Spatial BioCondition

Vegetation condition map for Queensland

Queensland Government

Prepared by: Queensland Herbarium and Remote Sensing Centre, Science and Technology Division, Department of Environment and Science

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Executive summary

The Queensland Government committed to a two-year scientific program to enhance Queensland's capacity to assess, monitor and report on the extent and condition of vegetation for the state. One of four key areas within this program was the goal to develop an approach to map the condition of Queensland's terrestrial vegetation, an area encompassing 1.73 million km^2, over space and time. This report outlines the approach taken to achieve this goal, through the development of Spatial BioCondition (SBC), a vegetation condition mapping workflow for Queensland.

Spatial BioCondition was developed to align with Queensland's site-based BioCondition framework, which is based on the concept that vegetation condition can be measured as the departure from its reference state, specific to each of Queensland's defined regional ecosystems. Consequently, the aim of Spatial BioCondition was to model the departure from the reference state, within regional ecosystems in remote sensing space, using three types of input data aimed at producing currency output for 2017:

1. Site-based training data comprising sites in reference state condition (state 1) and in condition states 2, 3 and 4 (response variables). Condition classes were selected as the response rather than a continuous score, to increase the number of fit-for-purpose data sites available within the project timeframe.
2. A suite of contemporary, state-wide remote sensing data (predictor variables);
3. Environmental domain mapping, represented by state-wide pre-clear RE mapping at the vegetation community level (Version 11).

The SBC workflow and framework were first tested in a trial study located in the Brigalow Belt Bioregion, using a mechanistic modelling approach. The trial study highlighted the critical importance of accurately geo-referenced and appropriately assessed training data, and limitations in the mechanistic modelling approach, particularly around the setting of thresholds in the continuous output data to demarcate the condition classes. Consequently, for state-wide application, considerable effort went into cleaning the training dataset, and an alternative machine learning (ML) model approach was developed.

For SBC model training or testing, a total of 48,012 candidate vegetation sites from across Queensland's terrestrial ecosystems were collated from existing data sources, new field survey and expert elicitation. However, less than half (49%) were assessed as suitable for use in either the training or testing of the models. Of these, 13,571 were reference sites that provided a sufficient sample to produce SBC model output with a 2017 currency for 2,267 (82%) of Queensland's vegetation communities, covering 89% of the state.

Four remotely sensed (RS) datasets, some with multiple bands, resulting in a total of 17 potential predictor variables, were selected for the modelling process. Where these RS datasets were part of a time series dataset, the data closest to 2017 were selected. Of the competing modelling frameworks tested, the ML model had superior accuracy than the mechanistic model, so it was selected as the framework for further analyses and to produce the SBC prediction of BioCondition classes.

Although ML models are thought to be difficult to interpret, recent advances such as the use of SHAP plots, which show the relationship between predictors and probabilities, have assisted in clarifying interpretation. The SHAP plots produced for the ML model used to predict BioCondition classes revealed that the most important predictor, the Fractional Cover Green Fraction standard deviation (FC_green_std), was stable over time in the high quality condition sites (class 1), suggesting these areas tend to be dominated by perennial vegetation, an attribute of site-based BioCondition assessments. Overall, the condition classes identifying the slightly degraded (Class 2) and moderately degraded (Class 3), were the most difficult to classify, with relatively low accuracy scores (F1-scores of 0.41 and 0.39 respectively).

We recommend that prior to operationalising a vegetation condition reporting framework for Queensland using SBC, further work is required including:

- Independent validation of the output, possibly within case study area/s currently being set up by other programs such as the Australian Agricultural Biodiversity Stewardship pilot program within Queensland
- Investigate sensitivity of the SBC to detect change over time
- Determine a method to spatially demonstrate levels of uncertainty in the output
- Address sampling gaps in the training data, including sampling in vegetation in class 2 and 3 condition

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1.1 The enhanced vegetation assessment and monitoring program for Queensland

The ability to assess and monitor vegetation condition is essential for governments to administer legislation and strategies relating to the landscapes and biodiversity covered by their jurisdiction (Neldner 2006; Oliver et al. 2021). The Queensland Government is committed to the protection and enhancement of its natural environment and to gather information to support environmental policy and legislation. It has committed to scientific program to enhance the Statewide Landcover and Trees Study (SLATS) and establish a vegetation condition monitoring and mapping framework for the state (DES 2019a). The intention of the program is to increase Government's capacity to inform a range of initiatives, including vegetation management, the Land Restoration Fund, Great Barrier Reef programs, fire management and planning and biodiversity conservation and threatened species management and planning. The program intends to achieve this through strengthened scientific collaborations within and between agencies and academic institutions and will utilise remote sensing tools and field observations (DES 2019a).

The four key project areas within the initial phase of the enhanced vegetation assessment and monitoring program are to:

1. Establish a high-resolution baseline woody vegetation extent map.
2. Develop methods for mapping and monitoring woody regrowth.
3. Transition SLATS from Landsat to Sentinel 2 satellite imagery and incorporate outputs of 1 and 2 above to provide a comprehensive woody vegetation assessment, monitoring and reporting framework for Queensland.
4. Develop and test enhanced approaches for mapping vegetation condition over space and time.

The focus of this report is project area 4; to develop an approach that will allow the spatial representation of terrestrial vegetation condition within Queensland's current, site-based vegetation condition assessment framework, BioCondition (Eyre et al. 2015). This project will build on the substantial science-base that has been under development in Queensland for the past 15 years, particularly in the fields of remote sensing and the assessment of woody cover and ground cover, regional ecosystem description and mapping, and vegetation condition assessment frameworks (BioCondition).

1.2 Vegetation Condition: what does it mean and at what scale?

The use of the term 'condition', as it is generally used by policy and management both in Australia and internationally, is underpinned by the assumption that its assessment will represent a measure of ecological composition, structure and function (sensu Noss 1990) along a continuum of 'poor' to 'good', relative to some desired state or potential.

Early definitions of vegetation condition were developed relative to grazing land management of rangelands, as the "health or productivity of both soil and forage of a given range, in terms of what it could or should be under normal climate and best practicable management" (Society of American Foresters 1944). Since then, the development of conceptual frameworks to better reflect ecological complexity, as well as the expansion of applications to which the concept of condition is often attached, means there can be ambiguity regarding what is meant by 'condition' (Keith and Gorrod 2006). Consequently, the context and purpose of the condition assessment needs to be clearly defined (Gibbons and Freudenberger 2006). For example, good condition for grazing land productivity does not always correspond with good condition for biodiversity (Eyre et al. 2010a; Parsons et al. 2017).

Vegetation condition is a multi-variate and multi-scaled concept, meaning that it cannot be measured directly. It is usually calculated as a model, or algorithm, combining various measurable attributes or indicators to give an overall condition metric or score. There is no agreed definition of vegetation condition in Australia. However, currently implemented vegetation condition assessment frameworks are all based on a similar concept, where the condition measure is derived from an ecosystem's current attributes relative to its reference state (Table 1).

Vegetation condition is applicable at multiple scales. At this stage, most Australian biodiversity condition assessment frameworks are applicable at the scale of the site, where condition attributes are measured in the field at a fixed site that represents a homogenous patch at a localised scale, and landscape-level condition attributes, relative to that site, can be calculated remotely. Recent work has extended the concept of vegetation condition assessment to remotely map vegetation condition at regional to global scales using systematic and repeatable methods, such as the Habitat Condition Assessment System, a national-scale program which aims to map habitat condition at a 0.01º resolution across Australia, which is currently being developed by CSIRO (Williams, 2019) Challenges that arise in transitioning from site-based condition assessment approach to spatial representation include:

- High dependence upon numerous suitable and representative input site-based data (Harwood et al. (2016), and limitations on the availability of that data
- Need for spatial data products that: are currently available; have been developed and tested; and represent vegetation condition attributes
- Assurance that mapped or modelled output adequately represents vegetation condition assessed at the local (site-based) scale
- Limitations of currently available regional scale spatial imagery to reliably distinguish plant species (such as transformer weeds, floristics) and separate vegetation strata (e.g. tree and shrub layers).

Table 1: Definitions of vegetation condition for biodiversity assessment frameworks in Australia

Jurisdiction	Terminology	Assessment	Definition	Reference
New South Wales	Vegetation integrity	Biodiversity Assessment Method	The condition of native vegetation assessed for each vegetation zone against the benchmark, being quantitative measures that represent the 'best-attainable' condition, for the Plant Community Type.	Office of Environment and Heritage (2017)
Victoria	Vegetation quality	Habitat Hectares	Measure of the intactness and viability of vegetation in relation to its site condition and landscape context, where site condition is the measure of the 'naturalness' or 'intactness' of a patch of vegetation using several site-based attributes assessed against a defined benchmark	Parkes et al. 2003; Department Sustainability and Environment (2004)
Queensland	Vegetation condition	BioCondition	The relative capacity of a regional ecosystem to support the suite of species expected to occur in its reference state, which refers to the natural variability of the stable land-based vegetation state that is mature and relatively long undisturbed in the contemporary landscape and in 'Best-on-Offer' (BOO) condition	Eyre et al. (2015)
Tasmania	Site condition	TasVeg	Measure of the 'naturalness' or 'intactness' of a zone using a number of site-based attributes assessed against a defined benchmark	Michaels (2006)
Northern Territory	Vegetation condition	NT Vegetation Condition Assessment (NTVCA)	The degree of difference from a benchmark type for a particular vegetation type, where the benchmark type represents its most natural or least disturbed state.	Brocklehurst and Price (2008)
National	Habitat condition	Habitat Condition Assessment System (HCAS)	The capacity of an area to provide the structures and functions necessary for the persistence of all species naturally expected to occur there in an intact state	Williams et al. (2018)

1.3 Queensland's BioCondition Framework

Queensland's *BioCondition* is a vegetation condition assessment framework that provides a measure of the capacity of a terrestrial ecosystem to maintain biodiversity values at a local or property scale. It is a site-based, quantitative and repeatable assessment procedure that provides a numeric score that reflects functional through to dysfunctional vegetation condition states for biodiversity. Its development was initiated in 2006 to assist with decision making in vegetation management and biodiversity conservation applications and has evolved through a substantial science-based research program (Eyre et al. 2010a; Kelly et al. 2011). It currently supports the Queensland Environmental Offsets Policy, bushland restoration prioritisation (e.g. Natural Resource Investment Program) and market-based programs such as Accounting for Nature and the Land Restoration Fund.

In BioCondition, vegetation condition is defined as the relative capacity of a site in a regional ecosystem to support the suite of species expected to occur in a site of the same regional ecosystem in its reference state, or 'Best-on-Offer' (BOO) condition. The intent of the vegetation condition metric generated by the BioCondition framework is that the higher the score, the more flora and fauna species will be supported relative to the ecosystem type, therefore the purpose of the BioCondition assessment is unequivocally to represent condition from a biodiversity perspective (Eyre et al. 2018).

There are three primary components that underpin the BioCondition framework; a suite of assessable attributes that are based on a pressure-state-response conceptual framework; a clear definition of the reference state from which benchmarks for the assessable attributes are set; and a scoring system that provides a condition metric that is comparable between and within ecosystems over space and time.

1.3.1 Assessable site based BioCondition attributes

When assessing BioCondition at the site or property scale, attributes, or indicators, of vegetation condition provide a reliable, cost and time-effective approach to assessing biodiversity values which are typically costly and time-consuming as well as require significant skills in species identification and assessment (McElhinny et al. 2005; Eyre et al. 2011). For the BioCondition assessment method, a set of 10 site-based attributes, and three landscape-scale attributes were selected based on;

- Their capacity to act as direct or surrogate measures of species diversity and/or ecological processes (Figure 1).
- How sensitive they are to detecting change due to management
- Level of correlation with each other
- How well they allow discrimination between sites of the same ecosystem type but different condition state.

The majority of site- based assessable BioCondition attributes are not currently available spatially, and typically do not have direct remotely sensed corollaries. However, there are predictor remote sensing variables which can be used that have a logical justification for their inclusion in a model (see examples, Table 2). Correlations between some field measured attributes of vegetation condition including litter cover, large trees, shrub cover and non-native species cover, and multi-spectral remotely sensed data tend to be poor (Lawley et al. 2016; Harwood et al. 2016). But others have been adaptively developed and continually tested (e.g. tree canopy cover and SLATS) and therefore offer great utility for mapping vegetation condition. At this stage, only two BioCondition attributes that are known to be important for biodiversity in many of Queensland's ecosystems (Figure 1) are spatially available, tested and reliably mapped across the state; tree (or woody) canopy cover and grass cover (or converse, being bare ground).

Landscape-scale attributes, including fragmentation and connectivity metrics, can be calculated from existing spatial datasets, namely SLATS woody cover data (DES 2018) and/or mapped regional ecosystems (DES 2018a). The development of a method to map the distribution and age of woody regrowth, as a project within the Enhanced Vegetation Assessment and Monitoring program (DES 2019a), will be a valuable data source in the assessment of landscape-level metrics.

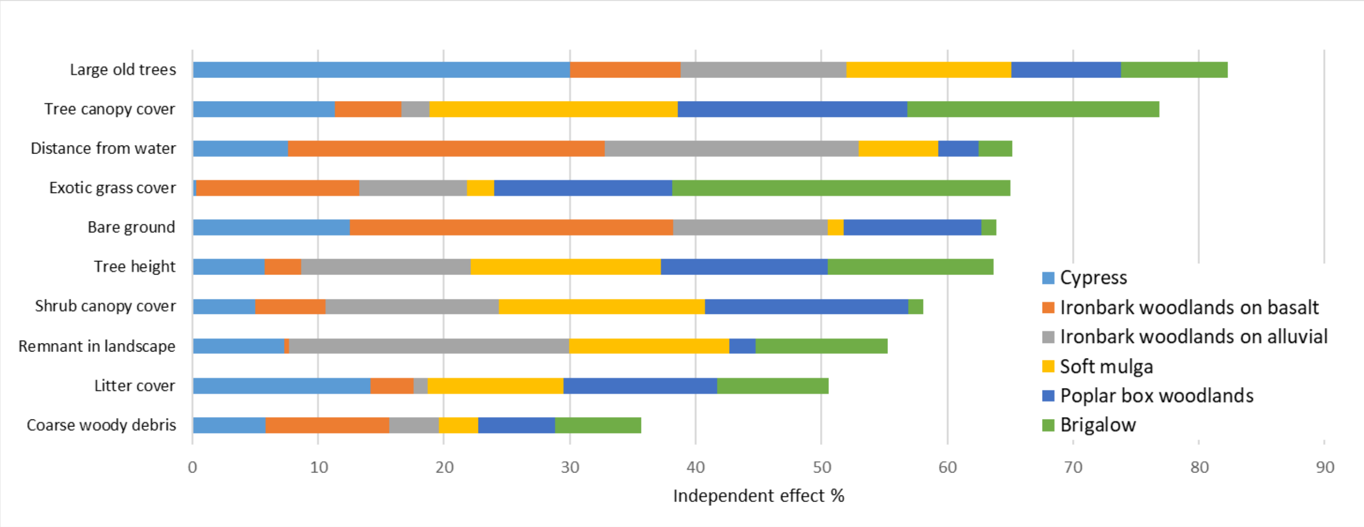

Figure 1: Important vegetation condition attributes for biodiversity (number of vascular plant, reptile, bird and mammal species), based on empirical research (Eyre et al. 2018). Data shown is the independent effects from hierarchical partitioning of species diversity data

1.3.2 Reference states and benchmarks

Ecological reference states provide context for the assessment of vegetation condition, by providing a baseline from which the degree of change in vegetation attributes can be measured. They essentially provide a similar function to control treatments in ecological experimental designs. The definition and identification of vegetation in its reference state is therefore a critical component of ecological assessments, whereby scientifically credible inference on change can be drawn (Hawkins et al. 2010; Borja et al. 2012). Benchmarks provide the numerical context for defining the reference state, where quantitative values are measured for attributes of biodiversity and/or vegetation from similar ecological types in the reference state (Eyre et al. 2015; McNellie et al. 2020).

In BioCondition, the reference state is defined as the stable state that is mature and relatively long undisturbed in the contemporary landscape (Eyre et al. 2015). Most other definitions of the reference state in Australia (see Table 1) are based on a premise of a pristine historical 'intactness' or 'naturalness', which is difficult to define, measure and test in contemporary times (McNellie et al. 2020). Consequently, this can lead to issues in the accuracy and precision of quantifying benchmarks (Hawkins et al. 2010; Eyre et al. 2015), which then compromises the condition score.

Most available benchmarks for Queensland's regional ecosystems have been measured from at least three sites in BOO condition during optimal seasonal conditions by Queensland Herbarium botanists and ecologists. These data are supplemented with appropriate existing detailed quantitative vegetation data where available. For rare, highly modified extant regional ecosystems, expert elicitation is used to set benchmarks.

Table 2: BioCondition vegetation condition attributes and reliability to measure at the site and landscape scale, and potential corollary spatial data [1]C = Compositional; F = Functional; S = Structural

Broad response	Site based BioCondition attributes	Attribute type C,F,S[1]	Biotic	Reliable to assess at site-scale	Reliable to assess at landscape-scale	Time series spatial data available or *not yet available (requires further research and development)
Species Richness	Native Tree/shrub/grass/ forb and other species richness	C	Direct	Y	N	*Models of species richness by plant functional groups using floristic site data
Cover	Tree canopy cover	F, S	Indirect	Y	Y	Fractional Projective Cover (FPC) Landsat 30 m resolution time series 1988 – 2014; Sentinel 2 10 m resolution 2015+ (woody cover, i.e. tree and shrub canopy combined); Auscover ALOS/ISAT 2009
	Shrub canopy cover	F, S	Indirect	Y	N	*Lidar/GEDI
	Native perennial grass cover	F, S	Indirect	Y	Y/N	Fractional cover Note: also includes non-native grass and annual grasses
	Non-native tree, shrub, grass, forb and other cover	C, F	Direct	Y	N	*Species Distribution Models (statistical, machine learning), For non-native grass NSW Seasonal Cover Disturbance Index (Fractional Cover)
	Organic litter cover	F, S	Indirect	Y	N	*Time series persistent non-green
	Bare ground (as converse of litter and native grass cover, coarse woody debris)	F, S	Indirect	Y	Y	Fractional cover
Structure	Coarse woody debris	F, S	Indirect	Y	N	*Lidar/GEDI/Terrestrial Laser Scanners (Muir et al. 2018)
	Large tree density	S	Indirect	Y	N	*Scarth et al. (2001) Landsat canopy size algorithms
	Recruitment of woody perennial species	S, F	Indirect	Y	N	Nil
	Tree canopy height	S, F	Indirect	Y	N	*Time series / regrowth mapping (DES 2019a). Lidar/GEDI
Landscape	Fragmentation and Connectivity	F, S	Indirect	N	Y	Fragmentation indices; Cost-benefit approach (Drielsma et al. 2007), based on Qld-based remnant/non-remnant coverage
	Remoteness from permanent water	F	Indirect	N	Y	Effective Distance from Water product Healy et al. (2020)

1.3.3 Scoring system

The BioCondition framework provides a vegetation condition metric for an assessment site, relative to its reference state, with a continuous value between 0-1. The intent of the metric is that the closer the score is to 1, the more fauna and flora species the ecosystem being assessed will support, relative to its type. The score is calculated by aggregating the measures of attributes from an assessment site relative to those attributes in the same regional ecosystem in its reference state. Some attributes are weighted more highly than others to standardise relative 'importance', meaning the degree to which the attribute:

- has a potential impact upon long-term condition (e.g. non-native plants)
- is a keystone feature and/or takes a long time to replace in a system if lost e.g. large trees attribute is the most highly weighted, given their relative rarity across many ecosystems. (Eyre et al. 2010b)
- has high relative habitat value based on empirical research

BioCondition currently uses a stepped ordinal scoring approach to score each of the attributes (BioCondition Version 2.2), which is simple to apply but tends to have low discriminatory power so is less sensitive than a continuous scoring system in detecting trend or change in condition over a temporal scale. It also relies on the selection of appropriate thresholds, which can be arbitrary. The BioCondition scoring system is currently being revised to use a non-linear continuous scoring approach similar to that used by the Biodiversity Assessment Method in New South Wales (Department of Planning, Industry and Environment 2020), because it is also simple to implement, avoids thresholds and can still account for natural variability and super-abundance.

The continuous BioCondition score can be classified into four classes (Table 3;

Figure 2) representing functional and relatively intact vegetation for biodiversity (class 1) through to highly modified native vegetation with low functionality for biodiversity (class 4). The four BioCondition classes allows alignment with other condition classification frameworks, in particular the Grazing Land Management ABCD framework (Bray et al. 2016). The BioCondition classification system can also be aligned with Queensland's regulated Vegetation Management framework under the Vegetation Management Act (VMA) 1999, particularly for vegetation classified under categories B, C and X (Figure 3).

Table 3: Broad BioCondition classes, definition, and description

BioCondition Class	BioCondition score	Definition	Detailed description
1	>0.8	Good quality remnant, relatively intact (typically mapped as VMA Category B)	Mature established vegetation with no or extremely minimal disturbance from weeds, fire, grazing, clearing, thinning, fodder harvesting or any other disturbance visibly altering the structure (of any layer) or species composition of the community away from the expected definition outlined by the Regional Ecosystem description.
2	0.6-0.8	Degraded remnant or advanced regrowth (typically mapped as VMA Category B or C)	Mature established vegetation impacted by disturbance(s) which have altered the structure or species composition of the vegetation community. Typically, the community will still meet the remnant vegetation criteria however some examples of– older regrowth also fit into this category. Examples are native woodland with a ground layer dominated by **Cenchrus ciliaris* or *Acacia aneura* open forest with minor fodder harvesting.
3	0.4-0.59	Non-remnant, some attributes missing or significantly below benchmark value (typically mapped as VMA Category X)	Non-remnant or regrowth native vegetation impacted by disturbance events and not meeting the remnant vegetation criteria. Includes young and some older regrowth. Some attributes may approach benchmark values however other attributes are either missing or significantly below benchmark value (e.g. exotic pastures with paddock trees and coarse woody debris, grassland with high exotic cover).
4	<0.4	Non-remnant, Crops, sown pastures, requires management to restore condition attributes (typically mapped as VMA Category X)	Non-remnant exotic dominated vegetation including crops and exotic pastures. Low biodiversity and habitat value. Includes: tree crops/orchards, exotic pastures with isolated paddock trees. Most attributes are significantly below benchmark value.

