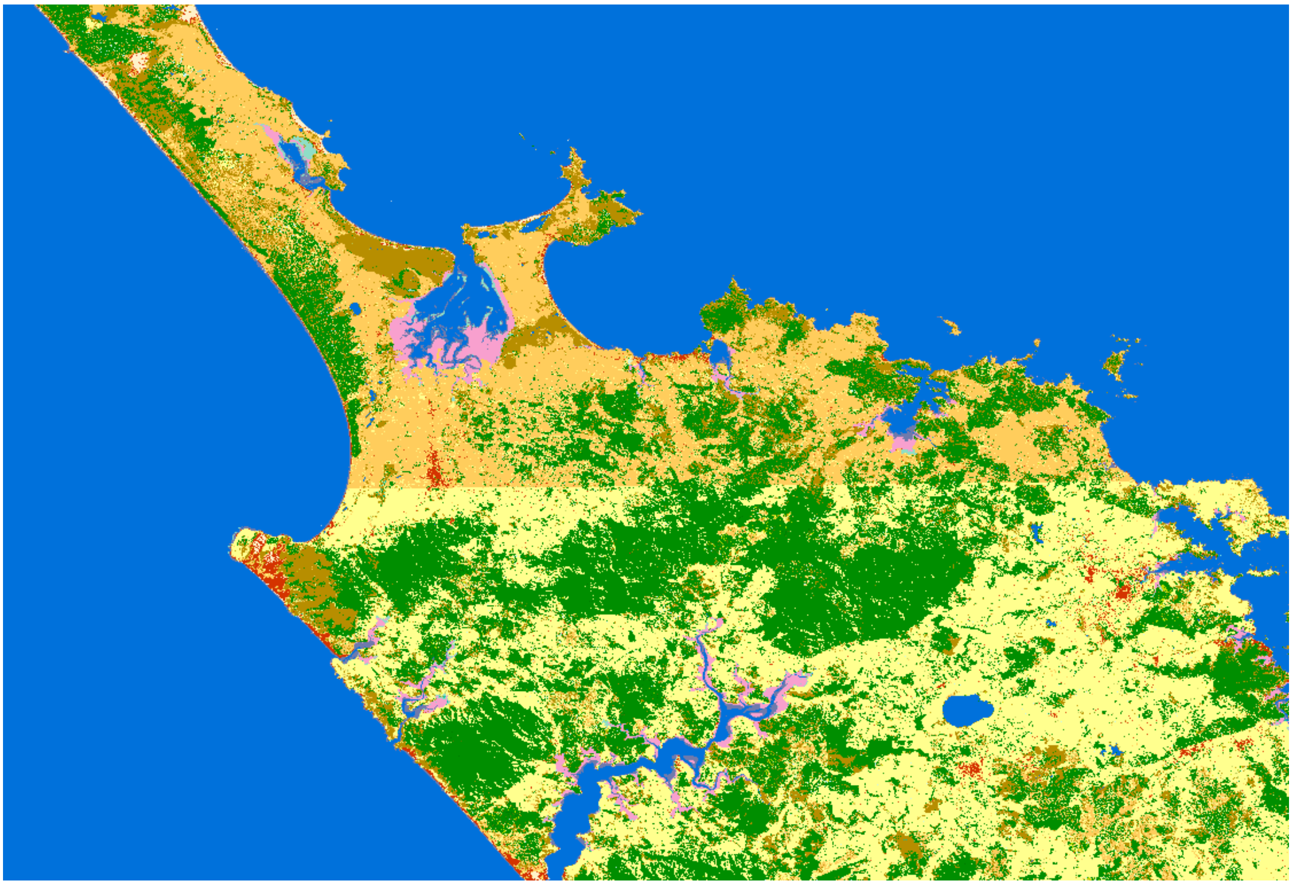

Figure 9. Gross 'boundary' error in Northland at the boundary of two 5° tiles in GLC_FCS30D.

