Extending the Victorian Land Cover Time Series (2021–2025)

Consistent multi-temporal land-cover and native vegetation extent mapping since 1987

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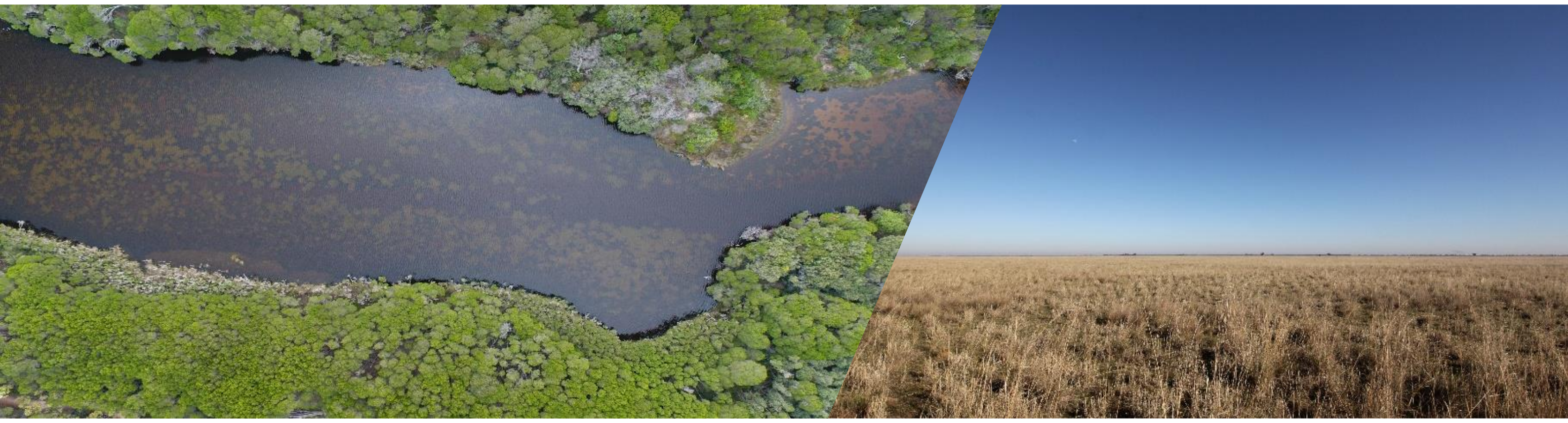
Project summary

The *Victorian Land Cover Time Series* is a statewide dataset that maps land cover across Victoria into 19 vegetation and land-use classes using satellite imagery and locally calibrated data (White et al. 2020). It provides a consistent basis for assessing the extent of native vegetation, improving the accuracy and repeatability of landscape-scale condition and change reporting, and underpinning environmental indicators used in monitoring and assessment to understand and respond to long-term landscape change.

Key project outcomes include:

- Extension of the existing statewide dataset by integrating new information for 2021–2025, resulting in a continuous native vegetation extent and land-cover record spanning nearly four decades (1987–2025).
- Delivery of contemporary, high-resolution (25 m) land-cover maps across Victoria, supporting conservation planning, natural resource management, and policy decision-making.
- Building on the Department of Energy, Environment and Climate Action's (DEECA) established native vegetation and land-cover mapping framework, the project advances remote sensing and machine-learning approaches to enable efficient, scalable updates and improved reporting of dynamic changes in native vegetation extent, spatial arrangement, and configuration.
- Collectively, the project strengthens the evidence needed to manage emerging land-use and environmental pressures, including urban expansion, renewable energy development, and climate-driven change.



Background

Landcover and native vegetation extent data are fundamental to conservation planning, natural resource management, and reporting. Historically, the production of these data in Victoria was infrequent, used varying methods, focused primarily on woody-vegetation and did not consider the context of remnant vegetation. Research led by the Arthur Rylah Institute (ARI) in 2020 (White et al. 2020) addressed this critical gap by developing a statewide multi-temporal land-cover dataset that accounts for dynamic vegetation extent and land-cover patterns. The *Victorian Land Cover Time Series* delivered a consistent dataset spanning seven time periods (epochs): 1987–1990, 1990–1995, 1995–2000, 2000–2005, 2005–2010, 2010–2015, and 2015–2019 (Figure 1). Building on this foundational work, the current project extends the time series through the addition of a new epoch (2021–2025).