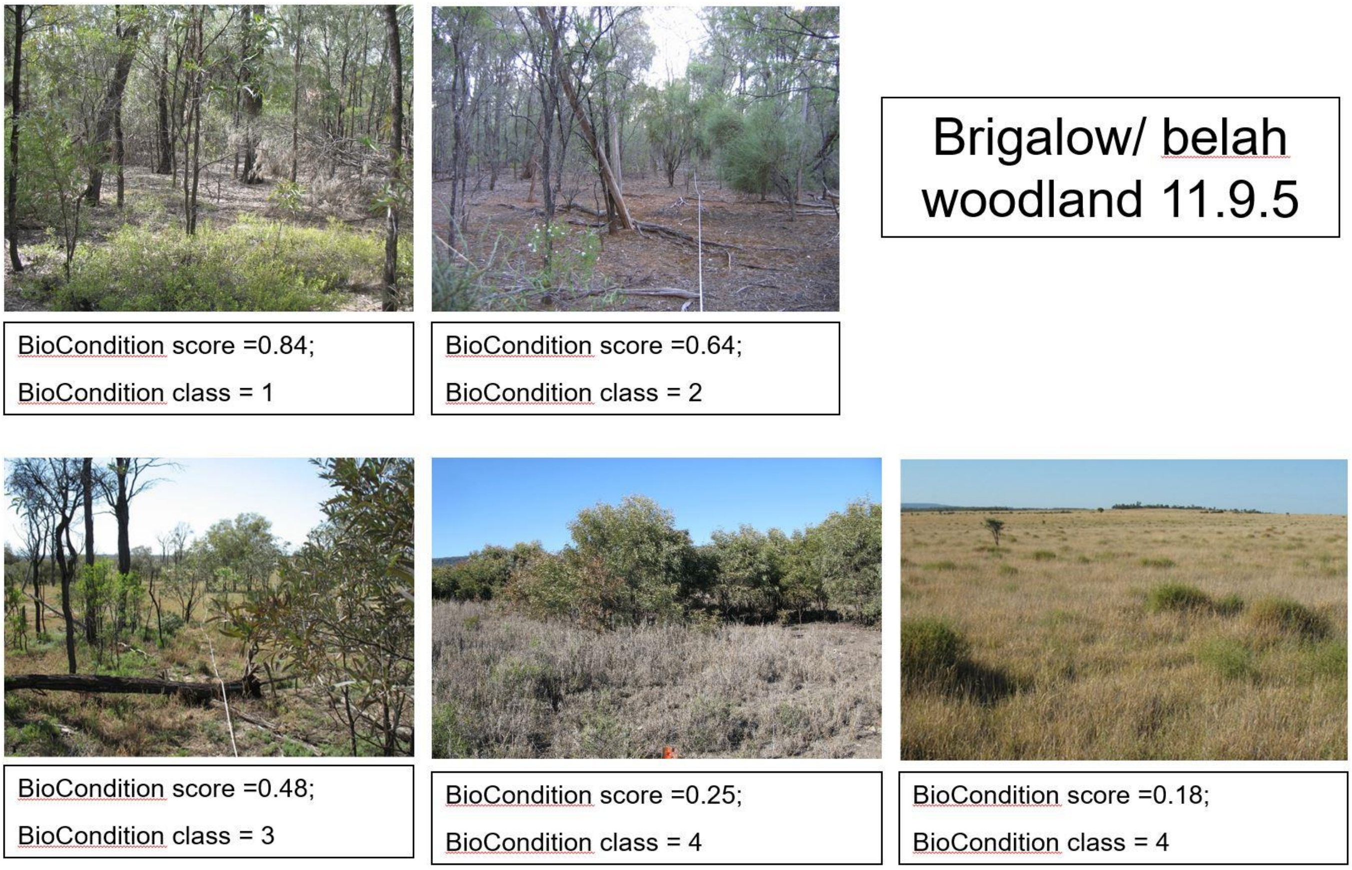

Figure 2: BioCondition scores and classes for various condition states of RE 11.9.5, *Acacia harpophylla* and/or *Casuarina cristata* open forest on fine-grained sedimentary rocks

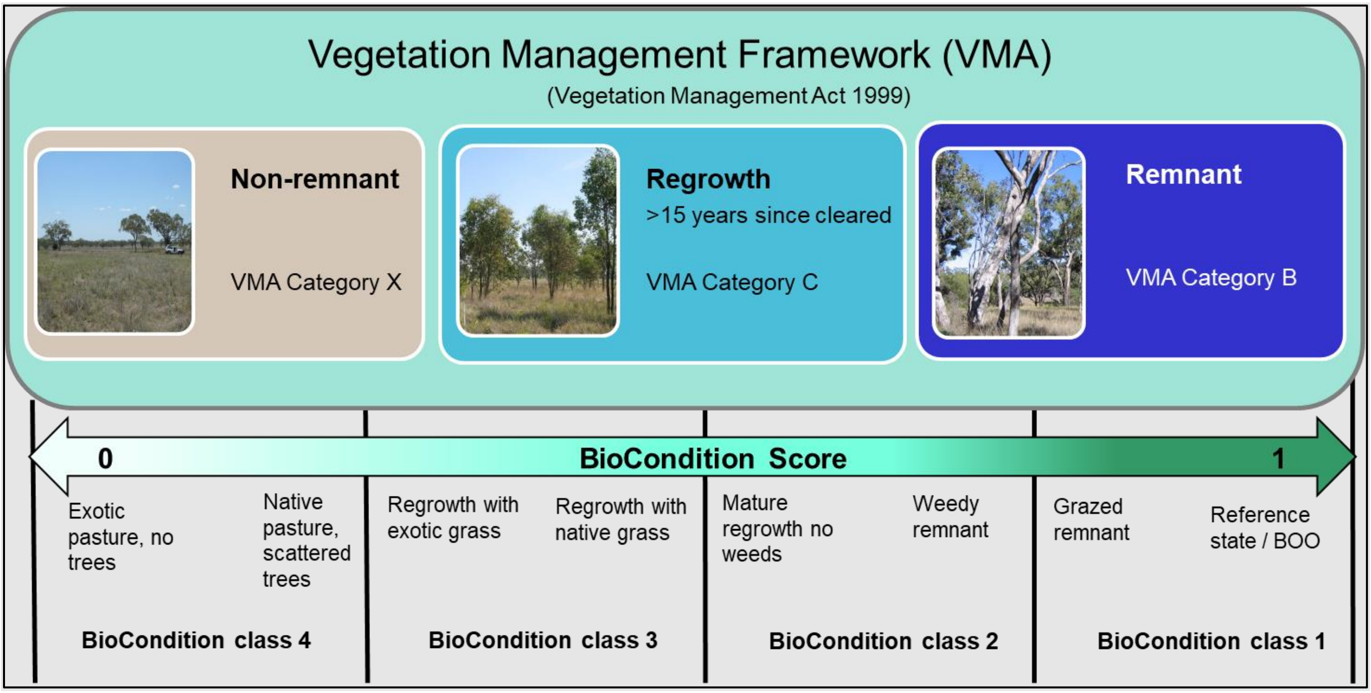

Figure 3: Schematic illustrating the relationship between Queensland's Vegetation Management framework, the continuous BioCondition score and BioCondition classes

1.4 Vegetation condition mapping approaches

There are numerous methodological approaches that can be taken to represent vegetation condition spatially. The majority of approaches have tested how to best predict vegetation condition, as a multivariate metric derived from site data, using a suite of suitable remotely sensed data across extensive geographic regions (Kocev et al. 2009; Lawley et al. 2016).

Broadly, four approaches that have emerged in the recent literature or discussions with vegetation condition mapping experts include:

1. Remote sensing (RS), and other spatial data that compare an observed value of vegetation attributes against their benchmark value
2. Broad State-and-Transition Models
3. Remote sensing models that use field-based reference (best-on-offer) sites as training data
4. Remote sensing models that use field-based vegetation condition sites as training data

To date, of these approaches, approach 3 and 4 have been tested, applied regionally in Australia, peer-reviewed and published. Approaches 1 and 2 have been conceptualised in the literature and have only very recently been applied in a mapping framework for Australian ecosystems (L. Shoo, GreenCollar pers. comm.; A. Richards, CSIRO, pers. comm.). The relative advantages and disadvantages of each approach are summarised in Table 4.

1.4.1 Spatial comparison against benchmarks using remote sensing data

Of the four approaches, this approach is the most analogous, in a spatial sense, to the site-based BioCondition vegetation condition assessment framework. This is because the method treats each data input as a stand-alone attribute which is compared against a benchmark value for that attribute and scored. Scores are then aggregated across all attributes to generate an overall vegetation condition score, like the BioCondition assessment procedure (Figure 4).

The key advantages of this approach are that the mapped outputs can be conceptually linked to ecological processes and functions, and therefore outputs can be easily interpreted and explainable to stakeholders. Another advantage is that the benchmarks used are dynamic. A key disadvantage – at this stage – is that most remotely sensed datasets cannot appropriately be used as stand-alone attributes to represent a field-based attribute (e.g. shrub canopy cover).

This approach is similar to that of Approach 3, in that it relies on a suite of reference site data for each environmental domain, which in Queensland can be based on the regional ecosystem mapping. The broad steps in the process are (Luke Shoo, GreenCollar, pers comm):

1. Collate or collect vegetation condition reference sites for each regional ecosystem
2. Extract time-matched attribute values from a spatial dataset for each of the reference sites
3. Determine the benchmark (median value) for each mapped time-series attribute for each regional ecosystem
4. Derive a composite map of benchmark values by attributing the regional ecosystem preclearing mapping with benchmark values for each attribute.

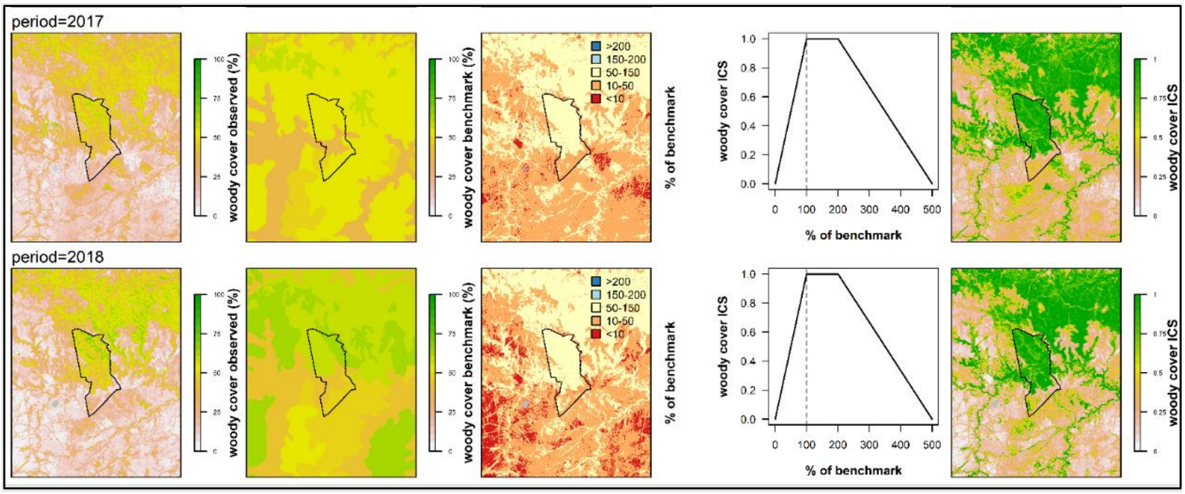

Figure 4: Example of Approach 1, where a remote sensing dataset, representing a BioCondition attribute (e.g. tree canopy cover) is compared against a benchmark to derive a BioCondition score (source and thanks to: L. Shoo, GreenCollar)

Table 4: Advantages and disadvantages of approaches to map vegetation condition at regional scales

Feature	**Approach 1** Spatial comparison against benchmarks	**Approach 2** Broad State-Transition Model	**Approach 3** RS models using reference sites	**Approach 4** RS models using condition sites
Condition metric used	BioCondition score	BioCondition class	Difference in remote-sensing space	BioCondition score
Advantages				
Relatively simple to implement and approach published			✓	✓
Relatively easy to collate training data, or training data not required	✓	✓	✓	
Provides conceptual link to ecosystem function or process for stakeholders	✓	✓		
Uses benchmarking type approach, which allows conversion to common currency	✓		✓	
Incorporates dynamic reference (time-matched) approach to mapping	✓		✓	✓
Vegetation condition is perceived as continuous	✓		✓	✓
Uncertainty easily partitioned and explained		✓		
Multiple alternate reference condition states are incorporated and explicit		✓		
Elements of condition that may inherently differ between ecosystems (e.g. tree canopy cover in woodlands vs grasslands) are explicit	✓	✓	✓ (if ecosystem mapping exists)	
Mapping can be automated across time and space	✓		✓	✓
Provides an adaptive platform for continuous improvement as new datasets and technologies become available	✓		✓	✓
Disadvantages				
High reliance on expert knowledge of characteristic of various condition states for different ecosystem types		✓		
High reliance on appropriately located and identified field-based reference sites	✓		✓	✓
High reliance on the availability of benchmarks for vegetation condition attributes for all vegetation communities for scoring condition	✓			✓
High reliance on RS data with quantified relationship with site-based condition attributes	✓			
Relies on completed benchmarks for ecosystems for scoring vegetation condition	✓			✓
High reliance on site data across all assessable units (e.g. broad vegetation groups) in various condition states	✓			✓
Relies on RS data alone (other data representing composition and function not explicitly incorporated e.g. non-native species)			✓	✓

1.4.2 Broad state-and-transition models

Broad state-and-transition models (STMs) describe structural, compositional and functional changes to an ecosystem driven by both natural events and human activities (Bestelmeyer et al. 2017). As in BioCondition, this framework identifies a reference state for the ecological community of interest. It then builds a narrative, using field condition data and expert knowledge, for the identification and description of broad vegetation condition states and the factors which divert them from their reference state, called transitions (Bestelmeyer et al. 2003). Many STMs have been developed to assist management of an ecosystem back to a preferred state, particularly in rangeland ecosystems (Westoby et al. 1989; Rumpff et al. 2011, Bestelmeyer et al. 2017).

STMs are most accurate when applied to specific vegetation communities that have been well studied (Bestelmeyer et al. 2003). Therefore, they can be difficult to apply regionally in highly diverse landscapes. Without appropriate supporting research, the drivers of transitions may not be well defined, which in turn can impact appropriate management recommendations, particularly in dynamic systems (Rumpff et al. 2011; Bestelmeyer et al. 2017). Consequently, the broadscale application of STMs across a range of ecosystems may potentially result in a prohibitive volume of data to process.

In Australia the Vegetation Assets, States and Transitions (VAST) conceptual framework has been developed (Thackway and Lesslie, 2005; Figure 5). The VAST framework defines seven vegetation cover types of increasing vegetation modification which are grouped broadly into Native and Non-native vegetation cover. It identifies the dominant vegetation modification factors present in Australia, namely clearing for development, forestry harvesting and production, invasion of non-native species, overgrazing and reduced fire intervals. This framework accepts various vegetation condition inputs and provides a consistent classification (Thackway and Lesslie, 2005) but additional development would be required to produce a complex model across multiple different vegetation types simultaneously. The state-and-transition simulation model (STSM) and associated software product (ST-sim) developed by Daniel et al. (2016) enables the application of state-and-transition model theory across large, vegetatively complex, areas focusing on land use/land cover change models. The model uses transition probabilities which can vary both spatially and temporally and are derived from external model outputs based on historic change data for independent drivers (eg; fire, clearing, agricultural land use). This manages the sometimes-random nature of transitions in vegetation communities and allows the model to be used to predict future change. Until recently, the disadvantage of STSMs were that they could only track discrete states. However, STMS have now been extended to allow continuous variables to also be tracked (Daniel et al. 2017).

Important advantages of STMs for defining and mapping condition is that change in condition states can be easily explained, ecological concepts can be simplified into categories, and that multiple alternate stable, or reference, states can be made explicit. However, a disadvantage is the use of a classification scheme to characterise each state, rather than a continuous scale (but see Daniel et al. 2017). Work has progressed to address this but there remains a dependency on externally modelled continuous inputs, such as carbon budgets or biomass, to inform the score. In those cases, STMs can only provide a continuous score for the individual input, not the state of the vegetation community overall. The approach also relies on substantial input from experts to define the various states for different ecosystem types. For practical application in Queensland at a state-wide level, state-transition models would need to be applied at the highest classification of Broad Vegetation Group (BVG, 5M). At finer resolution BVG classifications, or for regional ecosystems, substantial research and expert elicitation would be required to define condition states and transitions for numerous ecosystems.

Increasing vegetation modification from left to right

		Native vegetation cover			Non-native vegetation cover		
Vegetation Cover Classes	State 0	State I	State II	State III	State IV	State V	State VI
	Naturally Bare	Unmodified	Modified	Transformed	Replaced - *Adventive*	Replaced - *Managed*	Removed

Figure 5: The VAST conceptual framework (Thackway and Lesslie, 2005)

1.4.3 Models using remote sensing predictors and field-based reference training data

This approach is exemplified by the Habitat Condition Assessment System (HCAS), a national scale project that has gained recent traction through the publication of the method by Donohue et al. (2014) and Harwood et al. (2016). The HCAS project is a mapping approach developed by CSIRO in collaboration with the Commonwealth Department of Environment and Energy (DoEE) to provide a nationally consistent, landscape level map of habitat condition (Williams 2019).

In brief, this approach quantifies vegetation condition as the distance in remote sensing space, weighted by the distance in environment space, between a pixel and a similar pixel (i.e. within the same environmental domain) in its ecological reference state. The deviation from the reference represents loss in condition, and the condition score generated from the modelling procedure is the distance measure between the pixels. Field sites where the reference state has been determined on the ground, or sites that are remotely selected using expert knowledge and/or human land use (i.e. sites in national parks assumed to be in 'reference' state). Harwood et al. (2016) used a statistical technique in their modelling framework, generalised dissimilarity modelling, which models the pairwise difference between pixels as a function of differences in multiple environmental abiotic variables.

A conceptually similar approach to mapping condition, the dynamic reference-cover method of Bastin et al. (2012), has been applied to determine change in remotely sensed ground cover (Bastin et al. 2014). The dynamic reference-cover approach can be described as a regional benchmarking approach, where areas are compared to areas in the local vicinity that are in reference condition, to give a nominally climate-adjusted metric of ground cover and land management.

The primary advantages of this approach are that it is relatively simple to implement, particularly in Queensland where the regional ecosystem mapping can be used instead of modelling abiotic environmental domains. It also caters for environmental dynamism, and the approach has been peer-reviewed and demonstrated. The primary disadvantage of this approach is that it is difficult to link the steps in the approach with ecosystem process or function, because a number of vegetation condition attributes, such as exotic species cover and species richness, are not detectable using remote sensing data. The approach is also reliant upon a large and representative set of reference site data that adequately samples all defined environmental domains or ecosystem types. A clear definition of what is meant by the 'reference' state is also required (e.g. BioCondition BOO), to ensure variation between sites allocated to be in the 'reference' state is minimised. Definitions of 'reference' or 'good condition' may conceptually differ between various collectors of vegetation condition data, depending upon their assessment objectives.

1.4.4 Models using remote sensing predictors and field-based vegetation condition assessments as training data

In the various approaches to map vegetation condition described above, site-based vegetation condition data is used for model training in Approach 3 (training data representing the reference state) and the approach discussed here (training data representing the full suite of condition states). A similarly derived vegetation metric derived using the Habitat Hectares approach (Parkes et al. 2003) was successfully modelled across 40% of Victoria in one of the first attempts to model a vegetation condition metric at the landscape scale in Australia (Newell et al. 2006). The authors used a neural network modelling procedure and predictor variables included vegetation type, land-use, climate and lithology and state-wide tree cover mapping. Kocev et al. (2009) also used site-based training data derived from the Habitat Hectares method and remote sensing predictor variables. They used machine learning to model not only the overall vegetation condition metric across the state of Victoria using regression trees and ensembles of regression trees, but also each of the attributes that contribute to the overall Habitat Hectares metric, using multi-target regression trees, and ensembles of multi-target regression trees.

The major advantage of this approach is that the concept of condition can be continuous, rather than categorised into broad, pre-defined condition states. Another advantage is that, if available, a larger pool of training data (i.e. not just reference state data) can be utilised to train the model. Another advantage, like Approach 3, is that it is relatively simple to process and interpolate across vast areas if there is sufficient training data. A predominant disadvantage of this approach is the high reliance on a training dataset that is representative across ecosystems and the full range of condition states within those ecosystems. For a diverse area the size of Queensland, obtaining an adequate sample of training sites could be prohibitive. It is an important issue to address, as low sampling will lead to over- and underestimation of the condition scores and low accuracy in the mapped model output (Newell et al. 2006). Another difficulty with this approach is that the method is somewhat of a 'black box', where establishing clear links between the mapped output of the model and ecological function and process is problematic. This can make interpretation of the results and communication to stakeholders potentially challenging.

1.5 Overview of Spatial BioCondition workflow and framework

Following review of the four vegetation condition mapping approaches, the project team broadly selected Approach 3 (i.e. modelling with RS predictors and reference site training data) to form the basis of further investigation. The primary incentives that motivated the selection of this approach were because:

- Given the challenges faced by the Queensland Spatial BioCondition project, such as mapping diverse landscapes at a continental scale and tight time constraints, the approach has been shown to perform reasonably well in mapping broadscale vegetation condition.

- The main inputs required by the method include; sites in vegetation communities in reference condition; contemporary RS datasets; and mapped or modelled environmental domains, which are datasets developed and curated by the project partners (DES Remote Sensing Centre and Queensland Herbarium). The Remote Sensing Centre is responsible for the curation and development of statewide RS datasets, and employs skilled modellers experienced in the management of large, complex datasets. The Queensland Herbarium is responsible for the development, storage and curation of statewide reference site data and regional ecosystem mapping (representing environmental domains) and employs ecologists skilled in the collection and management of Queensland's vegetation data.

- The approach is adaptive and flexible in terms of type of modelling framework, definition of vegetation condition and quantity and variety of data inputs, so was suited for application using models and data tailored specifically for use in Queensland

The workflow developed to produce a state-wide map of vegetation condition for terrestrial ecosystems of Queensland (Spatial BioCondition) is summarised in Figure 6. The underpinning intent of the Spatial BioCondition framework was to model the distance, or departure, from the reference state within vegetation communities in remote sensing space, using three types of input data;

1. Site-based training data of sites in reference state (BOO) condition and 2, 3 and 4 states of condition (response variables). Condition classes were selected as the response rather than a continuous score, to increase the number of fit-for-purpose data sites available within the project timeframe.

2. A suite of contemporary, state-wide remote sensing data (predictor variables);

3. Environmental domain mapping, represented by state-wide pre-clear RE mapping (Version 11).

The workflow and framework were tested in a trial study located in the Brigalow Bioregion (DES 2020; Figure 8), using a mechanistic modelling approach. The trial study revealed the importance of having adequate (i.e. replicated, representative and clean) training data as well as some limitations in the mechanistic modelling approach, particularly around the setting of thresholds to demarcate the condition classes. Consequently, for state-wide application, an alternative machine learning (ML) model approach was also developed. Recent evaluations of ML against other approaches for mapping vegetation characteristics from pixels has shown it to be more accurate, reliable and easier to automate (Macintyre et al. 2018; Hamylton et al. 2020) Compared with mechanistic modelling, a key advantage of ML is that it can deal with large scale predictions and data issues around multiple space and time scales, but disadvantages include a reliance on very large datasets, and causality of input-output relationships are less clear (Baker et al. 2018).

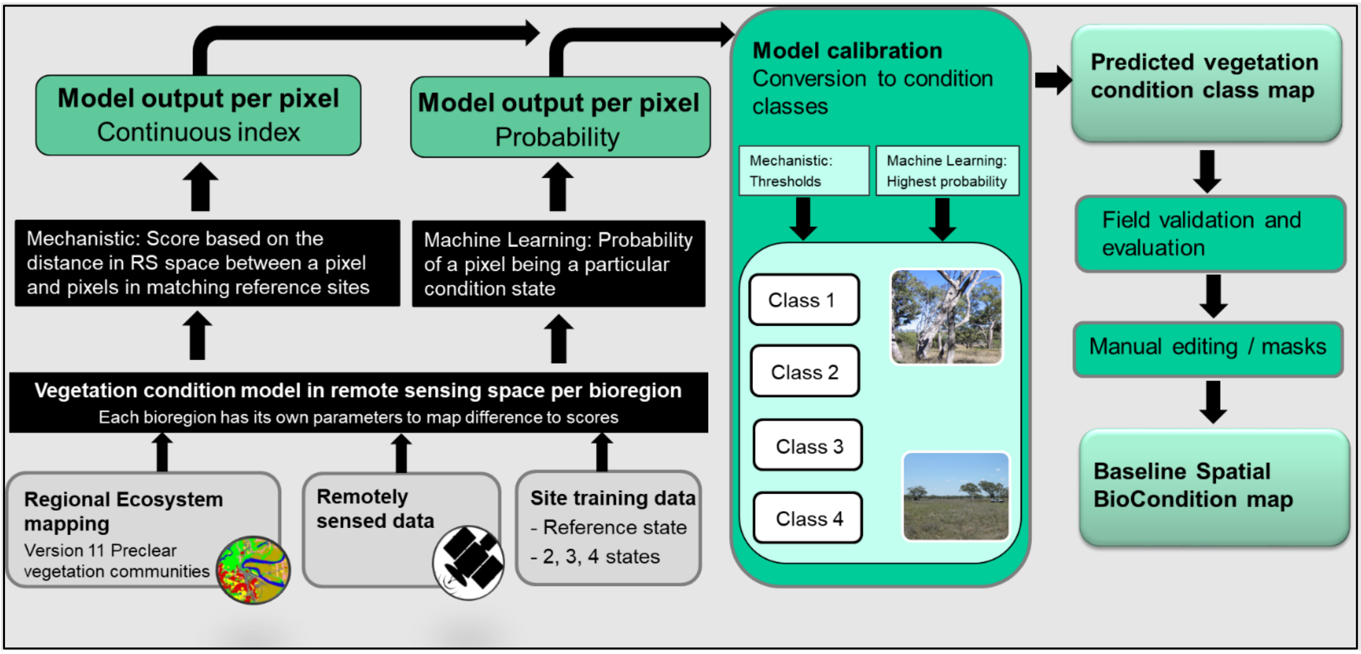

Figure 6: Overview of the workflow to deliver Spatial BioCondition, a landscape-scale map of vegetation condition of terrestrial ecosystems for Queensland

1.6 Project objectives

There are several policies, strategies and programs in Queensland that will benefit from a seamless, systematically and continuously applied representation of vegetation condition for biodiversity across terrestrial ecosystems, including;

- Assessment of native vegetation co-benefits of Queensland-based carbon offset projects under the Land Restoration Fund incentive program
- Identification of priority areas for offsets under the *Environmental Offsets Act (2014)*
- Support for the *Vegetation Management Act (1999)* regarding biodiversity benefits
- Queensland State of Environment reporting on vegetation condition as well as extent
- Support for Queensland's Biodiversity Strategy
- Threatened species recovery prioritisation for Queensland
- Support for agri-environment schemes such as carbon farming and environmental stewardship

The objective of Project 4 of the Enhanced Vegetation Mapping and Monitoring program was to establish *Spatial BioCondition* (SBC) - a mapping and modelling framework for the spatial representation of vegetation condition across the terrestrial ecosystems of Queensland, an extent of 1.73 million square kilometres and more than 2,842 mapped vegetation communities. The primary aims of the project were to:

1. Design the framework to be adaptive over space and time, i.e. to allow the incorporation of new spatial data as it becomes available;
2. To align with the conceptual framework of the site-based BioCondition vegetation condition assessment i.e. comparison between current state against reference states across all of Queensland's regional ecosystems, with a biodiversity focus;
3. To produce a prototype, baseline map of vegetation condition across Queensland's regional ecosystems.