Second, there is an anomalous seam across the full width of the North Island slightly south of Whanganui, which persists across time. This is approximately 550 m wide and appears as a continuous path, where 'cropland' (10) is mislabelled as 'built environment' (190); 'closed evergreen broadleaved forest' (51) is misclassified as 'open mixed leaf forest (broadleaved and needle-leaved)' (91); and marine areas are misclassified as 'flooded flat'. This does not seem to be a class transposition data error, yet all features within the anomaly are obviously systematically misclassified. The pattern of misclassification is stable across time and is not random. The explanation is again likely to be an issue related to the boundary of the locally adaptive models, since it is 5° south of the first anomaly and the data are produced in models that differ every 5°. Figure 10 shows part of this anomalous seam.

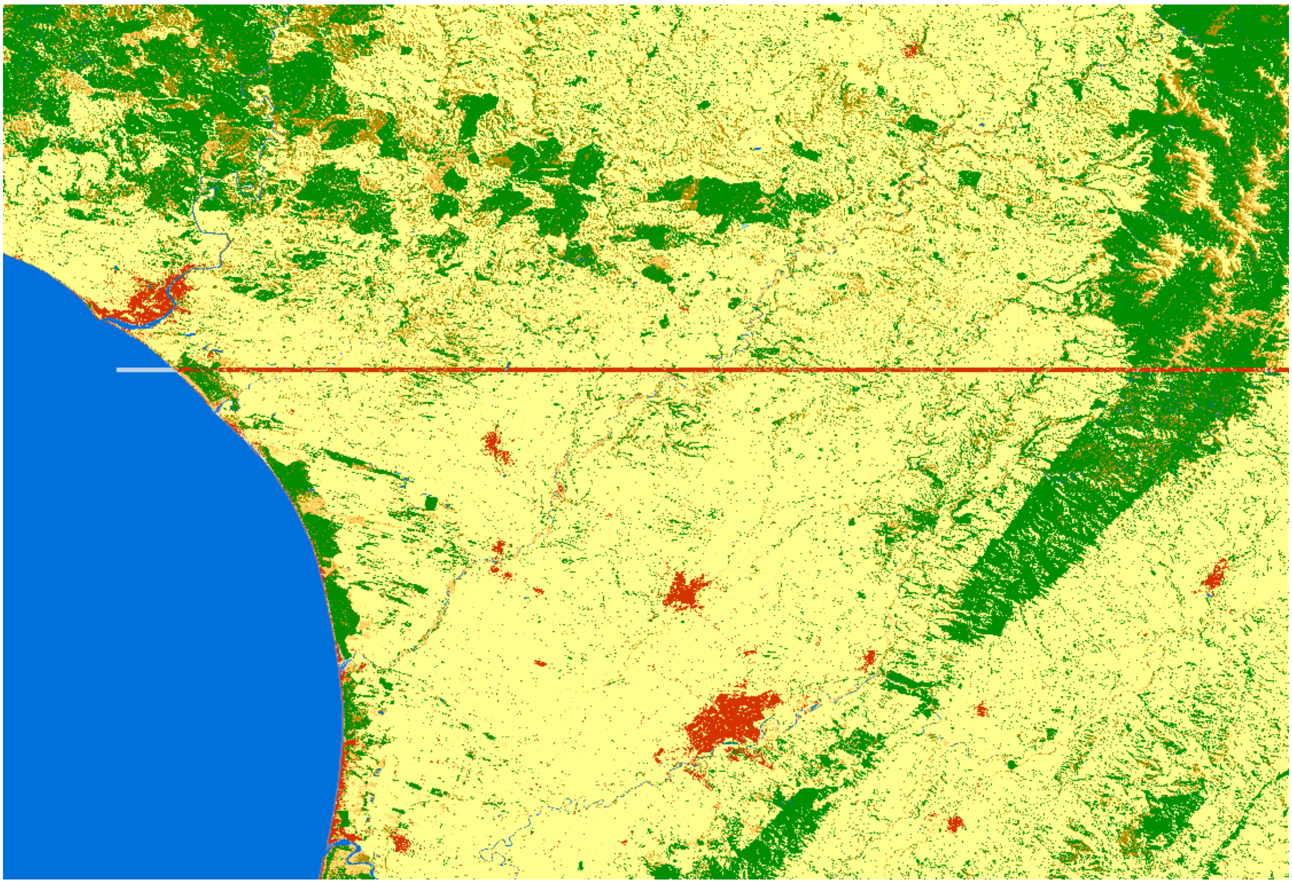

Figure 10. Gross 'boundary' error near Whanganui, at the boundary of two 5° tiles in GLC_FCS30D.

We also observed that in hill country with low-producing grassland or tundra, topographic shadowing is often classified as scrub (Figure 11).

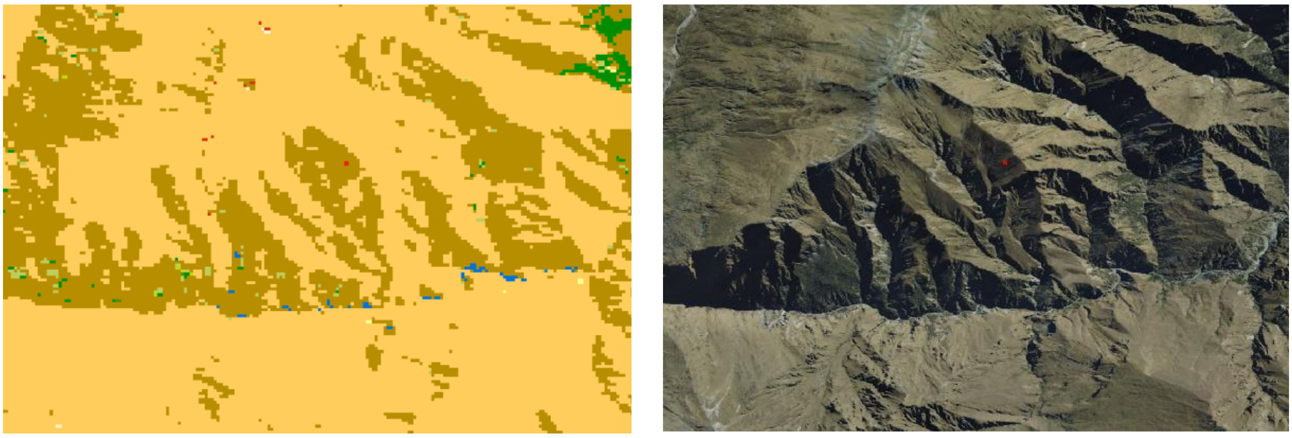

Figure 11. Hill-country area showing difficulty classifying areas of shadow (GLC_FCS30D).

As with Dynamic World, areas of permanent snow and ice in GLC_FCS30 are often confused with water bodies. Because many of these spurious water bodies occur at high elevation, this may be due to masking with a DEM with a much lower spatial resolution than the imagery used to classify the 'permanent ice and snow' category (although there is no recognition of this in the published papers). Figures 12 and 13 illustrate this.