The resulting native vegetation and land-cover dataset strengthens DEECA's capacity to track changes in vegetation extent over time, while integrating with existing biodiversity tools and systems to inform land-use management decisions.

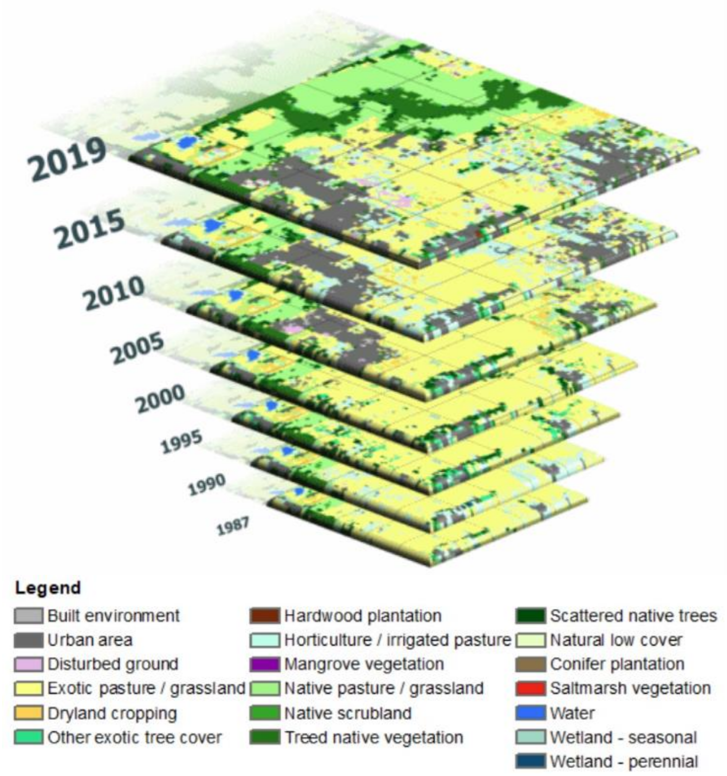


Figure 1. Victorian Land Cover Time Series 1987-2019. For more information on land-cover classes see Table 2.

Approach

DEECA's established land-cover mapping framework (White et al. 2020) was applied to develop consistent, spatially explicit land-cover datasets across Victoria through time.

The framework is structured to enable future enhancements, including the development of additional multi-temporal and spatial modelling products. Its application in the current project ensures that the 2021–2025 epoch is directly comparable with previous epochs.

Land-cover model inputs

The approach follows a structured hierarchy of data inputs and successive modelling steps, as described by White et al. (2020). Land-cover modelling inputs comprised thousands of observations for 40 land-cover attributes (the dependent data) and 72 spatially explicit predictors (the independent data) derived from remote-sensing imagery of Earth's land surface, as described below.

***Land-cover observations** (dependent data)*

The dependent data consisted of observational records interpreted across space and time from aerial photography and other reference sources (White et al. 2020). Each observation represents a specific location and time at which land cover was classified. From these observations, a set of 40 land-cover attributes was derived. These attributes represent the response variables in the modelling framework and describe the presence or probability of different land-cover types at a given location. Observations included both persistent land-cover states (e.g. long-term native vegetation) and transitions between states (e.g. clearing for cropping), enabling the representation of temporal dynamics across epochs. Most of these observation records were designated as exemplar observations used to define land-cover states and provide stable reference points for model development. These exemplar observations form the training data used to fit the land-cover models. Training data were compiled within a purpose-built land-cover database, which supports the storage, management, and updating of exemplar records through time (White et al. 2020). The database also stores all observational records and associated metadata and organises land-cover attributes within a semi-hierarchical classification structure, allowing multiple related attributes to be associated with a single location.

Remote-sensing predictors *(independent data)*

Independent predictor data comprised publicly available remotely sensed satellite products. A total of 72 data layers at 25 m resolution were generated for model development.

The primary data source for the previous time series (1987–2019) was the Landsat Thematic Mapper (TM) satellite series, which provides multispectral imagery at 30 m (resampled to 25 m) spatial resolution across six bands: blue (Band 1), green (Band 2), red (Band 3), near-infrared (Band 4), shortwave infrared 1 (Band 5), and shortwave infrared 2 (Band 6). Landsat imagery for 2021–2025 was divided into four overlapping seasons (spring: August–December; summer: November–March; autumn: February–January; winter: May–October). Following cloud and error masking, all available tiles were used to derive seasonal median composite multi-spectral images. Additional indices were calculated from the six native bands for each seasonal median image. The published Landsat-derived Water Observations from Space product (Geoscience Australia) and radar-based data from the Japanese Advanced Land Observing Satellite (ALOS), acquired using the PALSAR sensor, were also incorporated, contributing further predictor layers and resulting in 72 predictors overall.