2 Mapping vegetation condition for Queensland

2.1 Study area and currency for Spatial BioCondition (SBC)

2.1.1 Currency

This initial or baseline iteration of the SBC modelling framework has been configured to produce a spatial representation of vegetation conditions across Queensland's terrestrial ecosystems as at 2017. This version is based on: version 11 Regional Ecosystem mapping; a set of sites used to train and test models; and predictor variables, all specifically chosen or optimised to produce an output modelling condition across Queensland as at 2017.

2.1.2 Study area

The mapping method described in this report has been applied across almost the entire state of Queensland, Australia (Figure 7). Queensland occupies the north eastern quarter of the Australian continent, with an area of 1.73 million km^2 the state encompasses a broad diversity of climates, landscapes, ecosystems, geologies, soils and land uses. Approximately 80% of Queensland's native vegetation was considered extant in 2017, with historical land clearing and fragmentation concentrated in the south eastern quarter of the state (Figure 7). The Southeast Queensland, Brigalow Belt and the New England Tablelands Bioregions are considered predominantly fragmented landscapes, with more than 50% of the original pre-clear vegetation cleared. The pre-clearing native vegetation in Queensland was dominated by a variety of dry eucalypt woodlands and open forests (32% of the state); tussock grasslands and forblands (18%); Acacia dominated open forests, woodlands and shrublands (15%); Hummock grasslands (3%); wetland communities (2%); and smaller but significant areas of rainforests and scrubs; coastal communities and heaths; intertidal communities; wet eucalypt open forests; and *Callitris* spp. woodlands and open forests (Neldner et al., 2019b, DES 2018b).

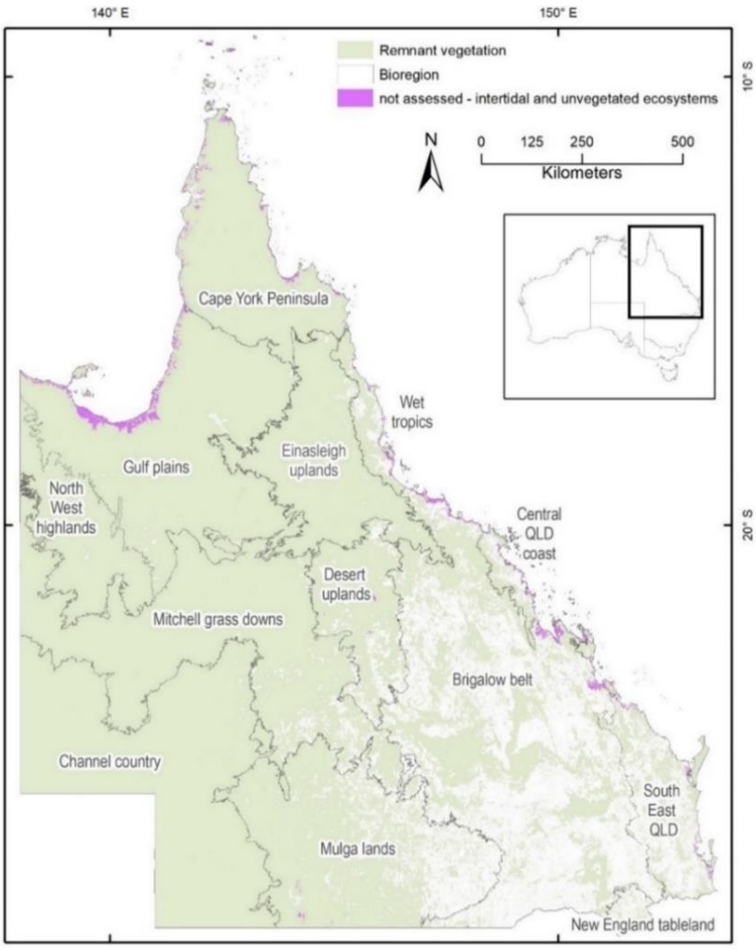

Figure 7: Study Region – Queensland, Australia. Showing bioregional boundaries, remnant vegetation extent in 2017 (green) and vegetation communities not assessed for BioCondition (pink).

Land use within the state is dominated by the grazing of introduced stock (80%). Historic and ongoing habitat clearing in Queensland has primarily been to support the pastoral industry, and recent clearing rates are highest in the eastern portion of the Mulga Lands Bioregion and in the Brigalow Belt Bioregion (Accad *et al*., 2021).

The extent of the Spatial BioCondition modelling framework reported on here is based on version 11 Regional Ecosystem (RE) mapping (DES 2018a; Queensland Herbarium 2019) which provides a consistent, seamless classification and spatial distribution map of pre-clearing and 2017 remnant vegetation communities (ecosystems) for the entire state predominantly at a scale of 1:100 000. Version 11 RE mapping describes and maps 2,842 vegetation communities within 1408 regional ecosystems which are grouped at higher-level classifications into Broad Vegetation Groups (BVG) at various scales (DES 2018a; DES 2018b; Queensland Herbarium 2019a).

The SBC framework was applied to 2,755 of the 2,842 vegetation communities in Queensland representing 99.2% of the land area of the state. The 13,366 km^2 (0.8%) of the state excluded from all stages of the model framework (Figure 7), comprises 51 non-terrestrial and 36 largely unvegetated communities as defined in Appendix 1, these communities/areas sit outside the specific remit of this project - to assess all terrestrial vegetation in Queensland. This report details the application of the SBC Modelling framework to the full pre-clearing extent of all 2,755 terrestrial and mappable vegetation communities.

2.2 Collation, assessment and scoring of site data used to train and test models

The predictive power of modelling is critically reliant on the number and quality of points of known condition (site data). The large scope of this project necessitated the investment of significant resources in the sourcing, collation and assessment of existing site data, identification of data gaps and where possible the collection of new site data. We used a hybrid system to set the minimum number of replicate ‘reference’ site data for each vegetation community. Communities with fewer reference sites than the prescribed minimum, were set to return no model result. For communities with a pre-clearing extent >1600 ha, a minimum of 5 replicates was set based on recommendations made by Butler et al. (2020), to have at least 5 samples per strata (to reduce the standard error to an acceptable 5% of the BioCondition scoring range). Communities with a pre-clear extent ≤1600 ha, used an area weighted sampling minimum. This was based on the recommended minimum ground observation density for land surveys at 1:100 000 scale (Neldner et al. 2019a) and is shown in Table 5.

Table 5: Minimum number of replicates for reference site data

Map unit pre-clearing area (hectares)	Minimum number of replicates
>1600	5
1200-1599	4
800-1199	3
400-799	2
<400	1

The collation and assessment of data used to train and/or test the SBC model was a multistep process and included:

- Sourcing existing (candidate) site data from state departmental databases, environmental consultancies, local government and national environmental data repositories.
- Assessment of all candidate data against suitability criteria.
- Iterative auditing of all data (existing and new, candidate and assessed) and the identification of data gaps.
- Field survey program to collect new data based on audit results.
- An expert workshop process to identify potential substitute or supplementary data.
- A second expert elicitation process for reference sites in identified data gaps.
- Scoring of training data using the BioCondition scoring method.

Sections 3.4 and 3.5 describe how the resulting assessed (clean) and scored dataset was partitioned into: training data (used to train the SBC model); and testing data (used to evaluate SBC model accuracy).

2.2.1 Sources of site data

Candidate sites, site data potentially suitable to train or test the SBC models, were collated primarily from ecological databases managed by the Queensland Department of Environment and Science (DES), specifically the Queensland Herbarium CORVEG database (CORVEG, 2020) and the Queensland Biodiversity and Ecosystem Research Database (QBERD, 2020). Descriptions of these databases including brief descriptions of the survey data and links to survey methods and specifications are given in Appendix 5. Site data was also sourced from the TERN Ausplots rangelands dataset (AEKOS, 2020) and a range of agencies that kindly shared site data collected using standardised (BioCondition) methods, including Brisbane City Council, Bush Heritage Australia and several environmental consultancies.

2.2.2 Assessment of candidate sites

To maximise data integrity all candidate sites were assessed against a series of assessment criteria, sites failing any criterion were excluded. Details of the assessment criteria and candidate site assessment process are provided in Appendix 5. In summary sites were selected as candidate sites if they were:

A. Assigned or could reliably be assigned to a valid version 11 regional ecosystem or vegetation community (Queensland Herbarium, 2019a);
B. Identified as being representative of the assigned vegetation community/regional ecosystem by the bioregional co-ordinator (see Appendix 1 for definition);
C. Collected or revisited in the field on or after 1st January 1995;
D. Identified as reference or BOO sites, and were in areas identified as remnant vegetation in version 11;
E. Regional ecosystem mapping (DES 2018);
F. Unique and not duplicated within any of the source datasets;
G. Recorded with a locational accuracy better than 200m;
H. Located in patches of homogenous vegetation of at least 90m x 90m, i.e. no closer than 45m to a structurally defined edge;
I. No closer than 90m to any other training site;
J. Scorable sites in QBERD with enough measured attributes relative to the maximum number of measurable attributes for the RE being assessed;

2.2.3 Data auditing

Audits of the number of candidate and assessed sites for all 2,755 vegetation communities were conducted iteratively. These audits identified priorities for (a) re-checking of existing data with various data curation issues preventing sites from passing the assessment criteria (b) field survey effort and (c) expert elicitation processes described below (d) benchmark development.

2.2.4 Field survey

2.2.4.1 Detailed vegetation condition assessment sites

Multiple field surveys were undertaken during 2019 and 2020, collecting detailed reference and assessment site data as per the BioCondition reference and assessment site methods (Eyre et al. 2015; 2017) as well as vegetation survey sites as per Neldner et al. (2019a). Priorities for survey effort were: (a) vegetation communities with large extents and insufficient data and (b) vegetation communities with many sites but no BioCondition benchmark to enable scoring of the many sites.

2.2.4.2 Rapid vegetation condition assessment sites

A rapid field condition assessment method (QVAL) was developed to supplement the number of detailed vegetation condition assessment sites (Appendix 7). The QVAL method was developed to align with the BioCondition 1,2,3,4 broad condition classification, and to be used in conjunction with available Ecological Condition Profiles (Queensland Herbarium 2018b). Ecological Condition Profiles are based on available BioCondition RE benchmarks, with the aim to reduce subjectivity in assigning condition classes, where Condition Class 1 represents the reference state from which benchmark values are derived.

Rapid vegetation condition QVAL field assessments were undertaken during the 2019-2020 field survey seasons. Sites were predominantly located randomly adjacent to roads while travelling to assess detailed vegetation condition assessments, but towards the end of the field collection phase, sites were targeted to fill gaps in the training/testing data set. Given the high number (n = 12) of observers using the rapid assessment method and the potential subjectivity of the approach, we investigated assessor variability and accuracy to confirm if the data collected using the method could be reliably used as training or testing data for the models. Full details regarding the methods and results of this investigation are given in Appendix 3. In brief, data collected using the QVAL method was found to be accurate enough for inclusion as training data for the SBC model.

2.2.5 Substitute and supplementary data

A series of bioregional expert elicitation workshops were conducted with bioregional co-ordinators and other Queensland Herbarium staff with experience working in each bioregion and were focused on identifying analogous vegetation communities within or outside the bioregion (for which we had existing and suitable 'reference state' data). Data, from the analogous RE's identified from this process, were then used as substitute or as supplementary reference data for communities with insufficient data. Such that a site or group of sites may be used as reference data for two or more analogous vegetation communities.

2.2.6 Investigation of desktop method for acquiring condition site data

An existing process to validate the SBC model output for the trial study area (see section 2.6.1 & DES, 2020), highlighted the possibility of supplementing 'reference state' site data with remotely derived 'desktop' data. Desktop condition training data has been used by the HCAS condition mapping method, although the authors noted the limitations of such data and a preference for actual field-based site data (Donohue et al. 2014; Harwood et al. 2016). The trial study area validation process required multiple assessors to allocate randomly selected points to broad condition class based on high resolution satellite image interpretation. To assess the utility of this method for acquiring condition site data and to investigate concerns regarding accuracy and variability between assessors, we analysed results from the trial area validation process. Full details regarding the method and results of this investigation are provided in Appendix 2. In brief, we found the described method unsuitable for both acquiring extra condition site data or validating model output and elected to use expert elicitation, described below.

2.2.7 Reference sites from expert elicitation

Vegetation communities with insufficient 'reference state' data were referred to a second expert elicitation process. This second expert elicitation relied primarily on the expert field knowledge of Bioregional Co-ordinators (Appendix 1) and other experienced staff at the Queensland Herbarium, however for a number of vegetation communities the pool of experts was widened, via an invitation on a NRM discussion forum, to include individuals with field experience from DES, QPWS, NRM bodies, consulting Ecologists and honorary associates of the Queensland Herbarium. Six Bioregional coordinators, one honorary associate and one QPWS ranger provided expert elicited sites. This method differs from the method described in section 2.2.6 in that it is tied to in situ field observations that validate the vegetation community and the recollection and expertise of the experienced individuals who collected those observations to confirm reference condition state.

Experts were given a list of vegetation communities (prioritised by pre-clear extent) with insufficient data and asked to identify, if possible, any previously collected Quaternary site data, (quaternary sites are basic field observations of vegetation composition, structure and landscape attributes used to verify RE mapping, Neldner *et al.* 2019a) or other locations that: (a) would pass the assessment criteria A, B, D, E, G and H; (b) they were confident from their knowledge of the area that the location was in a reference or BOO condition state; and (c) were guided by the provided potential disturbance datasets. The rationale and method used to compile and construct the potential disturbances is provided in Appendix 6.

2.2.8 Scoring

Cleaned candidate site data that passed all assessment criteria were given a site based BioCondition (Version 2.2) score using several methods depending on (a) data type (which attributes have data); (b) collection method (which method was used to collect the data); and (c) availability of a BioCondition benchmark to score against.

2.2.8.1 Detailed sites with BioCondition Benchmark

Detailed sites (all assessed QBERD and a subset of assessed CORVEG sites, see Appendix 5) attributed to vegetation communities with a published or draft BioCondition Benchmark (Queensland Herbarium, 2019c) were able to be scored as per the BioCondition assessment framework (Eyre *et al*. 2015), with resulting site based continuous BioCondition scores grouped into broad condition class as outlined in Section 1.3.3. Draft BioCondition Benchmarks are completed regional ecosystem benchmarks pending approval by the Bioregional Co-ordinators and publication on the Queensland Government website. To increase the number of sites that could be scored against a benchmark, both published and unpublished benchmarks were used. For this iteration of the report, benchmarks were available for 439 regional ecosystems (291 published and 148 unpublished).

Data scored using this method had to pass assessment criterion I - Sites had enough measured attributes relative to the maximum number of measurable attributes for the RE being assessed. This was assessed using the ratio of the maximum possible site-score (attributes measured) to the maximum possible site-score relevant to the ecosystem measured (measurable attributes for the ecosystem type). The criterion threshold varied depending on the ecosystem type (from 0.62 to 0.97). In general, ecosystems with fewer measurable attributes had higher ratio thresholds, such that training sites in these ecosystems had to have a higher proportion of measurable attributes measured to pass the criterion. Sites failing this criterion were excluded from the training dataset.

2.2.8.2 Detailed sites without BioCondition Benchmark

Detailed sites attributed to vegetation communities without a published or draft BioCondition Benchmark, (most sites from CORVEG, see Appendix 5), were not able to be scored as per the BioCondition assessment framework (Eyre *et al*. 2015). These sites were assumed to be in reference condition (broad BioCondition class 1) based on criteria for site selection outlined in Neldner *et al.* (2019a) unless evidence suggesting otherwise was known.

2.2.8.3 Other site types

All rapid condition assessment sites (QVAL sites) had their site condition estimated in the field (by trained and experienced recorders), directly into broad BioCondition class. All sites identified through the expert elicitation process were assumed to be in reference condition (broad BioCondition class 1) based on the site selection process/criteria outlined in section 2.2.7.

2.3 Predictor remote sensing variables

A suite of remotely sensed spatial datasets was collated and tested for use as predictor variables of vegetation condition in the Spatial BioCondition modelling framework (Table 6; Appendix 4). Candidate datasets were selected based on the following criteria:

- Available as a state-wide coverage
- Metadata and method available or published
- Available at a scale suitable for our modelling framework
- Operational and available at future dates
- Directly related to vegetation characteristics

These criteria imply that the model predictions and output will be produced statewide across Queensland, both now and in the future. The final criterion was determined to be important to avoid spurious correlation between vegetation condition and variables not directly related to vegetation condition, e.g. proximity to urban areas may improve predictive performance but does so due to secondary interactions with other predictor variables that have a direct correlation with vegetation condition.

Four remotely sensed datasets, some with multiple bands, resulting in a total of 17 potential predictor variables, were considered during the modelling process (Table 6). Where these RS datasets were part of a time series dataset, the data closest to 2017 (the currency for this project) were selected.

Table 6: Predictor remote sensing variables

Remote Sensing dataset	Variable name	Derivation
Minimum Foliage Projective Cover, 2016-2017	min_fpc	Sentinel 2
Seasonal persistent green 2017- dry season (June, July, August)	persistent_green	Landsat
Seasonal fractional cover, 2017- dry season (June, July, August) • Green fraction • Bare fraction • Dry fraction	green_fraction bare_fraction dry_fraction	Landsat
Fractional cover statistics, 2015-2018 Green Fraction • Minimum • Median • Maximum • Standard deviation • Range • Coefficient of variability	FC_green_min FC_green_med FC_green_max FC_green_std FC_green_range FC_green_varcoef	Sentinel 2
Fractional cover statistics, 2015-2018 Bare Fraction • Minimum • Median • Maximum • Standard deviation • Range • Coefficient of variability	FC_bare_min FC_bare_med FC_bare_max FC_bare_std FC_bare_range FC_bare_varcoef	Sentinel 2

2.4 Modelling framework

Two competing modelling frameworks were developed to test their potential to produce accurate vegetation condition maps; a simple mechanistic model, and a complex machine learning-based model. The mechanistic model is based on the HCAS method; it is simple to fit, computationally inexpensive to predict and easy to explain. The machine learning model is based on extreme gradient boosting classifiers, requires more input data than the mechanistic model, is computationally expensive to fit and complex, making it harder to explain. The final model (i.e., the one used to make the spatial predictions) was selected based on the consideration of the above-mentioned pros and cons together with the model performance. Both models were trained using the same training data and evaluated using the same methodology.

Both models were developed under the same assumption; that is, sites with similar environmental conditions and homogeneous vegetation communities should present similar remotely sensed (RS) characteristics. Therefore, any difference in RS characteristics between sites with similar environmental conditions and vegetation communities can be attributed to the difference in vegetation condition. Thus, the greater the difference in the RS characteristics between a particular site and its expected RS characteristics, the worse the condition of the site would be.

Under this assumption, vegetation condition at a given location is modelled by comparing the RS characteristics at that location with the RS characteristics of reference sites. Here the reference RS values are determined from sites in good condition (BioCondition class 1) drawn from locations with similar biophysical characteristics. The Queensland regional ecosystems (RE) map was used to identify such areas.

At each reference site $r, r = 1, \dots n_k$, within RE k, the median of a 90m x 90m window of j RS values was calculated, creating a dataset of RS_{rjk} values. The reference value for RS layer j within RE k was defined as the mean of these values (Equation 1).

$$\overline{RS}_{jk} = \frac{\sum_{r=1}^{n_k} RS_{rjk}}{n_k} \quad (1)$$

Consider a set of observed BioCondition classes at locations i, $i = 1, \dots n$, with n the total number of observations in the training data. Each observation corresponds to one of four classes so that $y_i \in \{1,2,3,4\}$ and each observation falls in exactly one regional ecosystem k. Modelling the BioCondition class y_i is performed by estimating the relationship between the observed class and distance in RS space of the observation to the reference RS values. That is,

$$y_i = f\left(d_{i1}, d_{i2}, \dots d_{iJ}\right),$$

with d_{ij} the relative distance between the RS values for layer j at site i and the reference RS values, given that site i is in RE k. We define d_{ij} as

$$d_{ij} = \frac{RS_{ij} - \overline{RS}_{jk}}{\max_j}, \quad (2)$$

where $\max_j$ is the maximum expected value for the j^{th} remote sensing variable and d_{ij} has a valid range from -1 to 1. Values close to 0 are indicators of good condition while negative or positive values further from 0 are in general indicative of poor condition.

To create the reference and training datasets, 75% of available field data was randomly sampled for training the models, with the remaining 25% used to evaluate the performance of the models. Only REs with sufficient reference locations as defined in section 2.2 (Table 5) were considered. When missing or insufficient, reference locations from analogous REs (identified using the process described in section 2.2.5) were selected. No reference data and therefore no predictions were made on REs with insufficient reference sites.

High correlation between predictor variables is a known issue that affects many different types of models. In most cases it doesn't affect the model’s prediction or accuracy, but it may affect the value of the parameters of the model and the relative contribution or predictive power of the predictor variables. Therefore, for each pair of highly correlated variables, the less important variable was dropped and not considered further in the model. The correlation between predictor variables was computed using the Pearson correlation coefficient. Variables were considered to be highly correlated if the Pearson correlation index was higher than 0.9.

2.4.1 Mechanistic model of vegetation condition

Similar to the field based BioCondition scoring and classification schema detailed in section 1.3.3, the rationale behind the mechanistic model was to initially calculate a continuous score, to represent the distance in the RS space and then classify that score to match the four BioCondition classes.

The distance in the RS space for an observation i in RE k is composed of the individual contribution of each RS variable (i.e., d_{ij}). To be able to combine the contribution of each RS variables in a meaningful way, they need to be scaled consistently. To achieve that, d_{ij} was transformed using a logistic function (Eq. 3)

$$d'_{ij} = \left(\frac{1}{1-e^{\kappa_j\left(d_{ij}-x_{0_j}\right)}}\right), \qquad (3)$$

where parameters of the logistic function (κ_j and x_{0_j}) were chosen such that the transformed distance for each RS layer had a range between 0 and 1. Values close to 0 indicate a site didn't show any departure from the reference site for that RS variable while a value close to 1 indicate a large difference in RS space for that variable.

The total distance in the remote sensing space was then obtained by adding the transformed relative differences for each of the J RS layers,

$$dRS_i = \sum_j^J d_{ij}. \qquad (4)$$

dRS_i has a theoretical range from 0, representing the best possible condition, to J, the number of RS layers, which represents the poorest condition.

Finally, the dRS values were split into the four broad BioCondition classes using a set of thresholds that maximises the agreement between the model and the training data as measured by the F1-score.

After removing the less important variable of each pair of highly correlated variables, a backwards elimination method was applied to obtain a model including as few independent variables as possible, without compromising the predictive performance of the model. To achieve this, the independent variables were sorted by their individual predictive ability as measured by the f1-score and eliminated from the model starting with the variable with the lowest predictive performance until the highest weighted F1-score was achieved. Two slightly different versions of this model were trialled; one with state-wide thresholds, and another with a different set of thresholds for each bioregion.

In summary, fitting the model involved finding values for κ and x_0 for each RS layer and then thresholding dRS to translate the continuous score into classes using the training data. Predictions on new data at site i within RE k are obtained by computing dRS using κ and x_0 followed by the classification of the continuous score using the thresholds obtained in the fitting process.

2.4.2 Machine learning model of vegetation condition

In this model, the relative distances in the RS space between each training point and its reference values (d_{ij}) was used to fit gradient boosting decision trees (GBDT). In gradient boosting, decision trees are built by splitting observations into branches based on feature values. The algorithm looks for the best split which results in the largest loss reduction. GBDT training process is gradual, additive and sequential. The algorithm begins by training a decision tree in which each observation is assigned equal weight. After evaluating the first tree, the weights of observations that are difficult to classify are increased and the weights for those that are easy to classify are decreased. The same process is repeated for a specified number of iterations. Subsequent trees help to classify observations that are not well classified by the previous trees. Predictions of the final tree ensemble are therefore the weighted sum of the predictions made by the previous tree models. The model was implemented in the Rust programming language (Matzakis and Klock, 2014) using the LGBMClassifier routine from the LightGBM library (Ke *et al*., 2017). The target values consisted of the BioCondition classes y_i with $y_i \in \{1,2,3,4\}$ and $i = 1, \dots n$. The feature values were the array of relative distances $\boldsymbol{d}$ with dimension $n \times J$.

Hyper-parameters are model parameters that are not directly learnt within the training process but can have a large impact on the predictive performance or computational complexity of the model. Typically, models have more than twenty hyper-parameters, but, commonly, only a small subset of those have large impacts on the model. We searched the hyper-parameter space, considering all the relevant hyper-parameter combinations, for the best cross-validation score. Overfitting, i.e., the addition of tree nodes that only describe a small number of observations making the model less generalizable, is a common problem in machine learning models (Shaffer 1993). Several hyper-parameters that depend on the number of observations and features of the training dataset are available in LightGBM to prevent overfitting. Appropriate values for such hyper-parameters were manually selected to prevent overfitting.

After dealing with the correlation between predictor variables, a forward selection method was used to choose the smallest possible subset of the remaining independent variables without affecting the predictive performance of the model. The process is based on the subsequent addition of variables sorted by importance until the addition of new variables does not improve the predictive performance of the model.