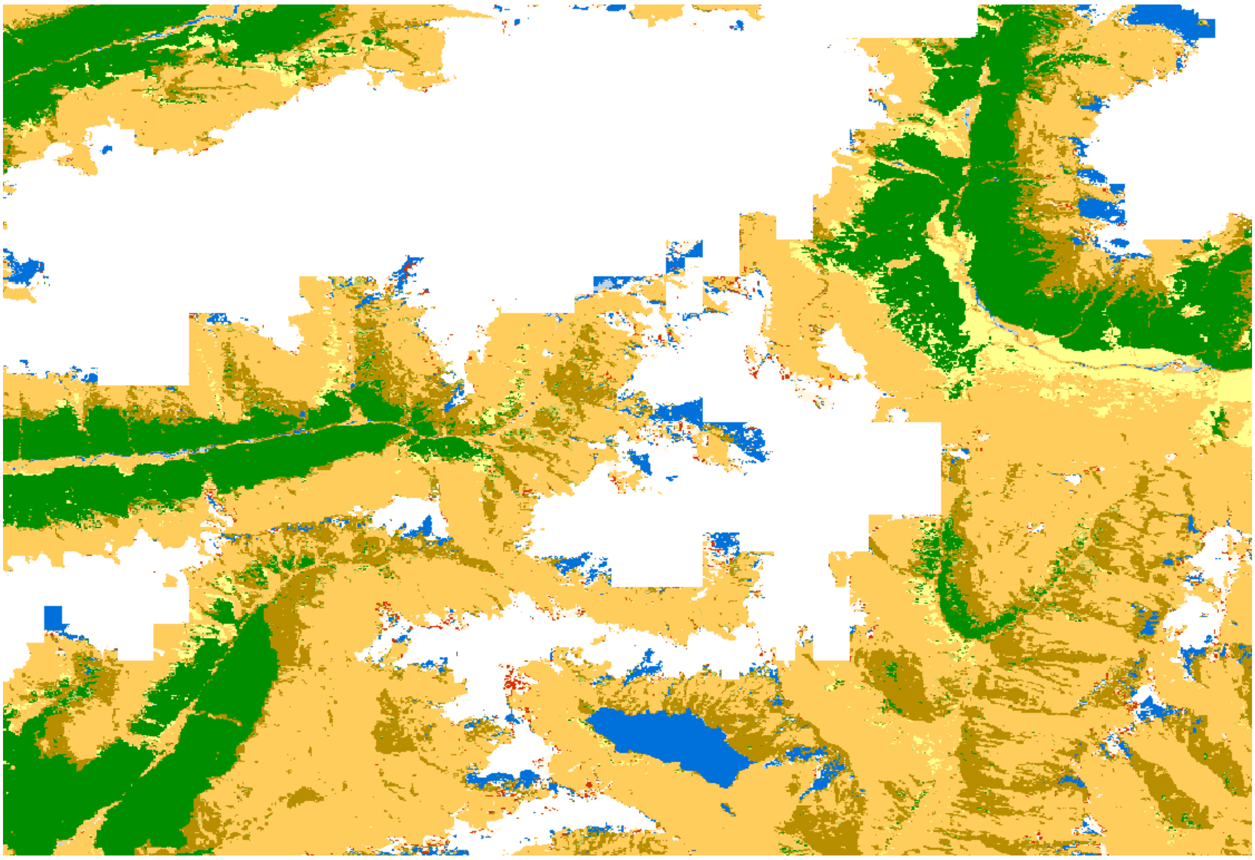

Figure 12. Area of ice and snow, showing low-resolution artifacts in an alpine environment, presumably from a masking process used to correct misclassifications of ice and snow (white) as water (blue) in GLC_FCS30D. Note that tarns have been lost in this process.