For the 2021–2025 epoch, an updated set of the 72 remote-sensing layers was generated to represent the new time period (see Table 1 for a summary of the data). For this epoch, Landsat 8 and Landsat 9 Operational Land Imager (OLI) data were used in place of Landsat 7 Thematic Mapper (TM), which ceased routine data collection in January 2024. As a result, Landsat 8 and 9 now provide the primary source of recent operational Landsat imagery. As described above, the same metrics and processing steps were applied using updated Landsat data for the new time series. Several data layers were retained from earlier epochs due to the absence of updated data, including ALOS PALSAR satellite data and Water Observations from Space (see Table 1).

Table 1. Summary of remote-sensing data products used to develop the land-cover models for the 2021–2025 epoch. The table summarises 15 remote-sensing data products (including Landsat and ALOS-2 imagery) from which 72 raster predictor variables were derived, along with the statistics calculated for each layer. Rows shaded in grey indicate layers retained from earlier epochs.

Remote-sensing data products	Summary of derived statistics
Landsat B1 – B7	Landsat OLI (25 m resolution) seven spectral bands (Bands 1-7) were summarised using the 25th, 50th, and 75th percentiles, calculated separately for each season within an epoch.
Landsat - Enhanced Vegetation Index	Seasonal median values calculated for each epoch
Landsat - Normalised Difference Moisture Index	Seasonal median values calculated for each epoch
Landsat - Normalised Difference Soil Index	Seasonal median values calculated for each epoch
Landsat - Normalised Difference Vegetation Index (NDVI)	Seasonal median values calculated for each epoch
Landsat - Normalised Difference Vegetation Index (NDVI) Delta	Difference between seasonal NDVI (25 m) and NDVI resampled to 125 m resolution, representing local deviation from the broader spatial context.
Landsat - Soil Adjusted Total Vegetation Index	Seasonal median values calculated for each epoch
Landsat - Specific Leaf Area Vegetation Index	Seasonal median values calculated for each epoch
Landsat - Normalised Difference Burn Ratio	Seasonal median values calculated for each epoch
Landsat - Normalised Difference Wetness Index	Seasonal median values calculated for each epoch
Landsat - Spectral Bathymetry	Seasonal median values calculated for each epoch

Landsat Min/Max 1987-2019	Minimum Summer Landsat band values for all epochs divided by the maximum summer band values for all epochs. NB: this measure is epoch-independent and was used to flag pixels that expressed massive fluctuations across epochs.
Landsat - Water Observations from Space	Landsat (25 m resolution), % of images detecting water across all epochs (1987-2019).
ALOS PALSAR - Horizontal Transmit – Vertical Receive Polarisation (HV)	ALOS PALSAR (L-band) at 25 m resolution, calculated minimum, maximum, median for 2005-2010 epoch.
ALOS PALSAR - Alos Ratio	Ratio of fine-resolution (25 m) HV backscatter to neighbourhood mean (5×5 window), representing local spatial heterogeneity.

Land-cover model development

Land-cover predictions for the 2021–2025 epoch were generated by applying the existing random forest machine learning model (i.e. from 1987–2019; White et al. 2020). This model was trained on existing dependent data (1987-2015) and applied to an updated epoch-specific set of predictor variables. No additional observation data were incorporated into the training dataset.

Temporal structure and model inputs - The modelling framework supports temporal change through the use of epoch-specific exemplar training data, while maintaining a consistent set of predictor variables across epochs (see below). This approach allows the model to capture both stable land-cover patterns and transitions over time, while ensuring comparability between epochs.

Model structure - The 40 land-cover attributes were modelled simultaneously using a multi-target random forest framework (Demšar et al. 2006; Kocev et al. 2007), producing probabilistic predictions for each attribute at each epoch (see 'Land Cover Model Development'). These probabilistic outputs were subsequently processed through a classification module to assign the 19 Victorian land-cover classes (Table 2), which form the final mapped products (Figure 2).