ML models have the reputation of being hard to interpret and are often referred to as 'black boxes'. To counteract this, several methods and techniques have emerged in recent years to explain machine learning predictions. The SHAP (SHapley Additive exPlanations) method, first introduced by Scott Lundberg and Su-In Lee in 2017, has become the most popular method to describe machine learning predictions. SHAP describes the relative impact of features on the predictions of the model by computing the relative impact of each feature on the eventual output of the model by comparing the relative effect of the features against the average. The SHAP python module (https://github.com/slundberg/shap) was used to compute SHAP values and generate plots.

2.5 Accuracy assessment

Two accuracy assessments were undertaken on both, the mechanistic model (MM) and the machine learning (ML) model. In both assessment methods the F1-score was chosen as the metric to evaluate the predictive ability of the models, comparing actual with predicted classes. The F1-score was computed as the harmonic mean of precision and recall. It ranges between 1, indicating perfect precision and recall and 0 if either precision or recall is 0.

The first accuracy assessment was a state-wide assessment performed using the 25% (5,720) of training sites that were withheld from training the model as validation points. The second accuracy assessment was an independent validation of model outputs in the trial study area, located within the Brigalow Belt Bioregion (Figure 8; DES 2020). In this assessment validation sites were randomly selected using a stratification of the pre-clear RE mapping and the condition classification output of an early iteration of the mechanistic model. A minimum of two sites per RE were selected for the 1st quartile, three sites for the 2nd, four sites for the 3rd and five sites for the 4th quartile, resulting in a total of 344 validation sites.

Inaccessibility of the randomly selected validation sites severely limited our capacity to validate sites in the field. To overcome this limitation, we adopted a remote validation approach where a single observer familiar with the ecosystems of the trial study area and BioCondition assessment methods classified each of the 344 validation points into one of the four BioCondition classes using: high resolution imagery (Earth-i 2017); aerial photographs; disturbance history information; and expert knowledge, in a method similar to that described in Appendix 3. The accuracy of the observer's classifications was first tested against an additional 56 site locations, which had been field assessed, scored and classified as per the BioCondition framework (Eyre et al., 2015). The tested accuracy for the observer (92%) was considered adequate to assess all 344 independent validation sites using high resolution imagery.

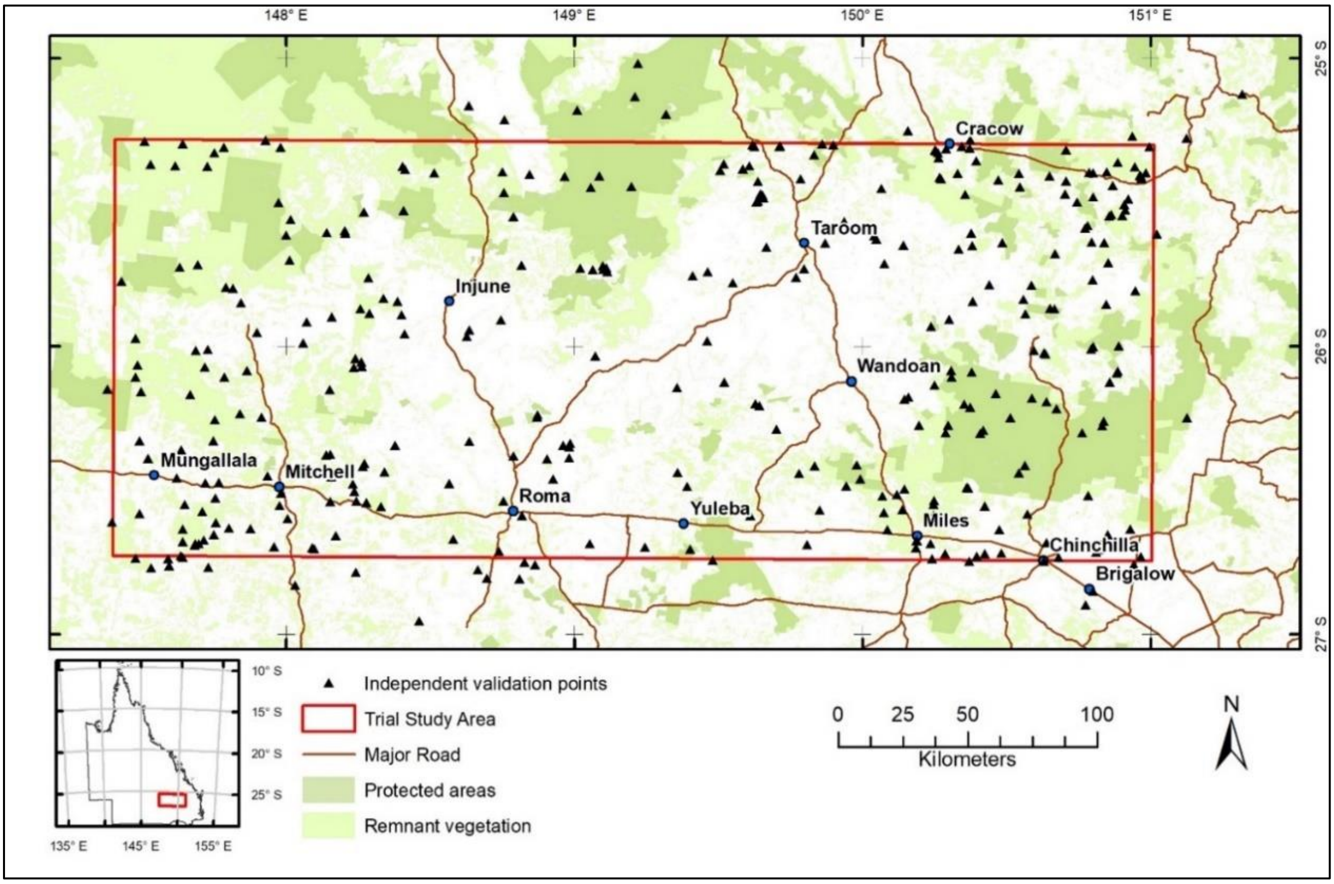

Figure 8: Trial study area and the distribution of the 344 independent validation points used to assess accuracy of Spatial BioCondition model outputs

2.6 Masking

The SBC Modelling framework was applied to the pre-clearing extent of 2,755 terrestrial and mappable vegetation communities. However, the potential for some areas mapped as vegetated in pre-clearing RE mapping to have been completely replaced by artificial environments (as at 2017) necessitated some masking of model outputs.

Areas from within the scope of this project and assessed using the SBC framework, where pre-clearing vegetation has been predominantly replaced by artificial environments have been intentionally removed from this iteration of the SBC model output using spatial masking. These areas have high spatial and/or temporal variability (from a RS perspective) and are not suited to the current scale of the SBC model framework and include: urban and industrial areas; and artificial water bodies.

We defined two spatial masks as follows:

(a) artificial water bodies - the 2017 extent of 'water' (polygons greater than 1 ha only) from version 11 Regional Ecosystem mapping (DES, 2018a);

(b) identified urban and industrial areas - the combined extent of the following datasets that does not intersect with 2017 remnant or high value regrowth (HVR) mapping (DES, 2018a):

- Built up areas (DNMRE, 2020);
- Queensland Land use Mapping (QLUMP) categories (DES, 2017b; ABARES, 2016):
    - 5.3.0 – Manufacturing and Industrial (Brisbane, Ipswich, Moreton Bay Regional, Redland, Gold Coast and Sunshine Coast local government areas only);
    - 5.3.3 – recreation and culture;
    - 5.7.1 – Airports/aerodromes;
    - 5.7.4 – Ports and water transport;

3 Results

3.1 Site Data used to train or test SBC model

In total 48,012 candidate sites were collated from existing data sources, field survey and expert elicitation. As shown in Table 7, 23,536 of these candidate sites passed all assessment criteria, were able to be provided with a broad BioCondition class and were considered suitable for use to train and test the SBC model. As part of this total are additional field survey data collected as part of this project,iIncluding 231 detailed sites (191 reference sites and 40 assessment sites), 11,661 sites collected using the QVAL rapid condition assessment method, and 1,858 expert elicited sites which were identified by six Bioregional coordinators, two Field Ecologists and one Honorary Associate from the Queensland Herbarium as well as one QPWS ranger.

The rapid assessment sites were evenly spread between the four broad BioCondition classes but were predominantly located in the southern half of the state and located along roadsides. Figure 9 shows the distribution of: all existing candidate data assessed; data found suitable for use (passed all assessment criteria); and newly collected and expert elicited data used.

Table 7: Number of existing and collected candidate sites; sites suitable for use; and suitable sites in each broad condition class and by scoring method

Source	Candidate sites		Suitable sites[3]	Broad BioCondition Class				Scoring Method		
	Existing[1]	Collected[2]	Existing & collected	Class 1	Class 2	Class 3	Class 4	Against Benchmark[4]	Field estimate[5]	Auto[6]
corveg	29,817	133	8,522	8,001	500	21	0	1,444	0	7,078
Qberd	2,897	98	1,292	522	564	159	47	1,292	0	0
QVAL		12,418	11,661	3,109	3,933	2,297	2,322	0	11,661	0
Expert[7]		1,862	1,858	1,858	0	0	0	0	0	1,858
other	787		203	81	63	36	23	132	0	71
Total	**33,501**	**14,511**	**23,536**	**13,571**	**5,060**	**2,513**	**2,392**	**2,868**	**11,661**	**9,007**

[1]Total number of collated existing sites that were assessed for suitability. [2]Total number of field survey sites and expert elicited sites that were collected as part of this project and assessed for suitability. [3]Clean existing or collected sites that passed all assessment criteria. [4]Eyre et al. (2015). [5]As per method described in Appendix 7. [6]Assumed to be in 'reference' state based on criteria for selecting suitable survey site locations, see Neldner et al. (2019a). [7]Expert elicited sites as described in section 2.2.7

3.1.1 Site data by vegetation community

The initial 'cleaned' site dataset (prior to expert driven substitution, supplementation, and elicitation of extra reference site data) comprised 11,713 suitable 'reference' sites (class 1). These were distributed unevenly across the 2,755 mapped vegetation communities in Queensland. Table 8 details the number and proportion of vegetation communities with sufficient (greater than or equal to the set minimum number of replicates for that RE) suitable reference site data; and the proportion of the mappable area of the state that they represent at three stages of the data acquisition process.

The dataset was unevenly distributed across vegetation communities with just over one third (956) of vegetation communities having sufficient data. However, the highly skewed area distribution of vegetation communities across Queensland meant that the data represented 72% of the mappable area of the state. The process to identify substitute or supplementary data from within the existing initial dataset found the equivalent of an extra 4,962 sites for 772 vegetation communities, increasing the number of communities with sufficient data by 503 and the area able to be modelled to over 77% of the state. The second process to identify extra reference sites through expert elicitation and specifically targeted to communities with large spatial extents and insufficient data, resulted in the identification of 1,858 sites in 558 vegetation communities increasing the number of units with sufficient data by 366 and the area able to be modelled to 91% of the mappable area of the state.

Table 8: Number of vegetation communities (map units) exceeding the threshold for the minimum number of suitable 'reference' state sites and the proportion of the mappable area of Queensland they represent

	Number map units	% map units$_1$	% of mappable area of QLD$_2$
Initial dataset	956	35	72
Initial dataset + substitute$_3$	1,459	53	77
Initial dataset + substitute$_3$ + expert$_4$	1,825	66	91

[1]Percentage of the 2,755 mappable vegetation communities. [2]Pre-clearing extent for all 2,755 mappable vegetation communities, approx. 1.71 million square km (99% of total area of Queensland). [3]Reference state site data identified through substitution and supplementation process outlined in section 2.2.5. [4]Reference state site data identified through the expert elicitation described in section 2.2.7

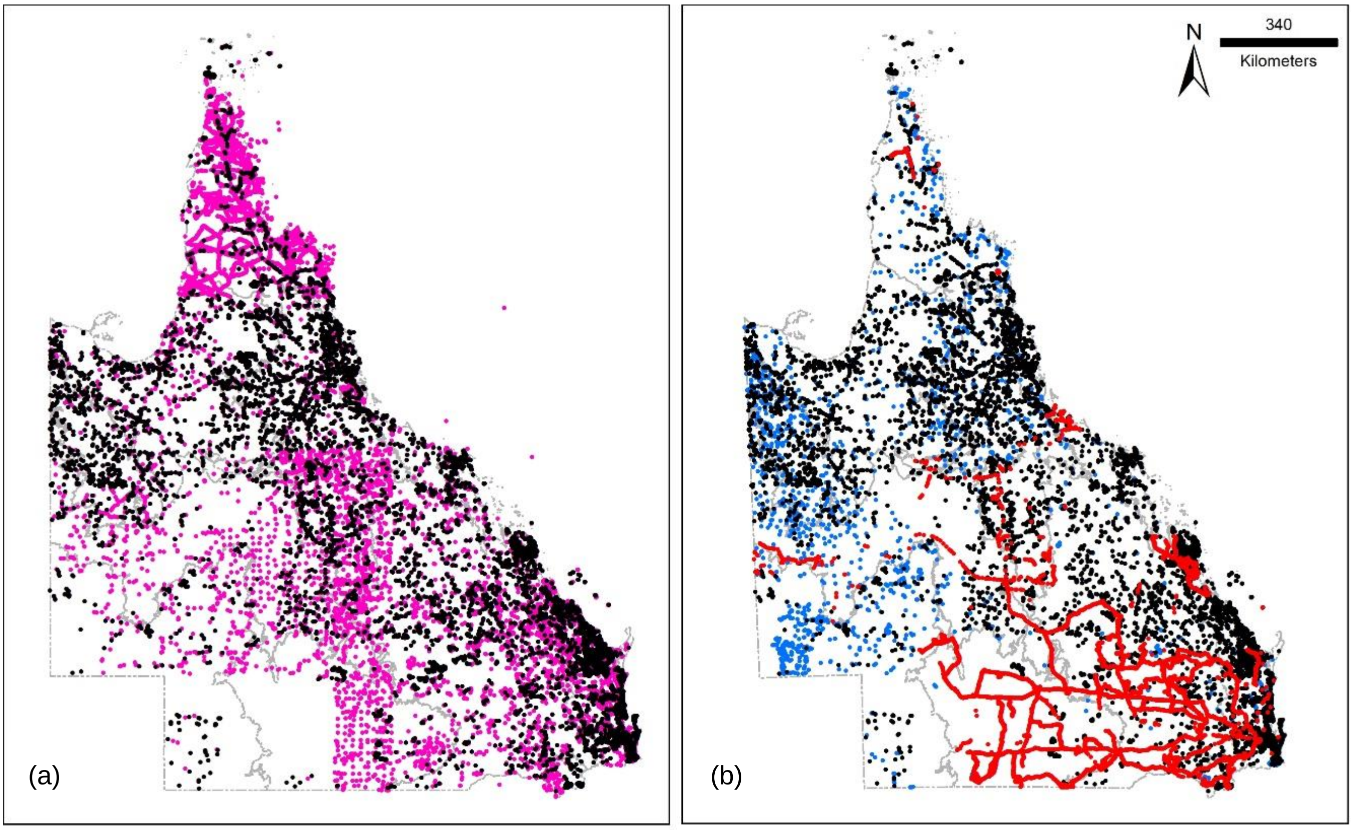

Figure 9: Site data (a) All collated existing candidate sites, showing suitable sites (black) and unsuitable/rejected sites (pink), and (b) All suitable data (existing (black), collected(red) and expert derived (blue) used in SBC model training and/or testing

3.2 Spatial BioCondition Models

Sufficient training site data was collated to produce Spatial BioCondition Model outputs with a 2017 currency for 2,267 of the 2,755 vegetation communities (82%), representing 1.54 million km^2 and 89% of the state. The remaining area was not mapped because it was either outside the scope of the project (i.e. non-terrestrial regional ecosystems including ocean, estuary, sand or shallow water), and unvegetated communities as mapped in the version 11 pre-clearing extent, and areas of mapped regional ecosystems for which there was insufficient training data to return model output.

3.2.1 Variable selection

Four pairs of highly correlated variables (where the Pearson correlation coefficient was greater than 0.90) were found (Figure 10) in the training dataset. Those were*: FC_green_range* and *FC_green_std* (*r* = 0.97*)*; *FC_bare_range* and *FC_bare_max* (*r* = 0.92*)*; *FC_bare_range* and *FC_bare_std* (*r* = 0.94); and *dry_fraction* and *bare_fraction* (*r* = 0.93).

The relative importance of each predictor variable for the MM and ML are shown in Table 9. The less important variable of each pair of highly correlated variables were for the MM, *bare_fraction*, *FC_bare_range* and *FC_green_range;* for the ML *dry_fraction*, *FC_bare_range* and *FC_green_range.* Those variables were not considered further, thus reducing the number of potential predictor variables to 14.

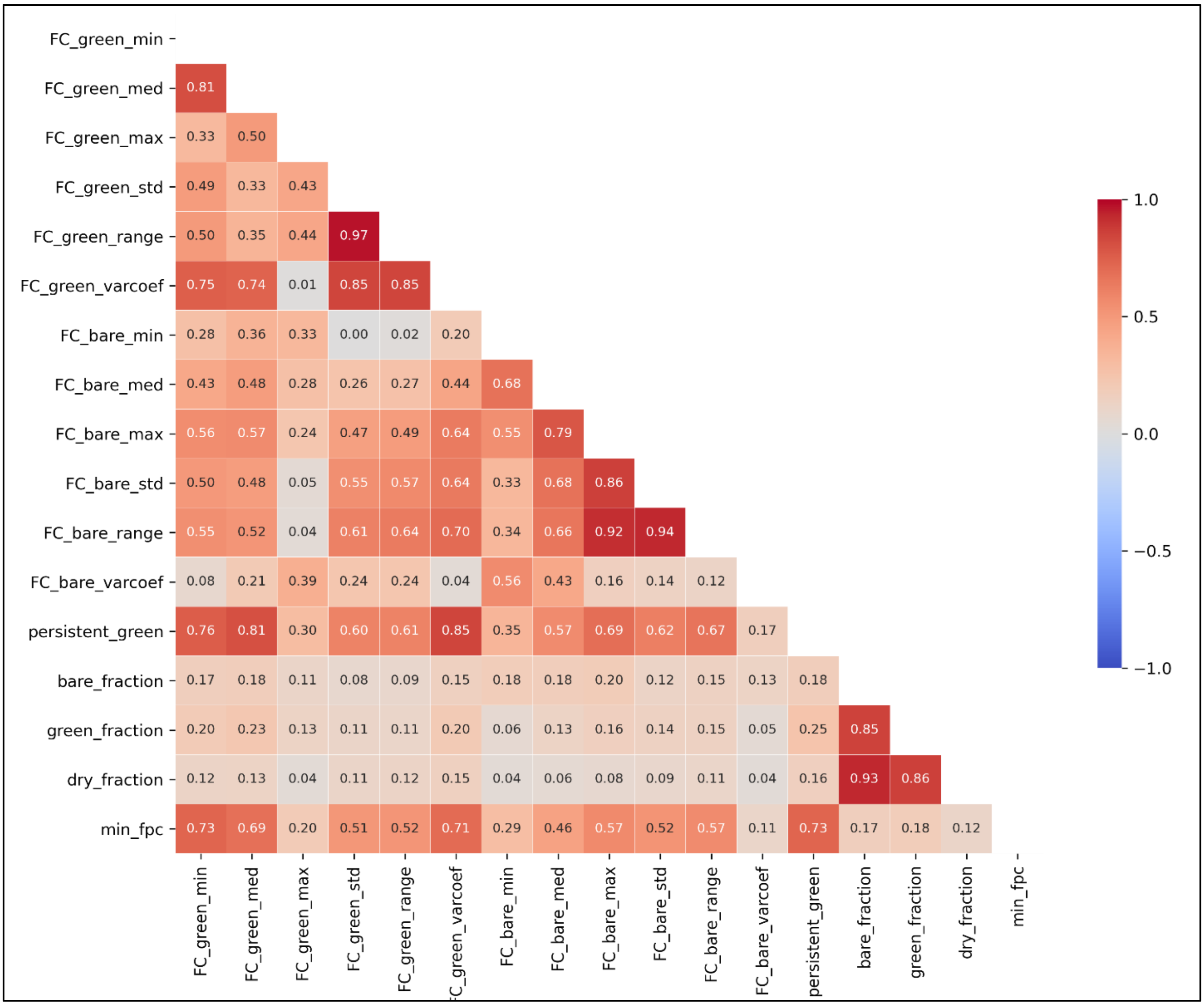

Figure 10: Pairwise correlation of predictor variables. Values represent the Pearson correlation coefficient.

The accuracy (F1-score) of each trialled model as a function of the number of potential predictor variables included in the model is shown in Figure 11. In all models a balance between goodness of fit (F1-score) and parsimony (complexity of the model) was reached at an intermediate number of potential predictor variables. In the case of both MM models the optimum number of predictor variables was reached when considering four predictor variables with an overall accuracy of 0.49 and 0.55 for the state-wide and bioregional model respectively. In both cases, considering fewer or more variables had a negative impact on accuracy. The ML model on the other hand, showed a positive monotonic trend, reaching a balance between goodness of fit and parsimony at seven potential predictor variables with and overall accuracy of 0.65. While the addition of more variables improves the model's performance, that improvement (less than 1% in overall accuracy) wasn't enough for the extra variable to be further considered.

Table 9: Predictor variable importance for the mechanistic and machine learning models.

Variable name	Mechanistic model (F1-score)	Machine Learning (SHAP value)
bare_fraction	0.19	2.47
dry_fraction	0.23	0.9
FC_bare_max	0.26	1.3
FC_bare_med	0.22	1.25
FC_bare_min	0.29	2.33
FC_bare_range	0.16	0.93
FC_bare_std	0.33	2.1
FC_bare_varcoef	0.24	0.75
FC_green_max	0.27	1.95
FC_green_med	0.26	1.83
FC_green_min	0.29	2.39
FC_green_range	0.17	1.05
FC_green_std	0.31	2.69
FC_green_varcoef	0.28	2.12
green_fraction	0.24	2.47
min_fpc	0.36	2.61
persistent_green	0.27	1.7

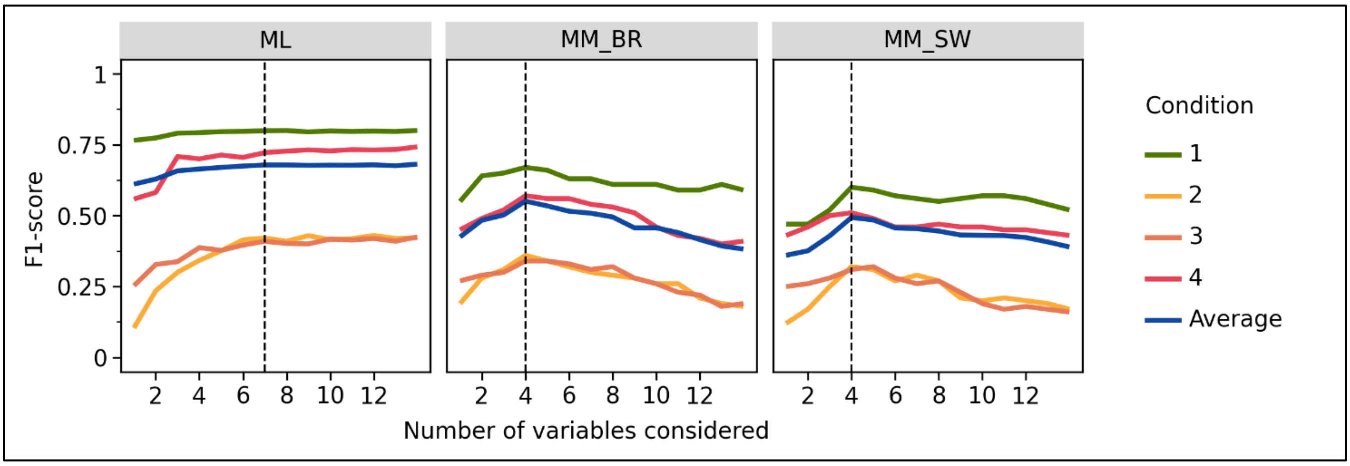

Figure 11: F1-score per class for different number of independent variables considered for each of the three models (solid lines) and number of variables considered in the final model (dashed vertical lines).

3.2.2 SBC Model evaluation

3.2.2.1 State-wide accuracy assessment

The accuracy of the models was evaluated and compared using the optimal number of predictor variables, those were, for the ML model, *FC_green_std, min_fpc, bare_fraction, FC_green_min, FC_bare_min, FC_bare_std*, and *FC_green_max* and for both MM models *FC_green_std, m*in_fpc, green_fraction, bare_fraction. Table 10 shows the precession, recall and F1-score for each BioCondition class and model.

The ML performed much better than the MM models with a weighted F1-score of 0.65, 18% higher than the best MM model (F1-score of 0.55). The bioregional variant of the MM had a slightly higher accuracy (F1-score of 0.55) compared to the state-wide variant (F1-score of 0.49). All the models showed balance between precision and recall, with less than 2% difference in all cases.