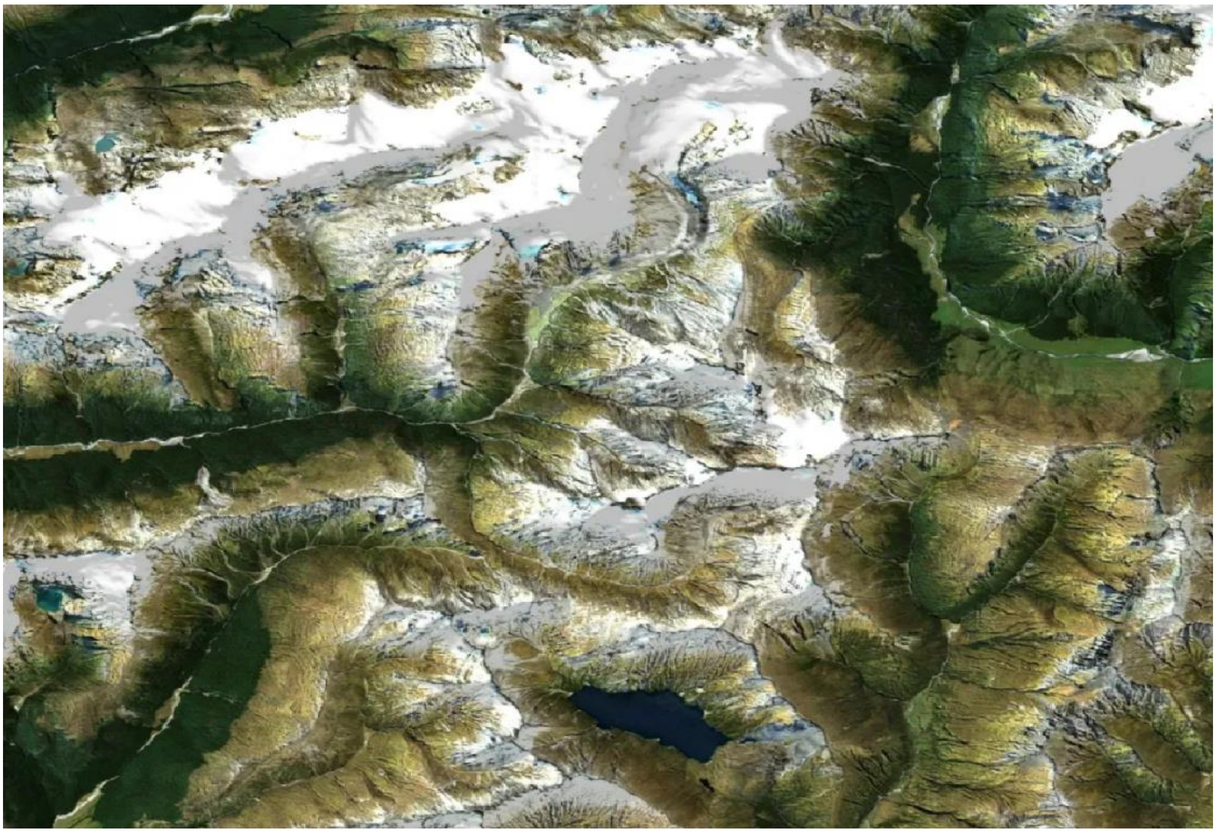

Figure 13. Aerial image equivalent for Figure 12, shown for context.

Impervious surfaces (red, class 190) represent built areas This class also occurs in speckled patterns across parts of high-altitude areas. Here, perhaps, they would be better represented as bare areas (class 200).

As pasture belongs to the rainfed cropland class rather than grassland in GLC_FCS30D, there is an absolute lack of distinction made in areas such as the Canterbury Plains, where we would expect to be able to draw a distinction between pasture and annual cropping.

6 Discussion

None of these three candidate global land-cover maps are suitable for most of the important New Zealand mapping needs. These major needs are:

1. fire fuel assessment (classes that indicate flammability are required, such as the difference between shrubs and trees; the spatial pattern is important; for this application, omission errors are worse than commission errors)
2. protective cover for soil erosion (a woody class is required; the spatial pattern is important because it is necessary to combine with slope from DEM)
3. national carbon accounting (the gross area in a region is an important metric)
4. on-farm carbon accounting (the gross area in farms is an important metric)
5. predator control (the fine spatial detail of trees is important, i.e. corridors of suitable land cover for habitat patch connectivity)

6 nutrient budgeting for water quality (delineation of cropping and orchards is important for modelling nutrient input to groundwater)

7 habitat loss (need to monitor loss of protected wetlands, and to have a useful wetland typology)

8 soil carbon sampling (a useful distinction within bare ground would be between rocks and gravel [i.e. bare and no soil] and bare ground with soil).