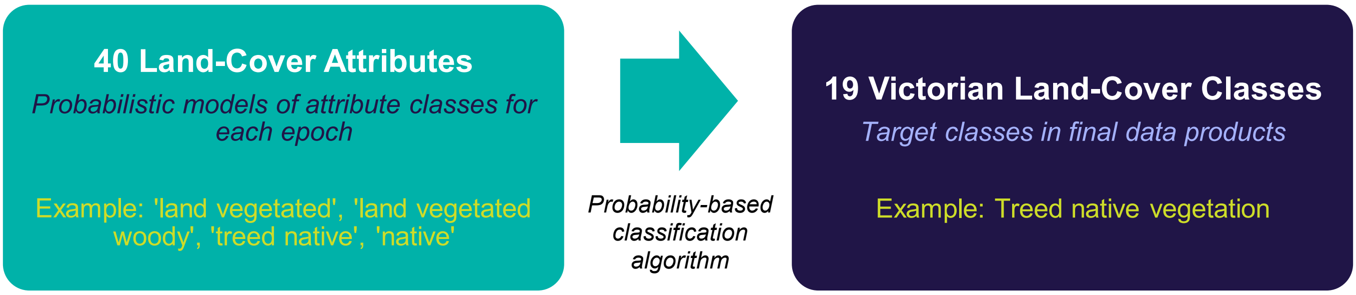


Figure 2. Land-cover classification workflow.
Overview of the workflow illustrating relationships between 40 Land-Cover Attributes, and their aggregation into 19 target Victorian Land-Cover Classes (Table 2).

Model outputs and post-processing

For the 2021–2025 epoch, the model produced 40 raster layers representing probabilities for each land-cover attribute. These outputs were post-processed through a classification procedure that assigned the most likely of 19 Victorian land-cover classes (Table 2) to each pixel.

During the classification procedure, related attribute classes were aggregated into broader target classes where appropriate (e.g. marine grass, marine bare ground, and deep water combined into a single 'Water' class). This resulted in a single land-cover map providing a spatially explicit representation of the 19 target classes across Victoria for 2021–2025.

Temporal filtering was applied to reduce noise and ensure consistency in land-cover classifications over time by stabilising class assignments across the full time series (i.e. all epochs). Pixel-level logic was applied to enforce consistent temporal trajectories where appropriate (White et al. 2020). Because the 2021–2025 epoch was classified independently from earlier data, this step was necessary to align results across all epochs and minimise spurious class transitions. Without filtering, small differences in predicted probabilities between time steps can cause pixels to fluctuate between closely related classes, despite minimal or no actual land-cover change. Lastly, spatial filtering was applied to remove implausible classifications based on land tenure.

Model uncertainty and classification performance were assessed using a confusion matrix derived from misclassifications in the final outputs (White et al. 2020).

Table 2. Victorian land-cover classes and descriptions.
The 19 land-cover classes used in this study represent aggregations of 40 underlying land-cover attribute classes derived through ensemble modelling and post-processing (White et al. 2020). Final class assignment for each pixel was determined by combining the attribute-level probabilities to identify the most likely target land-cover class.

Land-cover Class	Description
Built environment	Persistent unvegetated areas that are the result of commercial or industrial development.
Urban area	The admixture of streets, houses and gardens that characterises much of the medium to low density urban landscape typical of Australian cities.
Disturbed ground (Bare ground - not native)	Persistent unvegetated areas that are the result of anthropogenic activity other than urban development such as mining.
Horticultural/Irrigated pastures and crops	Regions of crop, pasture and parkland regularly subject to irrigation, particularly in dry months.
Dryland cropping	Regions that are regularly cropped and are not irrigated.
Exotic pasture/grassland	Herbaceous pastures that are predominantly composed of non-indigenous species.
Hardwood plantation	Tree plantations predominantly *Eucalyptus globulus*.
Conifer plantation	Tree plantations principally *Pinus radiata*.
Other exotic tree cover	Non-native tree-cover including conifer windbreaks, willows, along streams and rivers and varied ornamental plantings.
Water	Persistent surface water either fresh or saline – including rivers, lakes, dams, wetlands and the ocean.
Treed native vegetation	Native tree cover.
Scattered native trees	Native trees scattered in paddocks and woodland along roadsides and streams.
Native shrubland	Native shrub cover.
Native pasture/grassland	Grasslands and pastures that are predominantly composed of indigenous species grasses and/or low chenopod shrubs. Includes grasslands that have been 'derived' through the clearing of tree and/or shrub cover.
Natural low cover (Bare ground – native)	Environments that naturally have low to negligible vegetation cover such as coastal foredunes, saline lakebeds, claypans and rock-outcrops.
Wetland perennial (native)	Persistent, typically herbaceous cover comprised of native plant species that are tolerant of inundation or waterlogging.
Wetland seasonal (ephemeral – native)	Seasonal or ephemeral, typically herbaceous cover comprised of native plant species that are tolerant of episodic inundation or waterlogging.
Saltmarsh vegetation	Intertidal wetlands supporting native vegetation that are not mangroves.
Mangrove vegetation	Intertidal native vegetation supporting *Avicennia marina*.