The extreme classes (Class 1 and 4) were predicted with a much higher accuracy than intermediate classes (Class 2 and 3) in all models. The three models identified class 1 with the highest accuracy, 0.6, 0.67 and 0.79 for MM-SW, MM-BR and ML respectively, followed by class 4, 0.51, 057 and 0.71 for MM-SW, MM-BR and ML respectively.

Table 10: Evaluation matrix for three models showing precision, recall and f1-score for each class for: (a) mechanistic model using state-wide thresholding (MM-SW); (b) mechanistic model using bioregional thresholding (MM-BR); and (c) Machine learning model (ML).

	Precision			Recall			F1-Score			
Class	**MM-SW**	**MM-BR**	**ML**	**MM-SW**	**MM-BR**	**ML**	**MM-SW**	**MM-BR**	**ML**	**Support**
1	0.61	0.65	0.74	0.59	0.69	0.85	0.60	0.67	0.79	3163
2	0.34	0.39	0.50	0.31	0.34	0.36	0.32	0.36	0.42	1332
3	0.32	0.32	0.45	0.30	0.36	0.35	0.31	0.34	0.39	630
4	0.51	0.60	0.70	0.52	0.55	0.72	0.51	0.57	0.71	595
Weighted average	**0.50**	**0.55**	**0.65**	**0.49**	**0.56**	**0.66**	**0.49**	**0.55**	**0.65**	

3.2.2.2 Trial area accuracy assessment

The second evaluation of model accuracy (using the 344 points in the trial study area) yielded the results shown in Table 11. The machine learning model, achieved higher weighted averages than the mechanistic model for precision, recall and F1-score, reflecting the result for the state-wide evaluation. For both models, predictions of class1 achieved the highest accuracy followed closely by class 4 with classes 2 and 3 considerably less accurate.

The machine learning model was better at predicting all classes than the mechanistic model, achieving accuracy scores between 13 (recall, class 3) and 50 (precision, classes 2 and 3) percent. The overall accuracy achieved by both models was lower (27% lower for MM and 13% lower for ML) for this evaluation than the state-wide evaluation. Given the substantial difference in prediction accuracy between the mechanistic and machine learning models in both assessments, the latter was selected for further analysis and to produce the final SBC prediction.

Table 11 : Evaluation matrix for the mechanistic (MM) and the machine learning (ML) models using 344 validation points in the trial study area, showing precision, recall and f1-score for each class.

	Precision		Recall		F1-Score		
Class	**MM**	**ML**	**MM**	**ML**	**MM**	**ML**	**Support**
1	0.55	0.66	0.56	0.64	0.55	0.65	49
2	0.32	0.48	0.31	0.36	0.31	0.41	101
3	0.30	0.45	0.30	0.34	0.30	0.39	73
4	0.49	0.61	0.47	0.64	0.48	0.62	121
Weighted average	**0.41**	**0.55**	**0.40**	**0.49**	**0.40**	**0.52**	344

3.2.3 Effect of independent variables in SBC prediction

A summary plot showing the average impact of each of the predictor variables in the SBC's predictions by class is shown in Figure 12. Variables are shown in decreasing order of overall importance and the contribution of the predictor to the prediction of each class is represented by the length of the bar of the matching colour. The predictor that contributed the most to the model's output was FC_green_std (SHAP = 3.6), followed by min_fpc (SHAP = 3.2) and bare_fraction (SHAP = 2.1). The remaining four predictors (FC_green_min, FC_bare_min, FC_bare_std and FC_green_max) had a relatively lower overall contribution, with an average impact of less than half of the highest contributing variable.

The average impact that predictors had in predicting a particular class varied among classes. For class 1 and class 4, the most important predictors were FC_green_std and min_fpc, while the most important predictor for class 2 and 3 were min_fpc and bare_fraction.

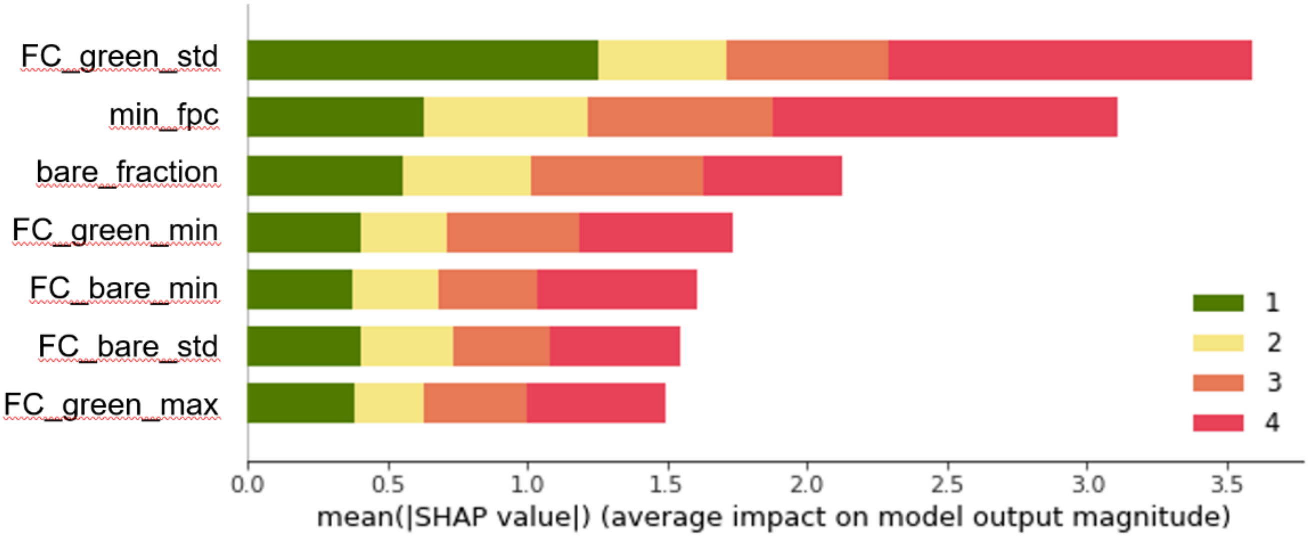

Figure 12: Average impact of each predictor variable on the model output by class.

Even though the summary plot gives important insights about the relative influence of each predictor in the model, it doesn't show how they affect the predictions. The SHAP plot (Figure 13) shows how the values of each independent variable changes the logarithm of the odds (SHAP value) of belonging to a particular class. The y-axis indicates the predictor variables in order of importance and the colour gradient indicates the value for that variable. Each point represents a row in the training dataset. Odds provide a measure of the likelihood of a particular outcome. They are calculated as the ratio of the number of events that produce that outcome to the number that do not. A log odds value of 0 represents an equal chance of being in the given class (even odds). Positive log odds indicate an observation is more likely than not of being in the class. Negative odds indicate an observation is more likely to *not* be in the class.

In this case, for example, the first row of the first panel, represents the number of trees that predicted class 1 divided by the numbers of trees that did not for different values of FC_green_std during the training process. High values of FC_green_std (red colour) were less likely to be classified as class 1 (negative SHAP values) while low values of FC_green_std (blue colour) were more likely to be classified as class 1 (positive SHAP values). Likewise, the following observations can be made from the SHAP plot:

- FC_green_std and min_fpc were the most important variables to predict class 1 and 4. As expected, the relationship between the predictor value and class membership was in opposite direction. That is, an increase in FC_green_std decreases the probability that the observation is in class 1 and increases the probability that an observation is in class 4. Similarly, high values of min_fpc increased the likelihood of an observation belonging to class 1 and reduced the likelihood of being in class 4. This pattern also holds for class 2 and class 3.
- Min_fpc was the most important variable to predict class 2 and 3. The relationship between min_fpc and class probability is positive for class 2 and negative for class 3.
- Bare_fraction is the second most important variable for prediction of class 2 and 3. The nature of the relationship is less clear than for min_fpc and FC_green_std. Extreme positive or negative values are indicative of a lower likelihood of being in both class 2 or 3, but increases the odds of being in class 1. Low Bare_fraction values are associated with reduced odds of being in class 4.

- The likelihood that an observation was classified as class 1 increased with low values of of FC_green_std, FC_bare_std and FC_bare_min, high values of min_fpc and FC_green_max and extreme values of bare fractions.
- The likelihood that an observation was classified as class 2 increased with low values of bare_fraction, FC_green_std, FC_bare_std and high values of min_fpc, FC_green_min.
- The likelihood that an observation was classified as class 3 increased with low values of min_fpc, bare_fraction FC_green_min and FC_green_max and high values of FC_green_std and FC_bare_min
- The likelihood that an observation was classified as class 4 increased with low values of min_fpc, FC_green_min and bare_fraction and high values FC_green_std FC_bare_std and FC_bare_min.

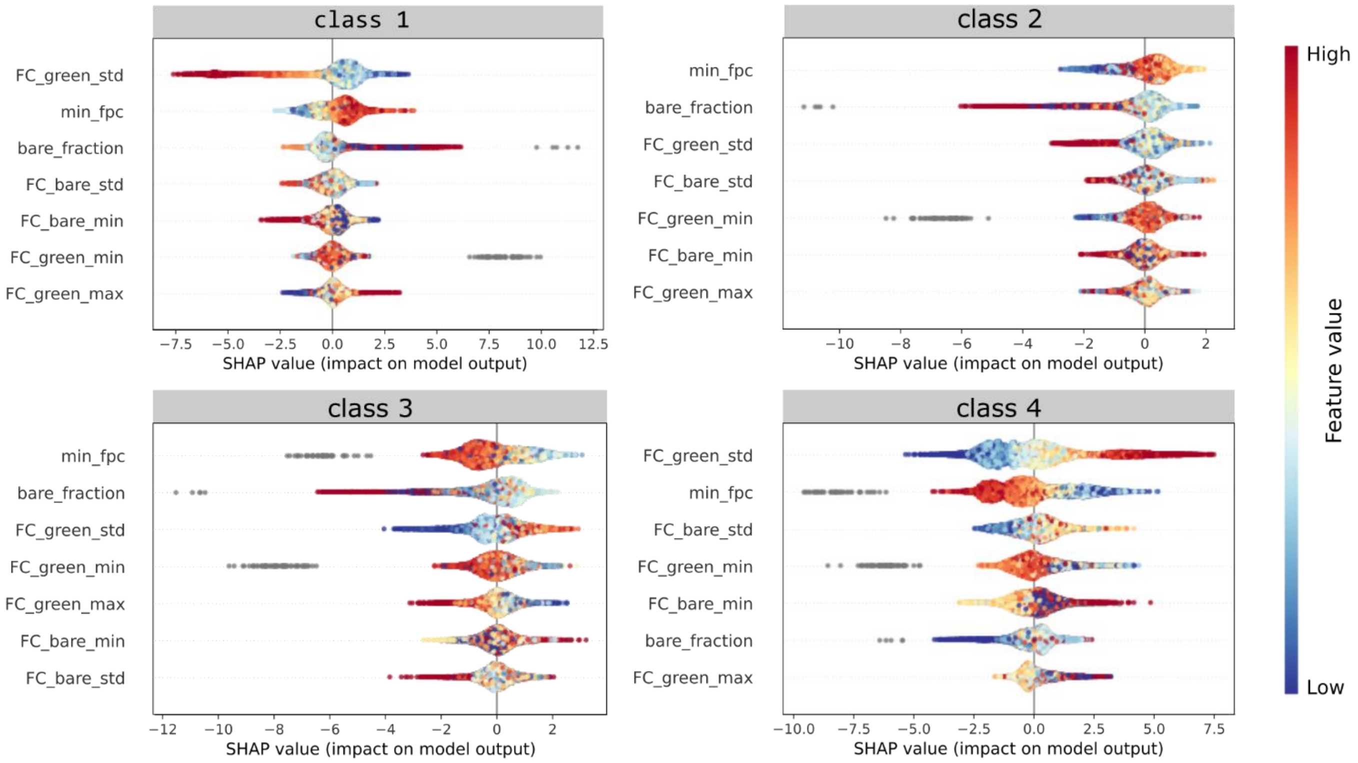

Figure 13: Relationship between predictors and SBC class probabilities. Predictors are ranked in descending order of importance. Values in the x-axis are the logarithm of the likelihood, with larger values indicating a positive increase in probability of being in the relevant class. The colour represents the predictor values, ranging from -1 in blue to 1 in red

4 Discussion

4.1 The importance of clean training data

Model performance (predictive power) is critically reliant on the quantity of training data as well as how well training data sites represent both the respective vegetation community and its condition state for Biodiversity (Newell *et al*. 2006; McNellie *et al*. 2015). The large scope of this project required a vast quantity of training data resulting in a high reliance on:

- collating as much existing site data as possible;
- collecting large numbers of rapid condition assessment sites (QVAL);
- using expert elicited sites to fill data gaps.

The success of this data gathering exercise required a careful balance between two competing imperatives: (a) to collate as many reference data points as possible; and (b) to maximise the accuracy and quality of the data points used. In an ideal situation sufficient training data for all map units would have been collected and scored as per the BioCondition method (Eyre *et al*. 2015) and representative of BioCondition in 2017. Time and resource constraints however precluded this possibility. As a result a range of compromises were required to ensure an adequate number of samples were obtained for as many map units as possible, meaning that some data which would be considered unsuitable in different (better) circumstances was retained for use to train or test the SBC model. These compromises (listed below) predominantly deal with BioCondition state for the large numbers of old, unscorable or rapidly assessed sites, but also the adequacy of sampling and distribution of sites.

Restricting data points used to train or test the model to only sites representative of 2017 BioCondition (collected in 2016 or 2017) would reduce the number of collated existing sites by more than 97% and exclude all rapid validation sites, resulting in a 98% reduction in the total number of suitable sites. Additionally, as most (91%) of the existing suitable sites and all rapid validation sites were **not** collected using the full BioCondition methodology, and most REs (85%) do not have a published benchmark, restricting data used to train or test the SBC model to sites scorable for BioCondition would have excluded more than 71% of existing and all rapid validation sites, resulting in an 89% reduction in the total number of suitable site data.

After checking for obvious disturbances, changes to land use or remnant status, we compromised by making the following assumptions about these old, unscorable or rapidly assessed sites and the adequacy and distribution of sampling:

Assumptions:

1. Unscorable existing sites collected after 1st January 1995 remained representative of a ’reference’ BioCondition state in 2017, based on an assumed strict compliance with the site selection guidelines in Neldner *et al.* (2019a) and continued remnant status.
2. Rapid validation sites (all collected in 2019) were representative of the BioCondition state at each respective location in 2017
3. Rapid validation site recorders’ estimates of overall BioCondition score were consistent and accurate representations of the measurable BioCondition at those locations. We tested assessor accuracy and variability for rapid validation (see Appendix 3) finding an overall accuracy of 73%.
4. That five replicates were sufficient as a minimum training data sample size for all vegetation communities greater than 1600 ha

4.2 Modelling vegetation condition

4.2.1 Accuracy assessment

The accuracy assessments at both the state-wide level and within the trial study area found similar overall patterns of accuracy between the two competing mechanistic and ML models. There was a moderate difference in overall accuracy favouring the Machine Learning model, which supported the decision that this model framework would be used as the foundation of the Spatial BioCondition framework.

The moderately lower level of accuracy found using the trial study area evaluation may be a reflection of the evaluation method. Our replacement of site-based assessments with desk-top based assessments introduced a source of potential error where the observer’s desk-top classification of a validation point may not accurately reflect the on ground condition at that point (evaluating against a false value).

Differences in the spatial distribution between training data points - skewed towards easily accessible locations; and validation points - randomised locations, may also be a factor. Model performance may be expected to vary spatially dependent on the density of training data. The state-wide evaluation of model performance used a randomly selected subset of the input data, which we can assume exhibits the same distributional characteristics as the broader training dataset, resulting in validation points having a distribution skewed toward locations with a high density of training data and better model performance. In contrast the trial study area evaluation used independent randomised validation points and therefore potentially sampled a greater number of locations with a low density of training data and resultant poorer model performance.

4.2.2 Model Interpretation

Machine learning models have a reputation for being difficult to interpret. Recent advances, such as the use of the SHAP plot (Figure 13) have gone a long way to dispel this aspect. The results from this analysis make intuitive sense, with high quality sites characterised as stable over time (represented by low values in FC_green_std), with dense woody vegetation (high min_fpc), and overall dense vegetation (low FC_bare_min, high FC_green_max). Low quality sites were largely the opposite, characterised by high temporal variation (high FC_green_std, high FC_bare_std), often non-woody (low min_fpc), and frequently bare (high FC_bare_min). Reasons why an observation would be more likely to be in classes 2 and 3 are less clear, although class 2 is more likely to have higher woody density (min_fpc) than class 3 and is more likely to be stable over time (low FC_green_std) when compared to Class 3. Classes 2 and 3 were also the classes most difficult to classify, with F1-Scores of 0.41 and 0.39 respectively (see Table 11). The impact of stability is interesting in these models, with one possible interpretation being that areas in good condition tend to be dominated by perennial vegetation, and so the variation in signal of vegetation indices would be less than sites with a higher proportion of annuals.

4.3 Limitations

1. Ongoing technical advances in remote sensing data capture and increasing resolution will mean that modelling and mapped representation of vegetation condition across landscape scales will evolve. Consequently, there are limitations around the use of a ‘baseline’ concept regarding Spatial BioCondition output. Although future modelling approaches may differ, modelled output will still be comparable. However, comparison and interpretation of outputs will be challenging.

2. Obtaining an adequate representation of site data used to train or test the SBC model across Queensland’s REs and condition states within the short time frame of the project (2 years) was challenging. Improvements made by the project team in cleaning existing data, digital data capture and automating condition scoring will assist future iterations.

3. Heterogeneous regional ecosystem polygons – Introduce a level of uncertainty as to which reference dataset (expected RS values) to assess against. The SBC model framework can assess an area against the expected RS values for all of the polygon’s component REs, however, is currently configured to return only the predicted condition for the spatially dominant RE. This is particularly challenging where the heterogeneous polygon has no spatially dominant component.

4. The model does not explain the causative links to drivers of change in vegetation condition for use in management planning. While the model can be interpreted in terms of the independent predictor variables, model outputs, particularly when classified, cannot identify specifically which site-based vegetation attributes have been impacted to shift the community away from reference condition.

5. Inaccuracies in the RE mapping potentially have a significant impact on the model. The model relies on this mapping to assign the reference RE for each assessment pixel. If the RE is incorrect then so is the reference state comparison and model prediction.

6. SBC model restricts site data used for training (and testing) to within a bioregion. The Bioregional expert workshops to identify analogous REs suitable for use as substitute or supplementary training data often recommended using data from REs in other bioregions. Future iterations of SBC can be re-configured to use additional training data from outside the bioregion where specifically recommended by bioregional coordinators.

4.4 Future work

In the short-term:

- Develop state-transition models for Queensland ecosystems to assist with interpretation of model output

- Test the SBC output with new independent field data. Potentially in a Queensland case study region that aligns with other priorities and keen stakeholders and clients (e.g. Burnett Mary Regional Group).

- Model the continuous BioCondition metric: Trial using a BioCondition continuous score as the response variable, rather than the categorical approach.

- Investigate emerging methods to output a spatial probability distribution, to allow predictive uncertainty estimation of the SBC model. Examples include Natural Gradient Boosting for Probabilistic Prediction (NGBoost; Duan et al. 2020).

- Demonstrate that the method can show temporal change in Spatial BioCondition using 2021 data.

- Incorporate landscape scale habitat variables to the modelled output: Landscape context has long been known to have a significant influence on the long-term viability of a patch of vegetation for biodiversity values (Andren, 1994; Fahrig, 2001). Landscape context does not only refer to fragmented landscapes with sharp or high contrast edged boundaries (e.g. vegetated versus cleared boundaries), but also intact landscapes where there are gradients of habitat quality or low contrast edges (e.g. increased grazing disturbance with distance from water points). In the BioCondition framework, landscape context attributes are included in the overall score of vegetation condition and contribute to 20% to the overall BioCondition score. The landscape-level attributes are scored depending upon whether the assessment is within a *fragmented landscape* (where three attributes are assessed - patch size, connectivity and context), or an *intact landscape* (where one attribute, distance to water, is assessed). Currently, modelled output of vegetation condition is based on site-based attributes only, and landscape scale habitat condition has not yet been incorporated in the modelled outputs. An innovative approach to represent landscape-scale habitat, the Habitat Cost-Benefit Approach (CBA, Drielsma et al., 2007), could be incorporated within the model to account for landscape scale habitat condition. The advantage of the CBA method is that it provides a value that represents most fragmentation metrics, which are highly correlated (McAlpine and Eyre, 2002). It provides a neighbourhood habitat grid (Benefit) which is a measure of habitat value-based connectivity to focal cells, and a permeability (Cost) grid, which can be generated from broad vegetation classification, such as cleared, regrowth and remnant vegetation. The concept has been applied in New South Wales (i.e. combining ecological condition with ecological connectivity) to create ecological carrying capacity mapping for the state (Love et al. 2020).

- Operationalise a temporal and spatial reporting framework for Queensland, and continue to work on training data capture, given that the ideal (to use training data from the reporting period) is not possible.

In the longer-term (i.e will require more resources and time):

- Address RE polygon heterogeneity: A program within the Queensland Herbarium to reduce the heterogeneity of mapped regional ecosystem polygons is in progress, where mixed polygons containing regional ecosystems with the highest level of variation in structure (e.g. grasslands and forests) will be targeted as the first priority, Currently, two-thirds of the state’s area is represented by heterogeneous RE polygons and it is expected that they will continue to form a significant proportion of RE mapping for the foreseeable future. Although the Spatial BioCondition modelling method enables the assessment of areas for each component RE of a heterogeneous polygon, the model currently only returns the result for the proportionally dominant component RE. There is therefore scope to investigate alternative methods for incorporating or presenting model results for heterogeneous polygons.

- Continue systematic collection of field-based BioCondition reference and assessment site data and generation of BioCondition benchmarks: Ongoing collection and collation of reliable standardised BioCondition site data and generation of BioCondition benchmarks will be a priority for modelling, mapping and validating vegetation condition across Queensland.
    - Ongoing strategic collection of field-based BioCondition reference sites, refinement and generation of additional BioCondition benchmarks enabling scoring of model training data;
    - Focus ongoing systematic collection and collation of field-based BioCondition assessment sites for use as training data from within priority Bioregions (Brigalow, Mulga Lands, Southeast Queensland, and Reef catchments);
    - Further development and testing of a rapid condition assessment method;

- Fine-scale mapping of woody and non-woody ecosystem transformer weed species: Investigate methods to reliably map the distribution of transformer weed species at the scale of the model output (e.g. machine learning of high-resolution remote sensing data products)

- Collect, collate and integrate spatial pressure datasets: Investigate methods to integrate the compiled spatial pressure datasets to adequately inform the vegetation condition mapping, and determine approaches to enable these datasets to be dynamic (i.e. matched with the time-series of the condition map). For example, the National Environment Science Program (NESP), Northern Australia Environmental Resources Hub project 3.3 has produced draft modelling of areas subject to high risk of impact from grazing across Northern Australia (NESP, 2019). At the time of publication these models were still undergoing refinement and review. The method appears promising and could potentially be used as an input into any future spatial pressure dataset. The index aims to estimate how likely areas are to be used for grazing, weighted by how likely appropriate stocking rates are going to be misjudged due to inter-annual pasture growth unpredictability and distance to permanent water. Areas with high levels of current grazing intensity and with low grazing suitability (low or unpredictable pasture growth) score highly for grazing impact risk. Scores were then weighted for distance from permanent water to produce a potential grazing impact index (NESP 2019).

5 Conclusion

- The Spatial BioCondition (SBC) framework presented here enables a comprehensive assessment of BioCondition at the state scale for all vegetated terrestrial ecosystems, the framework is aligned (integrated) with both the regional ecosystem and the site-based BioCondition frameworks.

- The SBC framework is adaptive such that future advances in remote sensing (new products and/or increasing resolution) can be easily incorporated.

- The developed mechanistic model (simple linear combination of relative differences in remotely sensed values between an assessment location and its reference) was not sufficient to accurately map BioCondition at the state scale with the currently available remotely sensed datasets and site-based training data.

- The developed machine learning model (Boosted regression trees) with its higher prediction accuracy appears a more appropriate method to map BioCondition at the state scale. Machine learning models are much more complex than mechanistic models and have a reputation as being difficult to interpret, however new tools (e.g. SHAP) have recently become available that greatly assist in explaining how predictions are related to the independent variables, however these still do not explain causative links to drivers of change in condition.

- Assessments of overall accuracy for the ML model indicate general suitability for predicting output across the state of Queensland, however the accuracy of model predictions will vary spatially due to either limited suitable training data or coverage issues with the predictor variables. Therefore, a method to spatially represent the reliability of predictions (uncertainty) requires further development.

- Models such as the SBC framework have critical dependencies on large sets of clean training data sampling all ecosystems in their various condition states, and Queensland is a massive and highly ecologically diverse area. Gaps in the adequacy and representativeness of the current training data collated for this project exist. Continuing work is required to satisfy this data imperative, including improvements in the efficiency of data collection (improvements to the method for rapid assessment and further investigations into collecting BioCondition data remotely) – for locations in both reference and other condition states.