The applicability of the three global land-cover data sets to these needs is compared in Table 3.

Table 3. Utility of global land-cover products for important use cases in New Zealand: tick means useful; cross means not useful; cross and tick means partially useful.

Use case	Dynamic World	WorldCover	GLC_FCS30D
Fire fuel	✗	✗ ✓	✗ ✓
Soil erosion	✗	✗ ✓	✗ ✓
National carbon	✗	✗ ✓	✗ ✓
Farm carbon	✗	✗ ✓	✗
Predator control	✗	✗	✗
Nutrient budgeting	✗	✗	✗
Habitat loss	✗	✗	✗ ✓
Soil carbon	✗	✗	✗ ✓

GLC_FCS30D is partially suited to the fire fuel, soil erosion, national carbon, habitat loss, and soil carbon use cases because of its taxonomy (detailed forest and wetland classes) and accuracy (reasonable agreement with the 2018/19 'Woody layer' indicated by the Jaccard index). But, like the others, it is still insufficiently accurate for reliable estimates, has poor cropland identification, is relatively coarse (30 m pixels), and contains two major anomalies that affect New Zealand.

WorldCover is partially suitable for fire fuel, soil erosion, national carbon and farm carbon uses because it is the most accurate overall when compared with LCDB v5 and the 'Woody layer'. Yet it is impossible to compare the 2020 and 2021 versions against each other due to methodological change, and its reliance on auxiliary data sets suggests that further temporal sequences are unlikely, which provides no means to reliably assess land-cover change over time. Its taxonomy is also too simplistic.

Dynamic World is subject to such gross errors, especially in tree cover, and uses such a very simple taxonomy, that together these issues make it completely unsuitable for all listed use cases.

7 Conclusions

None of the surveyed global land-cover data sets are well suited to land-cover data in the New Zealand context. Although these options generally come with the advantage of temporal sequence and coverage, and they are easy to obtain and use, they are still insufficiently accurate and use taxonomies that are not sufficiently descriptive for land cover in New Zealand.

WorldCover v200 (2021) stands out as perhaps the best option considered, but it is only available for a single year.

8 Limitations

Dynamic World is distinct from the other data sets we considered because it is not a published data product but rather a model that can be applied dynamically to Sentinel-2 imagery on the Google Earth Engine platform. Therefore, it is possible that more careful extraction (more sophisticated cloud masking, or use of its probabilistic classification information) could result in a better product. Dynamic World thus includes an element of user control and refinement that the others do not have. Of course, this makes it harder to assess it against the others fairly.

Other land-use maps are discussed in the literature, but it was not clear how to access the data and so they were not considered in detail here. One example of these is iMap World 1.0 (Liu et al. 2021). This is a 1985–2020 annual land-cover map produced in an analysis-ready format, at 30 m resolution, with claimed 80% overall accuracy for level 1 classification (29 classes) and 73% for level 2 classification (33 classes). There is no reason to think that this data set is likely to be superior to those already considered, but it does have useful taxonomic detail similar to GLC_FCS30D.

9 Recommendations

1 Despite being unsuitable for the identified purposes, the data sets we considered may still be suitable for some other applications. There is value in the long-term temporal sequence of GLC_FCS30D, and in the rapid dynamic production of Dynamic World, but these data sets should be used with care.
2 Developments in global land-cover data sets should be monitored, as it is an active and competitive domain with room for future progress.
3 In the short and medium term, validated land-cover data sets produced by New Zealand for New Zealand's needs (especially in terms of taxonomy and accuracy) are still necessary.