Findings

The 2021–2025 extension maintains continuity with the earlier land-cover time series while incorporating updated remote-sensing inputs, providing a contemporary basis for long-term monitoring of native vegetation extent and broader land-cover change across Victoria. This extension is supported by the retained modelling framework and the reported classification performance, but it should be read alongside the limitations and uncertainties section below, particularly for classes and regions with lower separability.

Land-cover model outputs

The final outputs comprised a land-cover grid (approximately 40,000 × 28,000 pixels) at ~25 m resolution in geographic projection for 2021–2025, representing the 19 target land-cover classes across Victoria (Figure 3). Supporting outputs included:

- Per-pixel probability layers for each of the 40 land-cover attribute classes.
- Summary layers representing the standard deviation of class probabilities across epochs, indicating areas of higher temporal variability.

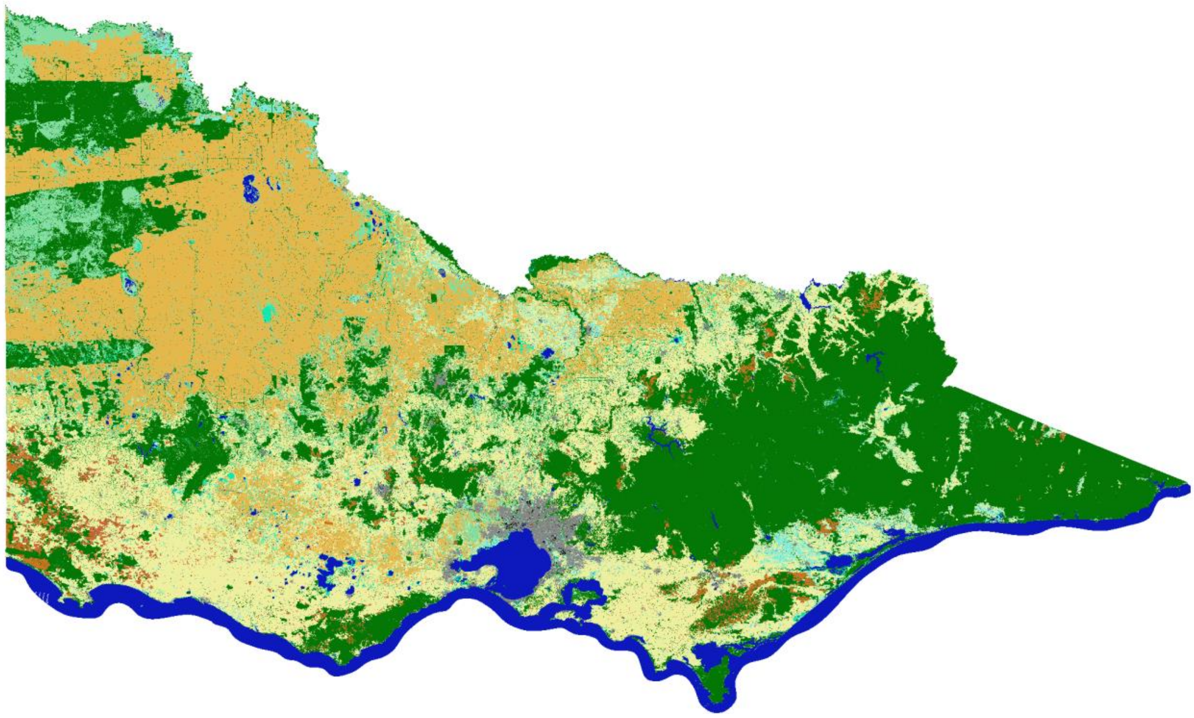


Figure 3. Land-cover classification 2021-2025.
The Victorian land-cover grid at 25 m resolution, classified into 19 land-cover classes (Table 2).