- Further work is required to: transition SBC to continuous rather than categorical scoring; incorporate landscape context into the framework; operationalise a temporal and spatial reporting schema; improve underlying regional ecosystem mapping accuracy.

We recommend that prior to operationalising a vegetation condition reporting framework for Queensland using SBC, further work is required including:

- Independent validation of the output, possibly within case study area/s currently being set up by other programs such as the Australian Agricultural Biodiversity Stewardship pilot program within Queensland

- Investigate sensitivity of the SBC to detect change over time
- Determine a method to spatially demonstrate levels of uncertainty in the output
- Address sampling gaps in the training data

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Appendix 1 Definitions

Term	Description
Benchmark	A description, in the form of quantitative values, of a regional ecosystem/vegetation community, for each site condition attribute assessed in BioCondition. Benchmarks representing the median or average characteristics of a mature and relatively undisturbed ecosystem of the same type, across the geographic extent of the Regional Ecosystem, and are derived from data collected at reference sites (Eyre *et al.* 2017). Benchmarks are subject to regular review and updates based on additional data.
Bioregion	Biogeographic regions are the primary level of classification of land for biodiversity values at both the national and state-wide scale. Thirteen bioregions have been defined for Queensland by (Sattler & Williams 1999), parts of five bioregions are small extensions of nationally recognised bioregions (Thackway and Cresswell 1995).
Bioregional Coordinator	An experienced Queensland Herbarium vegetation ecologist responsible for defining, describing and mapping regional ecosystems and curating associated field data for all or part of a particular Queensland bioregion.
Connectivity	Landscape scale spatial pattern of habitat that describes the degree to which habitat patches are connected by functional habitat. Connectivity relates to the capacity a species has to disperse through the landscape.
Condition attributes	Surrogates or indicators of vegetation structure, function and/or composition
Crown Cover (CC)	Sensu Walker and Hopkins (1990) is the percentage of the ground surface covered by the vertical projection of the periphery of plant crowns. Crowns are treated as opaque meaning that small gaps within the crown are ignored. Crown cover (%) of a stratum is measured for the stratum as a whole i.e. ignoring crown overlaps within a stratum.
Dynamic benchmark	A description that represents a mature and relatively undisturbed example of a regional ecosystem/vegetation community relevant to a particular location and time. Dynamic benchmark values for attributes can vary over time based on seasonal conditions.
Ecologically dominant layer (EDL)	The vegetative layer making the greatest contribution to the overall biomass of the site and the vegetation community.
Foliage Projected Cover (FPC)	Sensu Specht (1981) and Walker and Hopkins (1990) is the percentage of the ground occupied by the vertical projection of foliage. This is the same as projective foliage cover (PFC)
Heterogeneous polygon	A polygon (area delineated on a map) that has more than one vegetation community or regional ecosystem code. Regional Ecosystem mapping products have an upper limit of five codes per polygon (Neldner *et al*. 2019a), and provide the proportion of the polygon represented by each code
Homogeneous polygon	A polygon (area delineated on a map) that has only one vegetation or regional ecosystem code.
Non-terrestrial vegetation communities	Inter-tidal and sub-tidal vegetation communities: including all vegetation communities mapped as Landzone 1 in version 11 RE mapping (DES, 2018a). Vegetation communities on Quaternary estuarine and marine deposits subject to periodic inundation by marine waters, including mangroves, saltmarshes, saltpans, offshore tidal flats, tidal beaches, inter-tidal sedgelands, grasslands and herblands as well as areas mapped as ocean and estuary.
Regional Ecosystem	A vegetation community or communities in a bioregion that is consistently associated with a particular combination of geology, landform and soil (Sattler and Williams, 1999, Neldner *et al*. 2019a). The Regional Ecosystem Description Database (REDD) is maintained by the Queensland Herbarium and contains the current descriptions of all REs. Regional ecosystems and their extents referred to in this document are Version 11 RE mapping products and descriptions (DES 2018a; Queensland Herbarium 2019).
Largely unvegetated communities	A range of ecosystems or vegetation communities that are defined in REDD (Queensland Herbarium 2019a) as being dominated by areas devoid of vegetation, including: (a) bare rock on: headlands; creek beds; creek banks; and uplands; (b) bare sand in: riverbeds; sand blows and on beaches; (c) open water (fresh, saline, estuarine or marine waters) with little emergent vegetation; (d) various other bare substrates associated with intermittent, ephemeral or tidal waterbodies.
Vegetation community	An area of vegetation which is relatively uniform with respect to structure and floristics. The basic

	unit in the vegetation community classification within the regional ecosystem classification is the plant association or sub-association. A number of vegetation communities may make up a single regional ecosystem and are usually distinguished by differences in dominant species composition, frequently in the shrub or ground layers and denoted by a letter following the regional ecosystem code (e.g. a, b, c) (Neldner *et al*. 2019a)

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Appendix 2 Observer accuracy and variation using a desk-top method to assess BioCondition

Introduction

The independent accuracy assessment of SBC model outputs in the trial mapping area, highlighted the possibility of supplementing data used to train and test SBC models with remotely derived desk-top visual assessments of BioCondition. Systematic attribute-based vegetation condition assessment is resource intensive, thereby restricting the number of assessments undertaken. The availability of a cost-effective assessment method able to be rapidly applied over large areas would be beneficial. However unstructured visual assessments of overall condition are intuitive or subjective and have therefore been criticised for their reliability (Burgman, 2001). Desk-top condition training data has previously been used by the HCAS condition mapping method, although the authors noted the limitations of such data and a preference for actual field-based site data (Donohue *et al.* 2014; Harwood *et al.* 2016).

To assess the utility of this method for acquiring condition data and to investigate concerns regarding accuracy and variability between assessors we investigated of the use of a desk-top method to assess BioCondition remotely. The aims of the investigation were to:

- Quantify the accuracy or reliability of the desk-top method relative to site-based scores derived using the full BioCondition method;
- Quantify variability between assessors collecting data using this method;
- Determine if the desk-top method would be suitable for future use to rapidly collect data to train and test SBC models.

Method

The investigation method required multiple assessors to allocate a set of points to a broad condition class based on high resolution satellite image interpretation, expert judgment, and a range of contextual datasets.

Twenty-four assessors were selected with a range of experience in the use of BioCondition including: seven Bioregional coordinators with experience in vegetation survey and mapping, aerial photo and satellite image interpretation; seven field ecologists, and four Botanists all with experience in BioCondition assessments or vegetation mapping; four Zoologists and two Environmental scientists with experience in BioCondition assessments. General experience ranged from six months experience in BioCondition assessments to 40 years of experience in vegetation mapping.

Fifty-four survey locations previously assessed using the BioCondition method were selected from within the trial mapping area (DES, 2020) such that they:

- encompassed a broad range of REs within the trial area (34);
- were weighted for RE pre-clear extent within the trial area;
- were conducted as close as possible to 2017 (range 2016-2019);
- were distributed across the four BioCondition classes but prioritising classes 1 and 2 (class 1 - 19 sites, class 2 - 21 sites, class 3 - eight sites, class 4 - six sites);

For each survey location, all site measurements of BioCondition attributes, final site based BioCondition score and BioCondition class were withheld from assessors. In a GIS environment an assessment area surrounding each point was generated by applying a 0.5 ha transparent circular buffer, to approximate the same area of assessment used in the BioCondition method (Eyre *et al*., 2015). Assessment areas were checked to ensure vegetation across the area was relatively homogenous.

To assist with the assessment, all assessors were provided with high resolution satellite imagery and a range of contextual datasets. The top four datasets listed were mandatory to the process, the remainder provided as a guide and their use was optional:

- High resolution satellite imagery (Earth-i 2017)
- Definitions of the four BioCondition classes (Table 3)
- Remnant and pre-clearing version 11 RE mapping dataset (DES, 2018)
- Regional Ecosystem benchmarks (DES, 2020a)
- Regional Ecosystem technical descriptions (DES, 2020b),
- Composite SLATS change dataset for 1988-2017 (DES, 2017a)
- Fire scar mapping - subset 2015-2017 (DES, 2019b)

- Above ground biomass based on 2009 ALOS-1/Landsat/ ICESat data
- Height of dominant tree layer/EDL based on 2009 ALOS-1/Landsat/ ICESat data
- Land use mapping 2012-2017 (DES, 2017)
- Native regrowth distribution modelled on the composite SLATS change layer (DES, 2017a)
- Existing CORVEG, QBERD, QVAL and Quaternary site data for REs in the trial mapping area (CORVEG, 2020, QBERD, 2020 & Queensland Herbarium, 2020)
- Tenure (DNRME, 2020a)
- Geology - QLD 1:1M and QLD Geology detailed surface, structure and solid 2018 (DNMRE, 2020b)

Prior to the assessment all assessors were provided with training where they were familiarised with: BioCondition classes; photographic examples of a range of communities in the Bioregion in all four condition classes; the appearance of example assessment areas; and given an overview of the imagery and contextual datasets provided. We recommended assessment of imagery at 1:5,000 scale but assessors were free to inspect imagery at other scales.

Assessors were then asked to independently evaluate all assessment areas (in a GIS environment) by navigating to the location of each assessment area and using the provided imagery, contextual data and their knowledge/experience allocate each area to a:

- Regional Ecosystem;
- BioCondition class of 1-4, relative to the benchmark for the assigned RE;
- Confidence ranking – indicating their confidence in their allocation to BioCondition class (0-100 in four equal classes);

Completed assessments were collated and the individual accuracy or precision (the level of agreement between each assessor's estimated scores and the measured scores) and overall accuracy of all assessors calculated using confusion matrices. The ordinal nature of the data precluded the calculation of coefficients of variation therefore we examined variation between assessors by plotting the range of assessor estimates as box plots.

Results

Assessor accuracy

Overall, assessors using desk-top data correctly assigned a BioCondition class with an accuracy of 55.3%, with accuracy for individual assessors (producers' accuracy) ranging from 48% to 92% (Figure 14). One assessor with considerable experience in BioCondition assessment and a good knowledge of the trial area scored remarkably high (producers' accuracy of 92%).

Precision (accuracy of assessors) differed between the four BioCondition classes (Table 12). Classes 1, 2 and 3 had low precision with roughly half of all cases incorrectly assigned. More class 2 cases (251) were wrongly allocated to class 1 than correctly assigned (218), overpredicting class 1. Similarly, classes 2 and 3 achieved very low precision with a high number of BioCondition class 3 (46) cases wrongly allocated to class 2. Class 4 was the only BioCondition class that assessors could accurately assign desk-top points to.

Assessor variability

The range of assessor estimates of BioCondition class for all 54 assessment areas is shown in Figure 15(a-d), sorted by BioCondition class measured as per Eyre *et al*. (2015). Variation between assessors was highest for BioCondition classes 2 and 3 and lowest in class 4. Variability between assessors was relatively low for areas measured as BioCondition class 1, with assessors mostly agreeing (≤1 assessor disagreeing) on a single class for 8 areas (42%) or being evenly split between two consecutive classes in a further 6 areas (32%). A notable exception being site 3 where assessments were spread over all four classes. There was less agreement between assessors in areas measured as BioCondition class 2, with assessors mostly agreeing in a much lower proportion of areas (24%), and an increase in the proportion of areas (43%) with assessments spread over three classes. Site 36 has the least agreement for all classes. The least agreement between assessors as a proportion of assessment areas (13%) was in those measured as BioCondition class 3 (13%) which also had the highest proportion of areas (50%) with assessments spread over 3 classes. Assessor agreement tended to be best for areas measured as BioCondition class 4, with assessors mostly agreeing on a single class for 67% of areas.

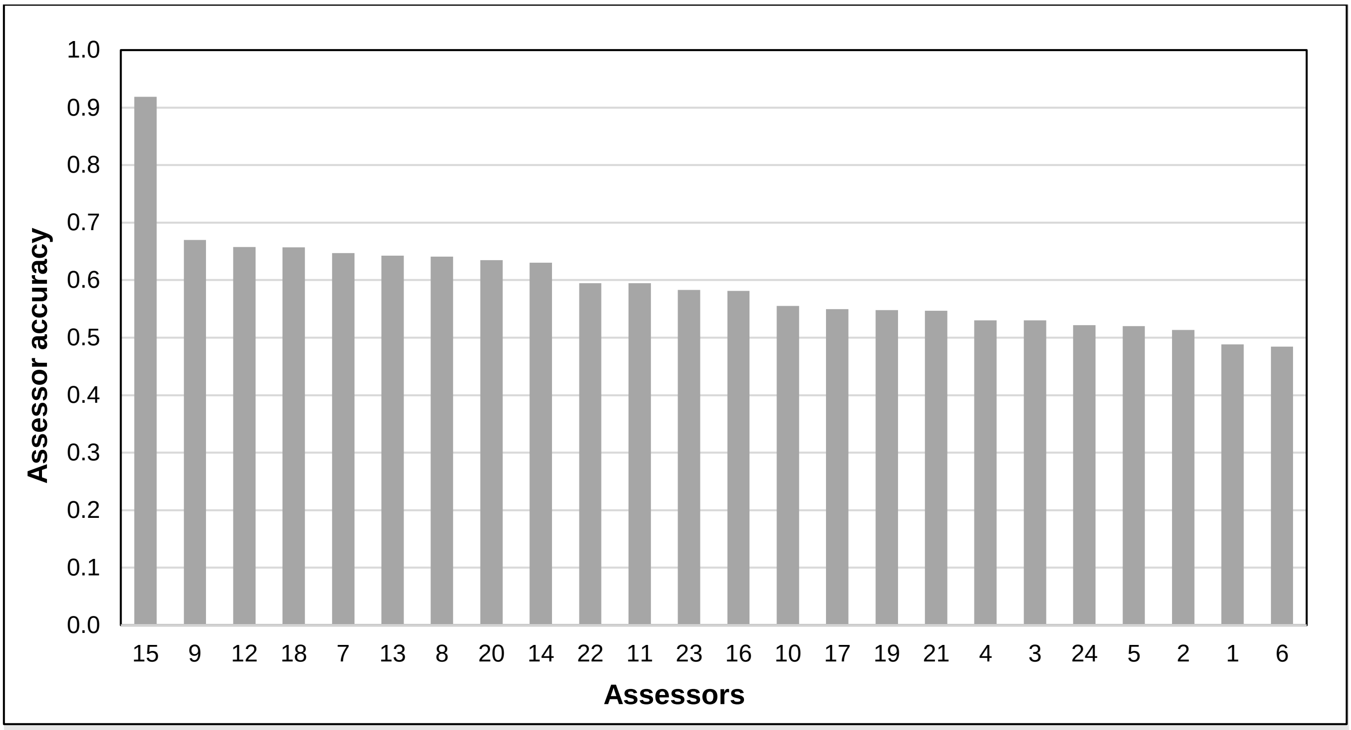

Figure 14: Individual precision (accuracy) for 24 assessors using a desk-top method to assign assessment points to a BioCondition class

Table 12: Confusion matrix for 24 assessors using a desk-top method to assign BioCondition class.

	Measured BioCondition class (Reference)					
Expert classifications (Predictions)	**BioCondition Class**	**1**	**2**	**3**	**4**	**Precision** (Producer's Accuracy)
	1	286	251	18	0	51.5%
	2	137	218	46	3	53.9%
	3	31	27	83	35	47.2%
	4	2	8	21	130	80.7%
	Recall (User's Accuracy)	62.7%	43.3%	49.4%	77.4%	

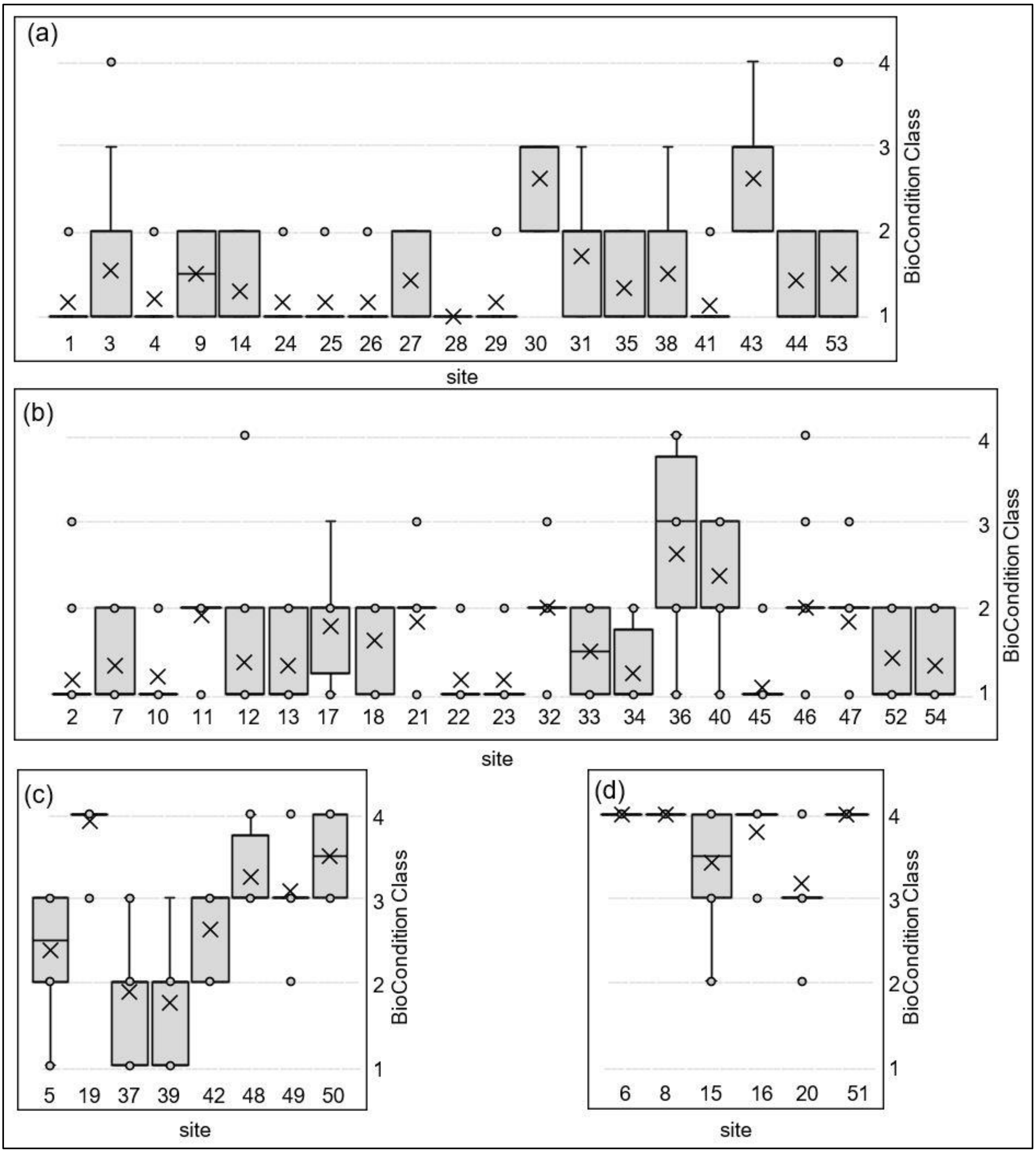

Figure 15: Boxplots of BioCondition Class allocated by 24 assessors using a desk-top method for (a) 19 sites measured[1] as class 1; (b) 21 sites measured[1] as class 2; (c) 8 sites measured[1] as class 3; and (d) 6 sites measured[1] as class 4. Boxplots show mean (X), median (--) quartiles and outliers. [1]Measured BioCondition scores (our point of truth) were obtained by undertaking systematic site based BioCondition assessments as per Eyre et al., (2015), scoring against a benchmark and allocating continuous score to BioCondition Class.

Discussion

The desk-top method has a lower precision (producer's accuracy) for all the BioCondition classes than the oblique photo-interpretation method described in Appendix 3 (Table 13). With only BioCondition class 4 being reliably assigned by the assessors. Based on these low accuracy measures, we found this desk-top method unsuitable to collect data to train and test SBC modelling.

Variation between assessors was highest for BioCondition classes 2 and 3 and lowest in class 4. BioCondition class 4 was relatively well defined and understood by all observers and in many cases easier to consistently recognise. Classes 2 and 3 can be highly variable and driven by different combinations of attributes many of which (as discussed below) are difficult to assess with this method.

It is likely that an assessor's ability to score the sites using the desk-top method is strongly influenced by how assessable individual key BioCondition attributes are using this method. Attributes such as the crown cover and possibly height of the ecologically dominant layer (EDL), and gross disturbance may be reasonably accurately interpreted from high resolution imagery by an experienced observer. However, several key BioCondition attributes such as: large trees; species richness; non-native plant cover; coarse woody debris; species recruitment; and shrub canopy cover are not readily discernible and therefore not assessable using the desk-top method, given the scale of available satellite imagery with a state-wide coverage (for examples see Figure 16), thereby simplifying the desk-top condition assessment to only one or two attributes. Three of these not assessable key attributes: large trees; species richness; and non-native plant cover are heavily weighted in the BioCondition scoring schema (Eyre *et al*., 2015). The difficulty the desk-top method has in assessing these heavily weighted key attributes most likely drives the poor overall agreement between BioCondition class assigned using the desk-top method and the BioCondition class derived from systematic site-based measurements.

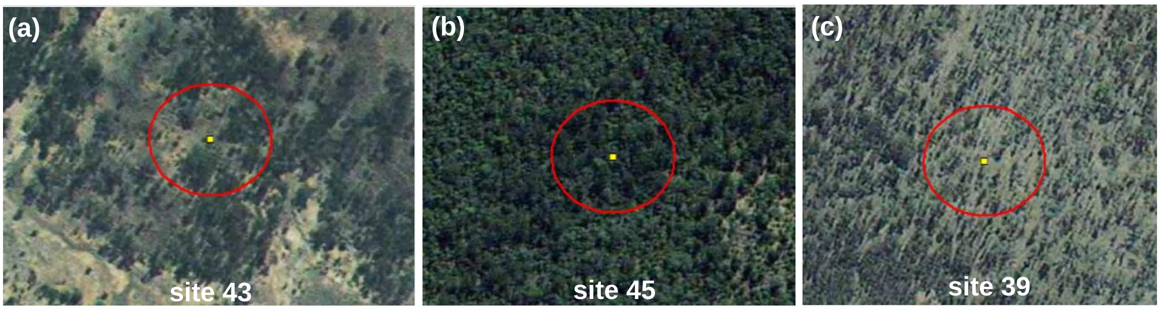

Figure 16: Three examples of assessment points misclassified by most assessors using a desk-top method to assign BioCondition class. Red circles denote the 0.5ha buffered assessment area.

Figure 16 illustrates the issues described above using three examples of areas incorrectly assigned by most assessors using the desk-top method. From left to right: (a) most assessors assigned this location to BioCondition class 2 or 3 and one to class 4, possibly based on its erroneous mapping as non-remnant, the site based measured BioCondition score of 0.82 puts it in class 1, scoring well for large trees, species richness, coarse woody debris and recruitment. (b) all but two assessors assigned this location to BioCondition class 1, the site based measured BioCondition score of 0.7 puts it in class 2, despite looking intact the location scored poorly for large trees, coarse woody debris and had a high abundance of weeds. (c) all but one assessor assigned this location to BioCondition class 1 or 2, the site based BioCondition measured score of 0.52 puts it in class 3, scoring poorly for large trees, recruitment, coarse woody debris, species diversity and the site had a high abundance of weeds.

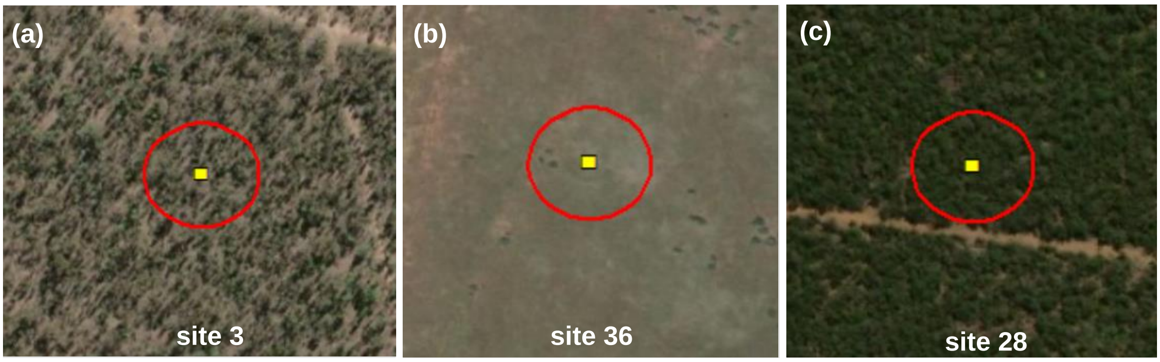

Figure 17: Three examples of assessment points illustrating assessor variation using a desk-top method to assign BioCondition class. Red circles denote the 0.5ha buffered assessment area.

Three examples illustrating the range in assessor agreement are shown in Figure 17. From left to right: (a) site with poor agreement amongst assessors who allocated the site across all four BioCondition classes, with most assessors split between class 1 and 2 but one each assigning it to class 3 and class 4, the site based measured BioCondition of 0.85 puts it in class 1; (b) site with very poor agreement amongst assessors (allocated across all four classes), the site is a grassland with a site based measured BioCondition score of 0.76 which puts it in class 2. A quarter of assessors put this site in class 4; (c) site with complete agreement amongst assessors (class 1) and agreement with site based measured score 0.87 which puts it in class 1.