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Appendix A: Approximate class concordances

	LCDB v5	Dynamic World	GLC-FCS30D	WorldCover	EcoSat Woody	Basic Land Cover
Forested	54: Broadleaved Indigenous Hardwoods 68: Deciduous Hardwoods 69: Indigenous Forest 71: Exotic Forest	1: Trees	51: Open evergreen broadleaved forest 52: Closed evergreen broadleaved forest 61: Open deciduous broadleaved forest (0.15 < fc < 0.4) 62: Closed deciduous broadleaved forest (fc > 0.4) 71: Open evergreen needle-leaved forest (0.15 < fc < 0.4) 72: Closed evergreen needle-leaved forest (fc > 0.4) 81: Open deciduous needle-leaved forest (0.15 < fc < 0.4) 82: Closed deciduous needle-leaved forest (fc > 0.4) 91: Open mixed leaf forest (broadleaved and needle-leaved) 92: Closed mixed leaf forest (broadleaved and needle-leaved)	10: Tree cover	3: Woody Vegetation	3: Indigenous Vegetation 11: Exotic Forest 12: Deciduous Hardwoods
Shrubland	50: Fernland 51: Gorse and/or Broom 52: Manuka and/or Kanuka 55: Sub Alpine Shrubland 56: Mixed Exotic Shrubland 58: Matagouri or Grey Scrub 80: Peat Shrubland (Chatham Is) 81: Dune Shrubland (Chatham Is)	5: Shrub & Scrub	120: Shrubland 121: Evergreen shrubland 122: Deciduous shrubland	20: Shrubland	3: Woody Vegetation	9: Unspecified Woody Vegetation 10: Narrow-leaved Scrub 13: Broadleaved Shrub
Cropland	30: Short-rotation Cropland	4: Crops	10: Rainfed cropland 11: Herbaceous cover cropland 12: Tree or shrub cover (Orchard) cropland 20: Irrigated cropland	40: Cropland	NA	14: Croplands
Grassland	15: Alpine Grass/Herbfield 40: High Producing Exotic Grassland 41: Low Producing Grassland 43: Tall Tussock Grassland 44: Depleted Grassland	2: Grass	130: Grassland	30: Grassland	4: Herbaceous Vegetation	4: Herbaceous Vegetation
Built	1: Built-up Area (settlement) 2: Urban Parkland/Open Space 5: Transport Infrastructure	6: Built Area	190: Impervious surfaces	50: Built-up	NA	NA
Wetlands	45: Herbaceous Freshwater Vegetation 46: Herbaceous Saline Vegetation 47: Flaxland 70: Mangrove	3: Flooded vegetation	181: Swamp 182: Marsh 183: Flooded flat 184: Saline	90: Herbaceous wetland 95: Mangroves	NA	15: Wetlands
Wetlands (including tidal)	Ditto 22: Estuarine Open Water	Ditto	Ditto 185: Mangrove 186: Salt marsh 187: Tidal flat	Ditto	NA	Ditto
Bare	6: Surface Mine or Dump 10: Sand or Gravel 12: Landslide 16: Gravel or Rock 64: Forest - Harvested	7: Bare Ground	150: Sparse vegetation (fc < 0.15) 152: Sparse shrubland: (fc < 0.15) 153: Sparse herbaceous (fc < 0.15) 200: Bare areas 201: Consolidated bare areas 202: Unconsolidated bare areas	60: Bare/sparse vegetation	2: Bare Ground	2: Bare Ground 6: Primarily Bare Ground
Ice	14: Permanent Snow and Ice	8: Snow & Ice	220: Permanent ice and snow	70: Snow and ice	7: Snow	7: Snow
Tundra	15: Alpine Grass/Herbfield	NA	140: Lichens and mosses	100: Moss and lichen		
Water	0: Not land 20: Lake or Pond 21: River 22: Estuarine Open Water	0: Water	210: Water body 0: Filled value	80: Permanent water bodies	0: Undefined 1: Water	0: Unclassified 1: Water
Remainder	33: Orchards, Vineyards or Other Perennial Crops				8: Glacial Lakes, Wet Rock, Water/Sediment	8: Glacial Lakes, Wet Rock, Water/Sediment 16: Orchards and Vineyards