Model performance and classification evaluation

Here we report on model performance described in White et al. (2020), as the existing model developed (1987-2019) was applied to the 2021-2025 epoch. Model performance was generally strong, with most land-cover classes showing high correlations (> 0.8) and R^2 values above 0.7. These results support the use of the framework for broad statewide interpretation and temporal comparison, particularly for structurally distinct classes such as water and treed vegetation. However, lower correlations and R^2 values for narrower or spatially limited classes, such as scattered trees on roadsides and in paddocks, indicate that fine-grained interpretation should be undertaken with greater caution.

In addition to White et al. (2020), here we supply the confusion matrix statistics, which quantify how well predicted classes match observed data. These were also high for the post-processed classification, with overall accuracy of 89.54% and balanced accuracy of 80.67%. Together, these metrics indicate that the final mapped outputs are robust, while also showing that performance varies by class. Class-specific results in Table 3 should inform interpretation for operational use.

Table 3. Land-cover Classification Accuracy Assessment.
Each of the 19 land-cover classes (classes described in Table 2) along with post-processed classification accuracy and error scores. Producer's accuracy reflects the probability that an observed class is correctly predicted, while user's accuracy indicates the reliability of each predicted class. The F1 score combines producer's and user's accuracy into a single metric, where 100% is perfect agreement.

Land-cover Class	Correct Count	Reference Total	Mapped Total	Producer's Accuracy	Producer's Error	User's Accuracy	User's Error	F1 Score
Built environment	1003	2365	1220	42.41%	57.59%	82.21%	17.79%	55.96%
Urban area	10815	11345	13336	95.33%	4.67%	81.10%	18.90%	87.64%
Disturbed ground	10394	11683	12719	88.97%	11.03%	81.72%	18.28%	85.19%
Water	3241	3693	3364	87.76%	12.24%	96.34%	3.66%	91.85%
Horticulture/Irrigated pastures and crops	14077	16157	16655	87.13%	12.87%	84.52%	15.48%	85.80%
Dryland cropping	85825	93852	93288	91.45%	8.55%	92.00%	8.00%	91.72%
Exotic pasture/grassland	95182	111353	102545	85.48%	14.52%	92.82%	7.18%	89.00%
Hardwood plantation	7249	8463	7649	85.66%	14.34%	94.77%	5.23%	89.98%
Conifer plantation	10496	10830	11352	96.92%	3.08%	92.46%	7.54%	94.64%
Other exotic tree cover	857	1699	1695	50.44%	49.56%	50.56%	49.44%	50.50%
Treed native vegetation	180673	186336	184119	96.96%	3.04%	98.13%	1.87%	97.54%
Scattered native trees	910	1621	2132	56.14%	43.86%	42.68%	57.32%	48.49%
Native shrubland	6580	11615	11188	56.65%	43.35%	58.81%	41.19%	57.71%
Native pasture/grassland	37424	45862	52594	81.60%	18.40%	71.16%	28.84%	76.02%
Natural low cover	7989	8894	10612	89.82%	10.18%	75.28%	24.72%	81.91%
Wetland perennial	2490	2951	4166	84.38%	15.62%	59.77%	40.23%	69.97%
Wetland seasonal	14269	17903	17890	79.70%	20.30%	79.76%	20.24%	79.73%
Saltmarsh vegetation	406	482	588	84.23%	15.77%	69.05%	30.95%	75.89%
Mangrove vegetation	221	241	233	91.70%	8.30%	94.85%	5.15%	93.25%

Limitations and uncertainties

As with any modelling and mapping exercise, several limitations and caveats apply to the delivered products. These factors affect how confidently different classes, regions, and types of change can be interpreted, and they should be considered when using the dataset for planning, reporting, or policy decisions.

- **Purpose and scope:** The datasets were developed primarily to support conservation planning, natural resource management, and monitoring of native vegetation extent. Caution is advised when applying these products to other purposes.
- **Remote sensing limitations:** All products are derived from remote-sensing imagery and may retain residual noise and uncertainty despite extensive correction and quality-control procedures. The 2021–2025 epoch uses data from newer Landsat sensors (Landsat 8/9 OLI differs marginally from previous Landsat sensor platforms), which may introduce subtle differences in signal characteristics. Radar predictors were derived from ALOS PALSAR data acquired primarily in the mid-2000s and were applied consistently across all epochs where more recent radar equivalents were unavailable. This may reduce sensitivity to temporal change, particularly where strong and persistent backscatter signatures are associated with both training exemplars and land-cover classes.
- **Modelled nature of outputs:** Land-cover maps are modelled products rather than direct on-ground observations and should therefore be interpreted as indicative. While efforts have been made to minimise model-related error and document known patterns of misclassification, inherent uncertainty remains.