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Appendix 3 Observer accuracy and variation in the rapid assessment of BioCondition

Introduction

A rapid, visual field vegetation condition assessment method (QVAL; Appendix 7) was developed to provide a time- and cost-effective method to supplement the limited number of detailed, measured, systematic vegetation condition assessment sites across Queensland. The rapid assessment method was designed to align with the BioCondition 1, 2, 3, 4 broad condition classes, and data collected using the method contributed to almost half (49.5%) of the final set of sites used to train and/or test the SBC models. The rapid assessment data was collected by trained Queensland Herbarium botanists and ecologists (n=12) while *en route* to field study regions throughout Queensland. Because of the large contribution that the rapid assessment sites made to the overall site dataset used, as well as the relatively large number of observers that contributed rapid assessments, an investigation was undertaken to determine the level of subjectivity and repeatability of the rapid assessment method. Specifically, the investigation aimed to:

- Test the overall accuracy of the QVAL rapid assessment method
- Quantify variability and accuracy between assessors

Ideally the variability and accuracy of the method and observers would have been tested in the field. However, due to time and COVID-19 pandemic travel restrictions a photo-interpretation approach was used as a surrogate test.

Method

The photo-interpretation approach required multiple assessors to allocate pairs of oblique site photographs to broad condition class using the QVAL survey method.

We selected 21 Queensland Herbarium staff, with varying levels of experience (six months - 40 years) in Regional Ecosystem Mapping and/or BioCondition assessment methods (Neldner et al., 2019, Eyre et al., 2015 and Eyre et al. 2017), including six Bioregional coordinators with experience in RE mapping, aerial photo and satellite image interpretation; six field ecologists with experience in BioCondition assessments or vegetation mapping; three Botanists with experience in BioCondition assessments or vegetation mapping; four Zoologists and two Environmental scientists with experience in BioCondition assessments. Level of assessor experience was ascertained through a questionnaire asking assessors to self-rank their experience in BioCondition methods, vegetation surveys, Regional Ecosystems and other related fields and was used to categorise assessors into two classes:

- ‘expert’ - having more than 10 years' experience conducting BioCondition assessment and reference surveys OR at least two years recent experience where most of their daily workload was BioCondition related; or
- ‘non-expert’ - do not meet the definition of ‘expert’.

Thirty-five survey locations from within the trial mapping area (DES, 2020) that had been previously assessed using the BioCondition method (Eyre et al., 2015) were selected from within the trial mapping area (DES, 2020) meeting the following criteria:

- had two oblique photographs, taken at the time of survey, that accurately represented the assessed condition rank;
- a version 11 Regional Ecosystem (Queensland Herbarium 2019) was attributed to the site;
- were distributed across the four BioCondition classes (Table 3) but prioritising classes 1 and 2 (class 1 - 10 sites, class 2 - 11 sites, class 3 - nine sites, class 4 - five sites)

The location, date of survey, attributed Regional Ecosystem, and non-native plant cover (%) was provided to the assessors. The BioCondition Benchmarks (DES, 2020a) and technical descriptions (DES, 2020b) for those Regional Ecosystems were also made available. Assessors could refer to remotely sensed products, and imagery that would normally be available during QVAL field assessments to assist in their scoring however a specific GIS environment was not provided. Assessors could refer to the GIS products provided to complete the desktop assessment described in Appendix 2.

Shortly prior to the assessment all assessors attended a demonstration workshop where the assessment method was outlined. Assessors were then asked to independently evaluate each of the 35 survey site photographs provided, their expert knowledge/experience, and to allocate each site to a:

- BioCondition class of 1-4, relative to the benchmark for the relevant RE;
- Confidence ranking, indicating their confidence in their allocation to BioCondition class (0-100 in four equal classes);

Assessors were encouraged to complete the exercise in a rapid manner to simulate rapid collection of data in a field situation.

Once completed the experts estimates of condition class for each of the 35 sites were compared (level of agreement) with the condition class generated from the systematic site-based measurement and scoring. Measured scores were treated as the true score for that location, allowing us to determine the individual and overall accuracy and variation for assessors. Confusion matrices were generated to calculate the overall group and individual producer and user accuracies (Precision and Recall), and an independent samples t-test was conducted to compare assessor accuracy between the expert and non-expert groups.

Results

Overall precision (accuracy) for all 21 assessors was 67.2%. Assessors could more accurately classify condition classes 1 and 4 from the photographs (Table 13; Figure 18). The confusion matrix in Table 13 illustrates that the precision (accuracy) of assessor's allocations was high for classes 1 and 4 but low for classes 2 and 3. Class 2 was frequently incorrectly recognised by assessors as being class 1 (80 cases) and class 4 frequently recognised by assessors as being class 3 (72 cases). All assessor's allocations to class were no more than one condition class away from the measured (reference) class except for one misclassification of one class 1 site to class 3.

Table 13: Confusion matrix showing errors of omission and commission between the different BioCondition classes.

	Assessed BioCondition class (Reference)					
Expert classifications (Predictions)	**BioCondition Class**	**1**	**2**	**3**	**4**	**Precision (Producer's Accuracy)**
	1	167	42	1	0	79.5%
	2	80	135	16	0	58.4%
	3	0	16	101	72	53.4%
	4	0	0	14	91	86.6%
	Recall (User's Accuracy)	67.6%	69.9%	76.4%	55.8%	

Expert versus non-expert assessors

Nine assessors are categorised as non-expert and 12 as expert (Figure 18). The mean accuracy (precision) for experts was 72% and for non-experts was 65%. An independent samples t-test found that there was no significant difference between the mean accuracy of the two groups ($t[11] = 0.117$, $p = 0.5$), and no significant correlation between the years of BioCondition experience of the assessors and their accuracy $\rho(19) = 0.19$, $p = 0.39$.

Spearman's Correlation (ρ) was also used to ascertain relations between the years of field survey experience of the assessors and their accuracy $\rho(19) = 0.27$, $p = 0.23$, As well as their years of experience in image interpretation (satellite, aerial photography) and their accuracy $\rho(19) = 0.26$, $p = 0.24$. None of these parameters showed significant correlations with the achieved accuracy.

Only 12 of the assessors who took part in this assessment collected rapid condition training data which was used to train the model. The mean accuracy for these 12 contributors was 73% (Figure 18).

Assessor variability

Variation between assessors in assigning each of the 35 photograph pairs to BioCondition class is illustrated in Figure 19 below. As in the desktop assessment (0) Assessor variation was highest for condition classes 2 and 3 and lowest in condition class 4. Assessors predictions were regularly spread across three condition classes for class 2 (54.5%) and class 3 (66.7%). Only two sites were able to be correctly allocated by all assessors using the photo pairs, both in condition class 4. Most (94.2%) of sites had condition allocated across at least 2 condition classes

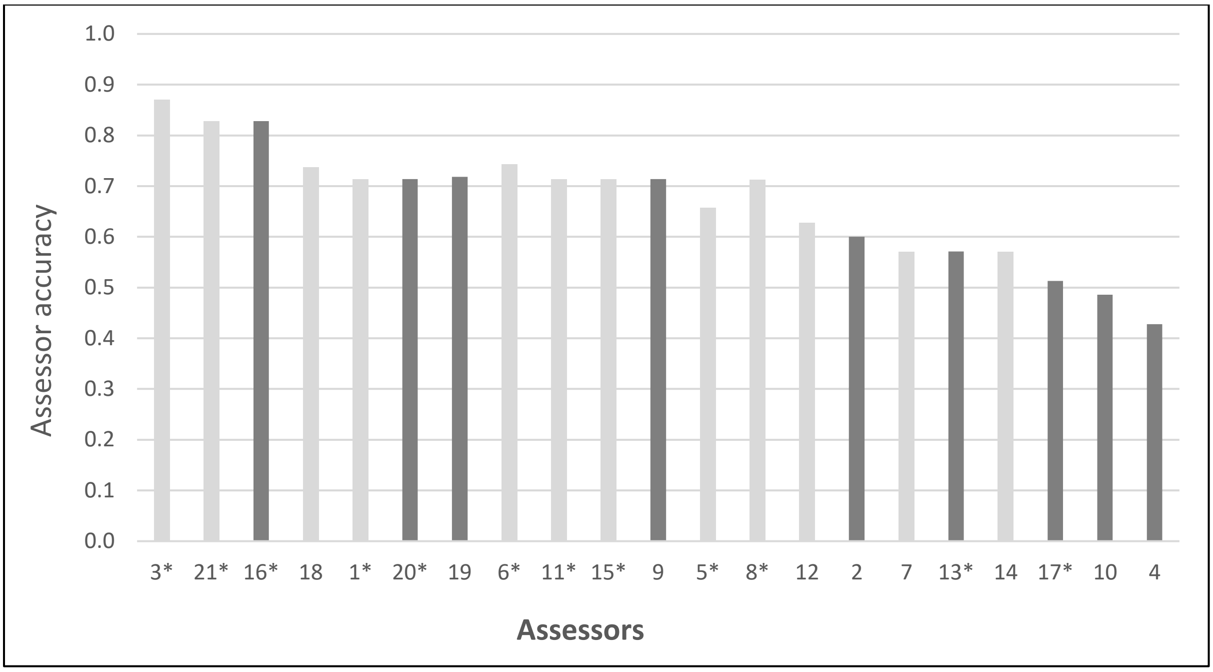

Figure 18: Accuracy for 21 assessors using photos to assess BioCondition classes. Light grey = expert assessors and dark grey = non-expert assessors. *Assessors who collected QVAL data used to train and test the SBC models.

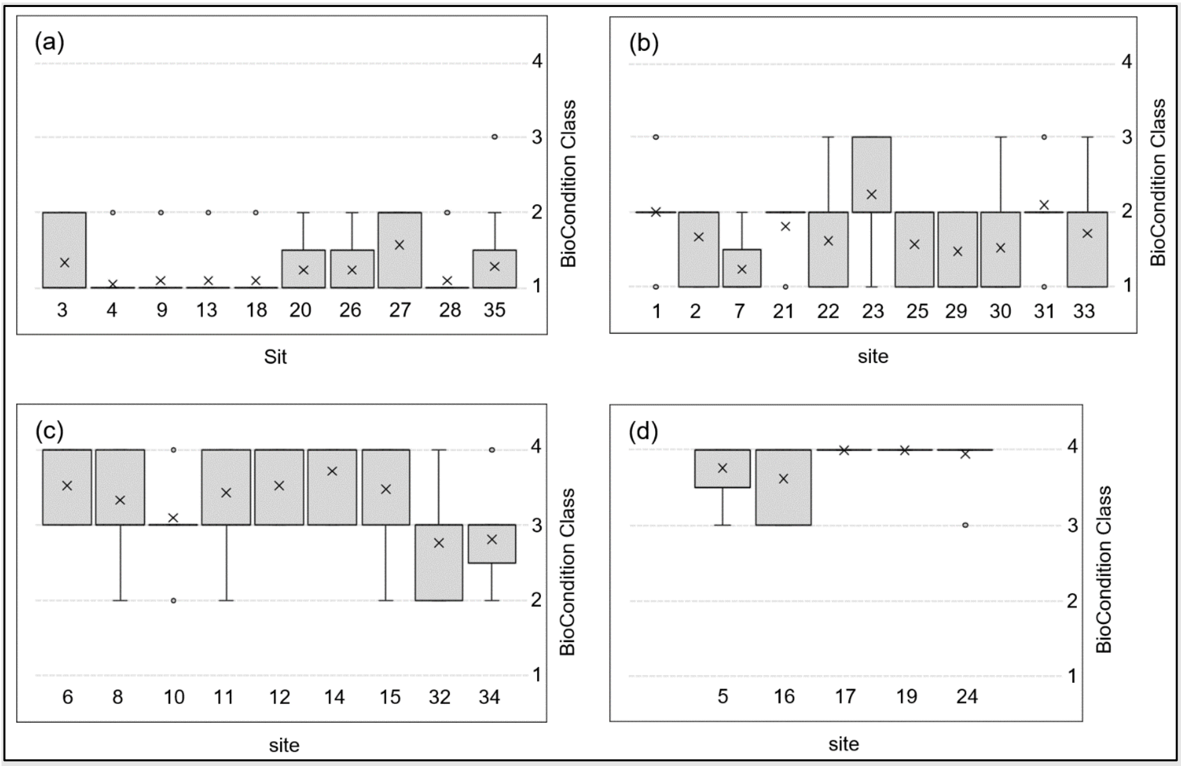

Figure 19: Boxplots of BioCondition Class assessed by 21 assessors using photos for (a) 10 sites measured[1] as class 1; (b) 11 sites measured[1] as class 2; (c) 9 sites measured[1] as class 3; and (d) 5 sites measured[1] as class 4. Boxplots show mean (X), median (--) quartiles and outliers. [1]Measured BioCondition scores (our point of truth) were obtained by undertaking systematic site based BioCondition assessments as per Eyre et al. (2015), scoring against a benchmark and allocating continuous score to BioCondition Class.

Discussion

Overall, assessors could more accurately identify condition classes 1 and 4 from the oblique photographs. These condition classes are generally distinctive and well defined (Appendix 7). Depending on the community type being assessed the definitions of condition classes 2 and 3 can overlap which makes rapid visual assessment difficult. BioCondition represents a continuum and categorising locations into four broad classes eliminates the nuance of a “high 2” or “low 3” in which case an assessor may over or underestimate the condition in a rapid visual assessment. This reinforces the need for additional information, particularly on vegetation structure and composition, for scoring vegetation condition.

There was an expectation when completing QVAL surveys that the assessor was familiar with the BioCondition scoring criteria, weightings, and the benchmark values associated with the regional ecosystem being assessed. All of these elements are important for standardised assessment of condition. Because of this we expected that expert assessors would have a higher accuracy and would therefore be more reliable when conducting rapid field surveys. The lack of a significant difference between the accuracy of assessments completed by expert vs non expert assessors and the high proportion of sites where observers allocated condition across two consecutive condition classes suggest that other factors may influence the accuracy of the individual assessors, other than experience. Limitations which may have influenced an assessor’s ability to score the sites correctly include:

- A reduced vantage point provided by the two landscape photographs restricting assessment of canopy cover and blocking view of objects in the distance or out of frame.
- No broader context is provided by the photographs which can help to inform condition scoring, assessors could refer to additional remotely sensed products to provide this information.
- There was also difficulty, due to scale, obstruction and image resolution, in identifying the full range and cover of individual taxa.

In situ (field) QVAL assessments do not share these limitations due to the increased mobility of the assessor to access different viewpoints. There is also the added benefit of at least one other assessor present with whom to discuss the characteristics of the community until a consensus is achieved on the condition class.

Twelve of the assessors who took part in the oblique photo assessment collected rapid condition assessment site data which was used to train or test the SBC model. Three of these assessors were non-expert, however the data they contributed was used because:

- They were partnered in the field with an expert assessor, or;
- They achieved a high accuracy in the oblique photo assessment indicating that they can accurately rapidly assess vegetation condition, or;
- They conducted assessments in priority ecosystems with limited site data in remote locations

The rapid field assessment method was found to be a far more accurate measure of vegetation condition than the desktop-based assessment of condition (Appendix 2). A rapid visual field assessment therefore merits further investigation, with the aim to develop a rapid vegetation condition survey that can be employed by adequately trained field personnel. In conclusion data collected using the QVAL method was found to be accurate enough for inclusion as training data for the SBC model.

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Appendix 4 Remote sensing predictor variables

Introduction

An initial set of remotely sensed (RS) data were selected for consideration as predictor variables for potential use in the Spatial BioCondition modelling framework, and are briefly described in Table 14. This set was compiled following advice from experts from the Remote Sensing Centre (RSC) of the Department of Environment and Science and the Joint Remote Sensing Research Program (JRSRP). Before any RS data was taken forward for further consideration in the Spatial BioCondition modelling framework, each RS datasets was assessed if:

1. The data was available as a state-wide coverage;
2. The metadata and method were available or published;
3. The data was available at a scale suitable for the proposed modelling framework;
4. The data would be available at future dates;
5. The data had been or could be shown to directly relate to vegetation characteristics;

A subset of the RS data were assessed against field measurements of specific vegetation attributes from existing site-based vegetation (CORVEG) and BioCondition survey data (DES, 2020), to provide some insight into the potential of the data to act as corollaries of BioCondition attributes (results are presented in Table 14).

Table 14: Remotely sensed datasets investigated as predictor variables in the Spatial BioCondition modelling framework. Datasets that were further considered in the modelling framework are shaded grey.
[1]checked and representative CORVEG and/or QBERD sites. The following abbreviations are used: T1 - tallest tree stratum excluding emergent trees; CC - Crown Cover; FPC - Foliage Projective Cover; EDL - Ecologically Dominant Layer See Appendix 1 for full definitions.

Remote sensing dataset	Description	Spatial Resolution	Corollaries with BioCondition Attribute	How was the dataset assessed? Was it considered further?
1.Woody extent	Woody extent product based on ~1m classification using Earth-i imagery. Min mapping unit of 0.5ha, (DES unpublished dataset)	10m	Wooded / non-wooded, Tree / shrub presence / absence	Visual assessment against high resolution satellite imagery (Earth-i 2017) **Not considered further** as QLD wide coverage was not yet available. Failed criterion 1.
2. Australian Woody vegetation cover	Best estimate of persistent green cover based on annual dry season Landsat imagery from 2000 to 2010 (Gill *et al.* 2017)	30m	Wooded / non-wooded	Visual assessment against high resolution satellite imagery (Earth-i 2017). Discrepancies largely attributed to differences in scale/resolution. **Not considered further.** Failed criterion 3.
3. Surface reflectance	Landsat and Sentinel 2 surface reflectance imagery with multispectral bands corrected to surface reflectance. (Flood *et al.* 2013)	10m, 30m	Species diversity, weed mapping (eg Camphor laurel trees)	Visual assessment against Camphor laurel data from the Gold Coast region (Ryan, 2018). Potential use for mapping exotic tree species in future. **Not considered further.** Failed criterion 5.
4. Vegetation Height 2009	Vertical plant cover profiles for the Australian continent derived through integration of ICESat GLAS waveforms with ALOS PALSAR and Landsat data products (FPC). All available ICESat data 2003-2009 were used to produce a single 2009 snapshot of height and cover. (Scarth *et al.* 2019)	30m	Tree height	This dataset was replaced with spatial dataset No. 7 below which has a closer correlation with T1 heights. **Not considered further.** Failed criterion 4.
5. Vegetation Crown Cover	Vertical plant cover profiles for Australia derived through integration of ICESat GLAS waveforms with ALOS PALSAR and Landsat data products (FPC). All available ICESat data 2003-2009 were used to produce a single 2009 snapshot of height and cover. (Scarth *et al.* 2019)	30m	Crown cover	**Not considered further** as more contemporary datasets were available. Failed criterion 4.
6. Vegetation structure 2009	Vertical plant cover profiles Australia-wide derived through integration of ICESat GLAS waveforms with ALOS PALSAR and	30m	Structural formation	Visual assessment against RE structural code mapping. **Not considered further.** Failed criterion 4.

Remote sensing dataset	Description	Spatial Resolution	Corollaries with BioCondition Attribute	How was the dataset assessed? Was it considered further?
	Landsat data products (FPC). All available ICESat data between 2003-2009 used to produce a single 2009 snapshot of structure (Scarth *et al.,* 2010)			
7. Vegetation Height derivative for T1	Original ALOS-1 / ICESat derived product (no 4 above) re-calibrated by Peter Scarth (2019). Site[1] height measurements) were used to re-model the RS height output to represent T1 height only.	30m	Tree height for T1	Correlations with Mean T1 height measurements at sites[1] collected during the years 2007-2011. (DES, 2020). **Not considered further.** Failed criterion 4.
8. Vegetation Crown Cover derivative for T1	Original ALOS-1 / ICESat derived product (no 4 above) re-worked by Peter Scarth (2019). Site[1] CC measurements were used to re-model the RS CC output to represent CC of T1 only (Scarth *et al.,* 2010).	30m	Crown cover for T1	**Not considered further**, as more contemporary datasets were available. Failed criterion 5.
9. Seasonal Persistent Green, Dry season only.	Landsat-based time-series product based on min. green fraction. Roughly equivalent to FPC. (TERN XWiki, 2020)	30m	Total Crown Cover	Correlations with field measurements of CC for T1, (where EDL was T1), from sites[1] collected during the dry season (June-August), of 2016-2017 (DES, 2020).
10. Minimum FPC	Minimum FPC (MinFPC) based on re-fitted woody index and time-series analysis of seasonal fractional cover. (DES, 2019)	10m	Total Crown Cover	Correlation with field measurements of CC for T1, (where EDL was T1) from sites[1] collected during the dry season (June-August), of 2016-2017 (DES, 2020)
11. FPC	Landsat-based FPC prediction based on time-series and manual thresholding process. Automated product also produced for single date data (Armston *et al.,*2009)	30m	Total Crown Cover	**Not considered further**, as an operational Sentinel derived product was available with better resolution (No. 10, Sentinel derived). Failed criterion 3.
12. Seasonal Fractional Cover (All fractions)	Landsat derived Land cover fractions representing the green, non-green and bare cover estimates per pixel. Operational products available, at least one image per standard calendar season. (Flood *et al.* 2013, Scarth *et al., 2015)*	30m	Crown cover / FPC / structure	No relatable field measurements available
13. Seasonal Fractional Cover (all fractions)	Sentinel 2 derived, green, non-green and bare fraction estimates per pixel. Multiple products available (Min, Max, Mean, Median, SD). (Flood, 2017).	10m	Crown cover / FPC / structure	Failed criterion1, Large gaps in spatial cover due to cloud, **Not considered further**
14. Seasonal Ground Cover (all fractions)	Landsat derived, green, non-green and bare ground cover estimates per pixel. Multiple products available (Min, Max, Mean, Median, SD) tested against mean values for certain seasons. (Trevithick *et al.* 2014)	30m	Ground cover, green, litter and bare ground	Correlations with field measurements of Ground FPC (where EDL was ground stratum), from sites[1] collected during 2015-2017 (dry season). (DES, 2020). Failed criterion 1. Large gaps in spatial cover due to cloud. **Not considered further**
15. Dynamic Reference Cover Method	Landsat derived groundcover comparisons between locations and local/regional (dynamic) benchmark(s) to give a (nominally) climate adjusted metric of land cover/land management. Bastin *et. al* (2012)	30m	Grazing, Ground cover condition	**Not considered further** - failed criteria 4 and 5.
16. Fractional cover statistics (all fractions)	Sentinel 2 Time series fractional cover including: minimum (band1); median (band2); maximum (band3); standard deviation (band4); range (band5); and coefficient of variability (band6). P Scarth (2019, pers. com.).	30m	Phenology, grazing, ground cover condition.	No available field measurements to relate.

Description of datasets taken forward

The four RS datasets that fulfilled the selection criteria and were then taken forward for trialling as predictor variables in the modelling framework are highlighted in Table 14 and described in the following. Further information on these datasets can be found at TERN XWIKI, Product Pages (2020).

Seasonal Fractional Cover 2017, Dry season: June-August (Landsat derived)

Australia wide, Seasonal Fractional Cover has been derived by the Joint Remote Sensing Research Project (JRSRP, TERN AusCover) from the analysis of Landsat TM, ETM+ and OLI data at an operational basis. The product has a spatial resolution of approximately 30 m, and a temporal coverage from 1986 onwards. Land cover fractions are retrieved by inverting multiple linear regression estimates in a least squares unmixing model (TERN XWiki, 2020b), and at least one image per calendar season is produced.

During the compositing of the seasonal fractional cover product, the method of the medoid is used, for the selection of representative pixels of three months (a season) of fractional cover imagery. The medoid is a multi-dimensional equivalent of the median. Using this method seasonal variability is captured, noise is reduced, and missing data due to cloud and shadow, is minimised compared with single date imagery (Flood, 2013).

The three bands of the dataset represent:

- Band 1 : Bare fraction representing bare ground, rock and disturbed soil
- Band 2: Green fraction representing green vegetation
- Band 3: Non green / dry fraction representing litter, dead leaf and branches
- Band 4: Model fitting error

The fractional cover model is well calibrated and validated and the endmembers linked to an intensive field sampling program whereby more than 1500 sites covering a wide variety of vegetation, soil and climate types were sampled to measure overstorey and ground cover following the procedure outlined in Muir et al (2011).

Seasonal Persistent Green 2017 (Landsat derived)

Australian wide coverage of seasonal estimates of persistent green cover, produced once per calendar season, is produced from the analysis of Landsat TM, ETM+ and OLI data (30m spatial resolution) by the Joint Remote Sensing Research Project (JRSRP, TERN AusCover). It is derived from the green fraction of the seasonal fractional cover time series (TERN XWiki, 2020a) described in the section above.