- **Scattered trees:** Isolated or small trees are difficult to detect reliably at 25 m resolution and may be substantially underestimated, particularly in dissected terrain and agricultural landscapes.
- **Temporal resolution:** Remote-sensing inputs were aggregated into discrete epochs (here, 2021–2025). While this approach improves robustness to noise and anomalous observations, it suppresses intra-annual and inter-annual variability. Consequently, dynamic land-cover processes (e.g. cropping cycles, fluctuating water extent, and seasonal wetlands) may not be resolved in every instance. Short-duration or intermittently expressed land uses—such as pivot irrigation operating for only part of the year—may not be reflected in the median spectral signal and are therefore potentially under-represented.
- **Training data limitations:** The 2021–2025 epoch applied an existing model using training data collected up to 2015. As a result, more recent land-cover changes (e.g. newly developed urban areas) may be under-represented in the training set and less reliably captured. Incorporating contemporary ground-based observations would improve representation of recent change but was beyond the scope of the current project.
- **Regional uncertainty:** Some regions and land-cover classes exhibit higher classification uncertainty, particularly in areas undergoing land-use transition. For example, the Grampians–Billywing and Delatite Arm–Lake Eildon regions have experienced transitions from pine plantation to native forest, while parts of the Strzelecki Ranges present challenges in distinguishing native forest from hardwood plantation. Classifications in these areas should therefore be interpreted in conjunction with contextual and historical information where available.

Recommendations for management and policy

The extended multi-temporal land-cover time series provides a robust and internally consistent evidence base for understanding landscape change across Victoria. It is well suited to long-term monitoring, broad-scale reporting, and integration with biodiversity and planning tools, particularly where consistency through time is important. Its application to finer-scale or class-specific decisions should, however, be informed by the reported accuracy results and the limitations outlined above, especially in dynamic or lower-confidence contexts.

Recommendations for application and use of the Victorian Land Cover Time Series (1987–2025):

- **Establish as a standard spatial baseline**: Embed the land-cover layers as a consistent spatial foundation for statewide planning and reporting across agencies and programs, with appropriate consideration of known limitations and uncertainty.

- **Maintain regular update cycles**: Formalise periodic updates (e.g. five-year epochs) to ensure temporal continuity, reduce reliance on ad hoc remapping, and support consistent long-term reporting.

- **Strengthen input data**: Invest in targeted on-ground observations to improve model training and integrate higher-resolution and complementary remote-sensing sources (e.g. Sentinel imagery) to enhance spatial and temporal sensitivity.

- **Preserve temporal comparability**: Maintain backward compatibility with earlier epochs to support robust long-term trend analysis, evaluation, and reporting.

- **Develop change and stability metrics**: Use derived metrics of persistence, transition, and change intensity to identify areas of stability, emerging pressure, and landscape transformation.

- **Support cumulative impact assessment**: Enable assessment of land-cover change across multiple planning and development cycles to better account for cumulative effects.
- **Target management interventions**: Prioritise conservation and management actions in areas exhibiting recent, rapid, or accelerating land-cover change.
- **Enable adaptive management**: Support iterative, evidence-based management through repeatable monitoring of landscape condition and change over time.
- **Align with reporting frameworks**: Integrate land-cover outputs with existing reporting systems (e.g. State of the Environment, biodiversity indicators, climate adaptation frameworks) to improve consistency and transparency.
- **Support outcome-based policy evaluation**: Use the time series to provide consistent, spatially explicit evidence of landscape change, enabling evaluation of policy effectiveness over time.

Further reading

White, M., Griffioen, P. and Newell, G. (2020). Multi-temporal Native Vegetation Extent for Victoria. Arthur Rylah Institute for Environmental Research Technical Report No 311. Department of Environment, Land, Water and Planning, Melbourne, Victoria.

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We acknowledge Victorian Traditional Owners and their Elders past and present as the original custodians of Victoria’s land and waters and commit to genuinely partnering with them and Victoria’s Aboriginal community to progress their aspirations.