The dataset is derived by fitting smoothing splines in multiple iterations per pixel through the full time series of seasonal fractional cover (green fraction only). Persistent green fractional cover for each season is estimated from the final spline iteration at each seasonal time step. Areas with seasonal fractional cover data gaps (eg due to cloud) may produce unreliable estimates of persistent green cover (TERN XWiki, 2020a)

Ecologically this dataset is intended to estimate the portion of vegetation that does not completely senesce, and remains green throughout the year, and primarily consists of woody vegetation (trees and shrubs). It is related to the BioCondition attribute of tree canopy cover.

Minimum Foliage Projective Cover 2016-2017 (Sentinel derived)

Queensland wide coverage of Foliage Projective Cover (FPC) - the percentage of ground area occupied by the vertical projection of foliage - has been modelled and produced by the Remote Sensing Centre (RSC) operationally during the years 1986 – 2014, using Landsat imagery. Lately there was a trial to derive this from higher spectral and spatial resolution Sentinel 2 reflectance imagery (10m).

Flood (pers. com., 2021) described the methodology of producing this unpublished dataset that was used in our spatial BioCondition Framework. In summary the original FPC model (Armston *et al*. 2009) for Landsat imagery was applied to Sentinel-2 imagery, using the Landsat/Sentinel-2 relationship discussed by Flood (2017). To overcome issues of cloud cover and shadows, and to create a Qld-wide map of Foliage Projective Cover, seasonal composites were produced, using the medoid methods of Flood (2013). A two-year period (8 calendar seasons) 2016-2017 was used for this dataset which coincided well with the assessment date of the current project. The two-year period was selected as a timescale relevant to tree growth (Flood pers. com., 2021).

Finally for each pixel the minimum FPC value over the two year period was allocated, resulting to a minimum FPC image for Qld for that period, representing the distribution of woody vegetation.

This dataset was not recommended for use in situations where the absolute magnitude of FPC is required (Flood, pers. com. 2021), and it may not be continued operationally, but it will be replaced in the future with a revised Sentinel 2 derived product.

Fractional Cover Statistics 2015-2017 (Sentinel derived)

Time series summaries of the Seasonal Sentinel 2 Fractional Cover (aca stage - seasonal fractional cover from surface reflectance inputs) produced by P. Scarth (2019 pers. com.) for the years 2015 to 2017.

A model originally developed for Landsat imagery (see Landsat derived Seasonal Fractional Cover product - above) has been adapted and used to derive land cover fractions representing proportions of green, non-green and bare cover from Sentinel 2 imagery to produce a similar 10 m spatial resolution product.

Temporal statistic products have been derived from the seasonal fractional cover datasets by P. Scarth (2019 pers. com.). Those statistics encompassed the: 5th percentile minimum, median, 95th percentile maximum, standard deviation, range, and coefficient of variation, for each fraction (green, non-green and bare).

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Appendix 5 Collation and assessment of existing site data

Introduction

The predictive power of modelling is critically reliant on the number and quality of training data points. The large scope of this project required an investment of significant resources in the sourcing, collation and assessment of existing training data. In this appendix we detail the sources from which we collated existing site data and how we vetted the candidate data for suitability. It is important to note that this assessment of candidate data required a pragmatic balance between two competing imperatives: (a) to collate as much training data points as possible; and (b) to maximise the accuracy and quality of training data. This appendix focuses solely on assessment of existing data, site data collected as part of this project is detailed in the results section of this report.

All spatial analyses were conducted in a Geographic Information System (GIS) and high-resolution satellite imagery used for inspecting site locations included: 2017 Earth-i mosaics, 1m resolution; and World Imagery map image server provided by ESRI which provides 0.5m Maxar satellite imagery at various dates for Queensland. Where doubts existed about the veracity, locational accuracy or representation of sites, they were excluded.

Method

The primary sources for existing candidate site data were ecological databases managed by the Queensland Department of Environment and Science (DES). Additional data was sourced from the TERN Ausplots rangelands dataset and from several agencies who kindly shared site data, collected using standardised (BioCondition) methods, including Brisbane City Council, Bush Heritage Australia and several environmental consultancies. A brief description of the primary source datasets and the types of site data they hold are provided in Table 15.

Table 15: Primary source datasets for existing candidate site data

Dataset (reference)	Description	Notes
CORVEG (CORVEG, 2020)	Ecological database for site-based vegetation data. Sites are used to define regional ecosystems and have generally been located to describe typical examples of vegetation types or regional ecosystems in remnant condition and the range of variation within them. Details regarding types of sites, sampling and survey methods are provided in Neldner *et al.* (2019).	Selected CORVEG sites were for the most part detailed site-based observations of vegetation composition, abundance and structure within a 50m x 10m quadrat, with a measure of basal area (where applicable) and notes on landform, landscape context, disturbance, soil and geology. A small subset with less detailed floristic information (tertiary or quaternary level sites) were still able to meet the selection criteria and were included as training data.
QBERD (QBERD, 2020)	Ecological database for a range of biodiversity and ecological research datasets. QBERD contains two classes of sites of utility to this project: (a) reference sites - used to derive benchmarks; and (b) assessment sites – used for assessing condition against benchmarks. A detailed explanation of the BioCondition assessment framework, benchmarks, site selection, survey methods and data recorded are provided in Eyre *et al.* (2015; 2017).	BioCondition reference sites are detailed site-based observations of vegetation composition, and abundance within a 50m x 10m quadrat, with notes on landform, landscape context, disturbance, soil and geology. However they differ from CORVEG in the following aspects: structural attributes are assessed over a larger area (100m x 50m); additional information on tree stem diameters, coarse woody material and recruitment of tree species are collected; and stricter criteria apply for selecting site location (restricted to the 'best on offer' examples of a vegetation community). Assessment sites are similar to reference sites but collect less detailed information on disturbance and stem diameters. Importantly assessment sites can be located in vegetation in any condition state.
TERN Ausplots (AEKOS, 2020)	Ausplots rangelands dataset, a series of environmental plots established for long term monitoring. Details regarding sites, sampling and survey methods are provided in White et al., (2012)	Detailed site-based observations of vegetation (composition, abundance and structure, basal area, leaf area index) and soil (composition, characterisation, density) within a 100m x 100m quadrat and to 1m deep for soil cores. With accompanying notes on landform, landscape context, disturbance and geology.

BCC (Brisbane City Council)	Brisbane City Council, BioCondition assessment site dataset for the Brisbane City Council local government area. Data collected and scored using BioCondition method (Eyre *et al.*, 2015)	As per QBERD assessment sites, above

We assessed all collated existing candidate sites against criteria A-H listed in Table 16. The criteria were designed with the explicit aim of improving predictive model accuracy and preventing model degradation through the removal of erroneous, conflicting or unsuitable data points. These were identified by assessing for spatial accuracy, duplication and proximity issues as discussed in McNellie *et al.* (2015), as well as for representativeness and spatial issues which are specific to the assessment area and modelling framework used in this project. Criterion I is specific to the scoring of QBERD sites using the BioCondition assessment framework (Eyre *et al*., 2015). Assessment criteria were applied in the order listed in Table 16, sites failing any applicable criterion were excluded from the suitable site dataset.

It is important to note that the resolution or scale of the modelling framework (dependent on the predictor variables, study area and base regional ecosystem mapping) influence the scale of any spatial assessment of candidate training data (for example analysis of proximity to a road or another site). The modelling framework described in this report used an assessment area of 90m x 90m, (a grid of 9 pixels, each 30m x 30m). The value assigned to each training point for each predictor variable is the average of values across the 90m x 90m assessment area.

On this basis criterion H sets a minimum distance between sites of 90m to avoid training or testing the model on data that is conflicting (ie sites representing different units or condition states having overlapping assessment areas). Likewise, to prevent large differences within an assessment area criterion G sets a minimum distance of 45m to a structural edge such as clearings, roads, fence lines, or an abrupt change in vegetation structure.

Table 16: Selection criteria used to assess candidate training data for suitability.

Criterion	Description
A	sites were assigned or could reliably be assigned to a valid, mapped version 11 regional ecosystem or vegetation community (Queensland Herbarium, 2019);
B	sites were identified as being representative of the assigned vegetation community/regional ecosystem by the bioregional co-ordinator (see appendix 1 for Appendix 1 Definitions);
C	sites were collected or revisited in the field on or after January 1 1995
D	sites identified as reference or BOO sites were in areas identified as remnant in version 11 regional ecosystem mapping (DES, 2018)
E	sites were unique and not duplicated within or between any of the source datasets;
F	recorded geo-referencing accuracy was better than 200m
G	sites were in patches of structurally relatively homogeneous vegetation of at least 90m x 90m, ie no closer than 45m to an edge;
H	Sites were no closer than 90m to any other training data site, ie 90m x 90m assessment areas for each training point do not overlap;
I	Sites had enough measured attributes relative to the maximum number of measurable attributes for the RE being assessed.[1]

[1] Criterion I is specific to the scoring of QBERD sites using the BioCondition assessment framework (Eyre *et al*., 2015)

Criteria A and B address the representativeness of the site data with respect to regional ecosystems (REs). The SBC modelling framework described in this report uses REs and their mapped extents as environmental domains, hence all locations within an REs extent are measured against the reference state site examples for that particular RE. The framework described in this report is based on version 11 regional ecosystem mapping and definitions (Queensland Herbarium, 2019). It is on this basis that assessment criteria A and B ensure that all suitable sites were assigned or reliably assignable to a valid, mapped version 11 ecosystem or vegetation community, and that they were considered representative of that community. Non-terrestrial vegetation communities (as defined in Appendix 1) were treated as invalid ecosystems and training data for these communities failed at criterion A.

The use of many existing (archive) site data required decisions regarding the currency of the data (how recent the site data is and therefore how well it represents that location in 2017). In assessment criterion C we made a pragmatic decision to restrict the dataset to sites collected or revisited after 01/01/1995. This removed site data collected more than 22 years prior to this project. Existing sites where the date of acquisition is unknown (these are stored in the databases as collected on 01/01/1900) therefore also failed criterion C and were excluded.

Assessment criterion D was an additional currency check, consisting of a spatial analysis to identify existing candidate sites identified as being in reference condition only that intersected with areas identified as non-remnant (cleared and/or disturbed) in regional ecosystem mapping (DES, 2018) at any time since the date surveyed and before then end of 2017 (currency of this report). Identified sites were checked against high resolution satellite imagery prior to exclusion. Two examples of candidate sites that failed criterion D are shown in Figure 20, in both examples the areas were remnant vegetation at the time the sites were undertaken and clearly identifiable as having been subsequently cleared.

Figure 20: Two examples of existing reference site[1] data that failed criterion D, identified as non-remnant in 2017. On the left is a survey site collected in 2003 where the area has since been cleared and developed for housing. On the right is a survey site collected in 1998 where the area has since been cleared and mined.
[1]the geo-referenced centre point for each site is represented by a yellow circle and the surrounding box approx. 90m x 90m represents the area assessed by the model as representative of the site.

Spatial errors

The importance of geo-spatial accuracy when using existing site data in modelling is discussed in McNellie *et al*. (2015). Spatial errors caused by datum shift were reduced by sourcing most existing candidate sites from actively curated DES databases where site locations are stored in both the original datum and converted to GDA94 (WGS84) with mandatory fields recording the source/derivation and approximate accuracy of the location data. Where data regarding the source/derivation and approximate accuracy was missing, we examined textual information associated with the sites, original field datasheets, reports etc, and where possible contacted individuals who collected the data to fill any gaps or resolve any uncertainties.

Sites with missing locational accuracy data that were collected prior to the widespread uptake of Geographic Positioning Systems (GPS) (i.e. sites before 1997) were assumed to have spatial accuracy worse than 200m. Those collected after 1997 (earlier if the use of a GPS was recorded) were assumed to have spatial accuracy better than 200m. At assessment criterion F all existing candidate sites with a recorded (or assumed) locational accuracy worse than 200m were excluded. Figure 21 provides an example of an existing candidate site that fails criterion F. In this example the allocated RE and accompanying textual data indicate that the site represents RE 9.8.7, semi-evergreen vine thicket (SEVT). Examination of high-resolution imagery clearly indicates that the sites geo-location places the site outside of SEVT, clearly visible as dark green closed vegetation, and in open Eucalypt woodland.

Figure 21: Example of an existing candidate site[1] that failed criterion F. Site represents semi evergreen vine thicket (SEVT) but is geo-located in open eucalypt woodland and away from SEVT (clearly visible on imagery as dark green areas). [1]the geo-referenced centre point for each site is represented by a yellow circle and the surrounding box approx. 90m x 90m represents the area assessed by the model as representative of the site.

To identify true duplicates, re-visits and near-neighbours a spatial analysis of all candidate sites using the suitable minimum distance between sites of 90m was undertaken, associated textual information was examined for sites identified by the spatial analysis. Identified true duplicate pairs (or multiples) and re-visits were treated as per McNellie *et al*. (2015), with only the most recent site visit retained for re-visits. Assessment criterion H deals with sites identified as near neighbours (<90m distant) these required close examination of their associated textual information and location using high resolution satellite imagery.

Sites identified as near neighbours included some true duplicates and some re-visits which had transcription errors in their co-ordinates, these were treated as per McNellie *et al*. (2015). Unique sites identified as near-neighbours that had intentionally or unintentionally been located close together (For example numerous sites sampling various closely spaced communities) required pragmatic decisions regarding which to keep and which to remove.

The use of existing site data as reference state locations to train and test a modelling framework with an assessment area of 90m x 90m necessitated some further spatial criteria. Assessment criterion G excludes sites within 45m of a structural edge (non-remnant areas, roadsides). Spatial analyses of distances between existing candidate sites and (a) non-remnant areas and (b) mapped road/tracks were used to identify problematic sites for closer examination of associated textual information and location using high resolution satellite imagery. Sites not able to be resolved were excluded.

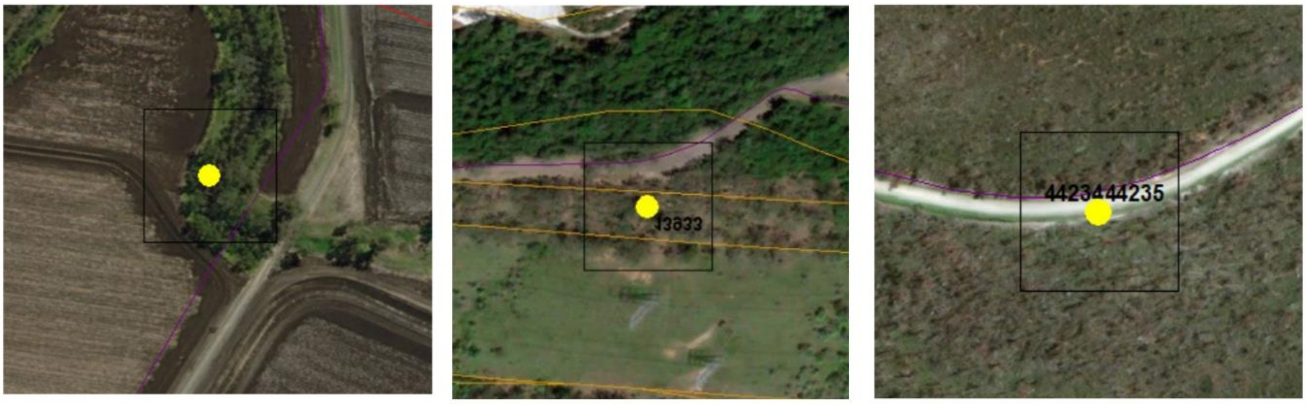

Figure 22: Three examples of existing site[1] data, the left and centre examples fail criteria G, less than 45m from an area identified as non-remnant in 2017. On the right is a true duplicate pair, which fail both criterion G, (located on the road) and criterion E. [1]the geo-referenced centre point for each site is represented by a yellow circle and the surrounding box approx. 90m x 90m represents the area assessed by the model as representative of the site.

A sizable number of candidate sites initially failed criterion G or even D due to their geo-referencing placing the site on or close to (<45m from) a road (Figure 22). This was often a result of historical practices or technological constraints where survey sites collected immediately adjacent a road or track were unfortunately geo-referenced to the survey vehicle location on the roadside (power requirements and slow location fixing in early GPS models favoured in-vehicle usage). Examination of textual information and high-resolution imagery enabled many of these to be reliably relocated such that they passed the criteria. This large and resource intensive task highlighted the critical importance of both recording accurate site location information and location selection for vegetation survey sites.

Figure 23 provides a visual example of the application of proximity criteria based on assessment area dimensions (criteria G and H). Candidate training data from a survey intensively sampling littoral vegetation on a coral cay are shown. Eight sites fail criterion H, less than 90m from another site (i.e. those with overlapping boxes), four of these also fail criterion G as they are less than 45m from identified non-remnant areas (buildings). Four sites (on southern edge of island) fail criterion G (not homogenous across assessment area), with high percentages of their respective assessment areas a mix of littoral scrub vegetation, bare areas and ocean. Additionally, the westmost of the four sites is also less than 45m from identified non-remnant areas (buildings) and fails criterion H.

Figure 23: An example of existing site[1] data that fail due to the assessment area dimensions (criteria G or H).[1]the geo-referenced centre point for each site is represented by a green square and the surrounding box approx. 90m x 90m represents the area assessed by the model as representative of the site.

Variation in sampling density

The survey methodologies for Regional Ecosystem mapping, BioCondition and Ausplots provide specifications for the location and density of sample sites (Neldner et al., 2019; Eyre et al., 2017; White et al., 2012), aiming for a proportionate geographic distribution and adequate sampling of ecosystems at the bioregional or greater scale. Whilst the associated datasets are not necessarily free of any sampling biases, efforts have and continue to be made to reduce these where possible. Compatible sampling methods and scales enables CORVEG, QBERD and TERN datasets to be easily integrated without introducing extra sampling bias. This was not the case with the inclusion of data from projects designed and collected at local scale.

The inclusion of the BCC dataset, (692 sites) required the exclusion of some otherwise suitable site data for a small number of REs. This was to prevent the introduction of any biases resulting from having a high proportion of training data concentrated in a few very small locations. Whilst the BCC local government area (LGA) has an area of 1,380 km^2, less than 40% of this area is classified as natural areas (remnant and regrowth native vegetation) and the ‘natural’ area of individual REs may be only a few hundred hectares. Sites sampling these REs may be highly concentrated in these very small remnants. For this reason, 296 otherwise suitable sites from the BCC dataset were excluded from the final dataset.

An example of this situation is the RE 12.3.20 - *Melaleuca quinquinervia*, *Casuarina glauca +/- Eucalyptus tereticornis*, *E. siderophloia* open forest on low coastal alluvial plains which has a pre-clearing distribution of around 16,300 ha, occurring from just north of Bundaberg, south to the NSW border. For this RE we were able to collate 16 suitable sites from CORVEG, distributed across the latitudinal range of the RE (Baffle Creek to the southern end of Moreton Bay). From the BCC dataset we collated an extra 30 suitable sites from an area of about 230 hectares, mostly from 2 small areas at Tichi-Tamba reserve (Figure 24) and near Nudgee. To reduce any potential bias by having such a large portion (65%) of site data for the RE from just two very small geographic areas a pragmatic decision was made to discard 24 of the BCC sites, whilst maintaining a maximal geographic spread amongst the 6 retained sites.

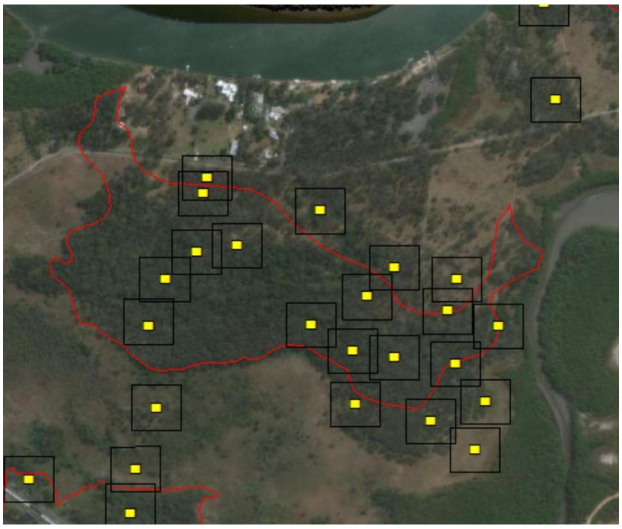

Figure 24: An example of high site[1] density from a dataset collected at a local scale. [1]Each sites geo-referenced centre point is represented by a yellow square and the surrounding box approx. 90m x 90m represents the area assessed by the model as representative of the site.

Results

A total of 33,499 existing candidate sites were collated. After all spatial analyses, investigations and the application of all 10 assessment criteria, 9,828 existing sites were found suitable for use. The total number of collated existing candidate sites, the number of these that passed and failed at each criterion and the number that passed all criteria are listed in Table 17. It is important to note that many sites fail multiple criteria but are counted here only at the first instance of failure. Therefore, the numbers provided in Table 17 are reflective of the order in which criteria were applied (A-J). Figure 25 shows the spatial distribution of both the total collated existing candidate site dataset and suitable site dataset (the passed all criteria) described in Table 17 by source dataset.

Many (8,151) candidate training sites (including both collated existing sites and sites newly collected as part of this project) were identified as requiring checking against high-resolution satellite imagery or associated textual data during the assessment process. This was a time-consuming task. Table 18 details the number and proportion of sites identified as requiring checking as well as the number and proportion of checked sites that were: excluded from the final dataset; found to be OK, requiring no action and retained; and found to have issues that were resolvable such that the site would pass all assessment criteria and retained.

Table 17: Existing candidate sites, total, number that failed and the number of candidate sites remaining (in brackets) at each assessment criterion, listed by source.

Assessment criteria [1]	CORVEG	QBERD	TERN	BCC	total
Total collated existing candidate sites	**29,817**	**2,897**	**93**	**692**	**33,499**
A - valid, mapped version 11 RE	13,459 (16,358)	5 (2,892)	4 (89)	32 (660)	13,500 (19,999)
B - representative	4,564 (11,794)	2 (2,887)	16 (73)	25 (635)	4,607 (15,392)
C - collected on or after 01/01/1995	2,093 (9,701)	0 (2,887)	0 (73)	0 (635)	2,093 (13,299)
D - remnant in version 11 RE mapping (clearing post survey)	371 (9,330)	5 (2,882)	0 (73)	0 (635)	376 (12,923)
E - not duplicated	564 (8,766)	113 (2,769)	0 (73)	4 (631)	681 (12,242)
F - geo-referencing accuracy better than 200m	99 (8,667)	1 (2,768)	0 (73)	9 (622)	109 (12,133)

G - minimum patch dimension 90m x 90m	208 (8,459)	4 (2,764)	1 (72)	109 (513)	322 (11,811)
H - proximity to another site >90m	43 (8,416)	0 (2,764)	0 (72)	84 (429)	127 (11,684)
I - sufficient scorable attributes[3]	na	1,560 (1,204)	na	na	1,560 (10,124)
J- sampling density[4]	na	na	na	296 (133)	296 (9,828)
All criteria[2]	**21,401 (8,416)**	**1,693 (1,204)**	**21 (72)**	**559 (133)**	**23,671 (9,828)**

[1]Full descriptions of assessment criteria are given in table 15. [2] The total number that failed any criterion and the number remaining that passed all criteria (in brackets). [3]Criterion specific to the scoring of QBERD sites only using the BioCondition assessment framework (Eyre *et al*., 2015). [4]Although not a selection criterion, some BCC site data were excluded based on sampling density.

Table 18: Site checking efforts, checking of individual collated and collected candidate sites against high resolution satellite imagery[1], accompanying textual data[2] or other datasets. Number and proportion of sites: identified and checked; excluded from training dataset after checking; OK and requiring no action; and resolvable such that all assessment criteria were passed.

Number of sites	CORVEG	QBERD	TERN	BCC	Expert[3]	QVAL[4]	total
Total of existing collated[5] and newly collected[6] candidate sites	**29,950**	**2,995**	**93**	**692**	**1,862**	**12,418**	**48,010**
Identified and checked (percentage of total above)	**3,427 (11.4)**	**345 (11.5)**	**93 (100)**	**692 (100)**	**122 (6.5)**	**3,472 (27.9)**	**8,151 (17.0)**
Excluded (percentage of checked sites)	584 (17.0)	43 (12.5)	21 (22.5)	559 (80.7)	4 (3.3)	757 (21.8)	1,968 (24.1)
OK - no action required (percentage of checked sites)	658 (19.2)	146 (42.3)	42 (45.2)	115 (16.7)	45 (36.9)	1,522 (43.8)	2,528 (31.0)
Resolvable (percentage of checked sites)	2,064 (60.2)	156 (45.2)	30 (32.3)	18 (2.6)	73 (59.8)	1,193 (34.4)	3,534 (43.4)

[1]Earth-i mosaics for 2107 - 1m resolution; and ESRI World Imagery map image server- 0.5m Maxar satellite imagery at various dates. [2]Textual descriptions of site location, vegetation community, landscape position etc. recorded when site was collected. [3]Expert elicited sites collected as part of this project, described in section 2.2.7. [4]Rapid vegetation condition sites collected as part of this project, described in sections 2.2.4.2 and appendix 7 (Queensland Herbarium, 2020). [5]Existing site data collated from various data sources see tables 16 & 14. [6]New detailed, rapid and expert elicited sites collected as part of this project, described in sections 2.2.4.1, 2.2.4.2, 2.2.7 and reported in section 5.1.

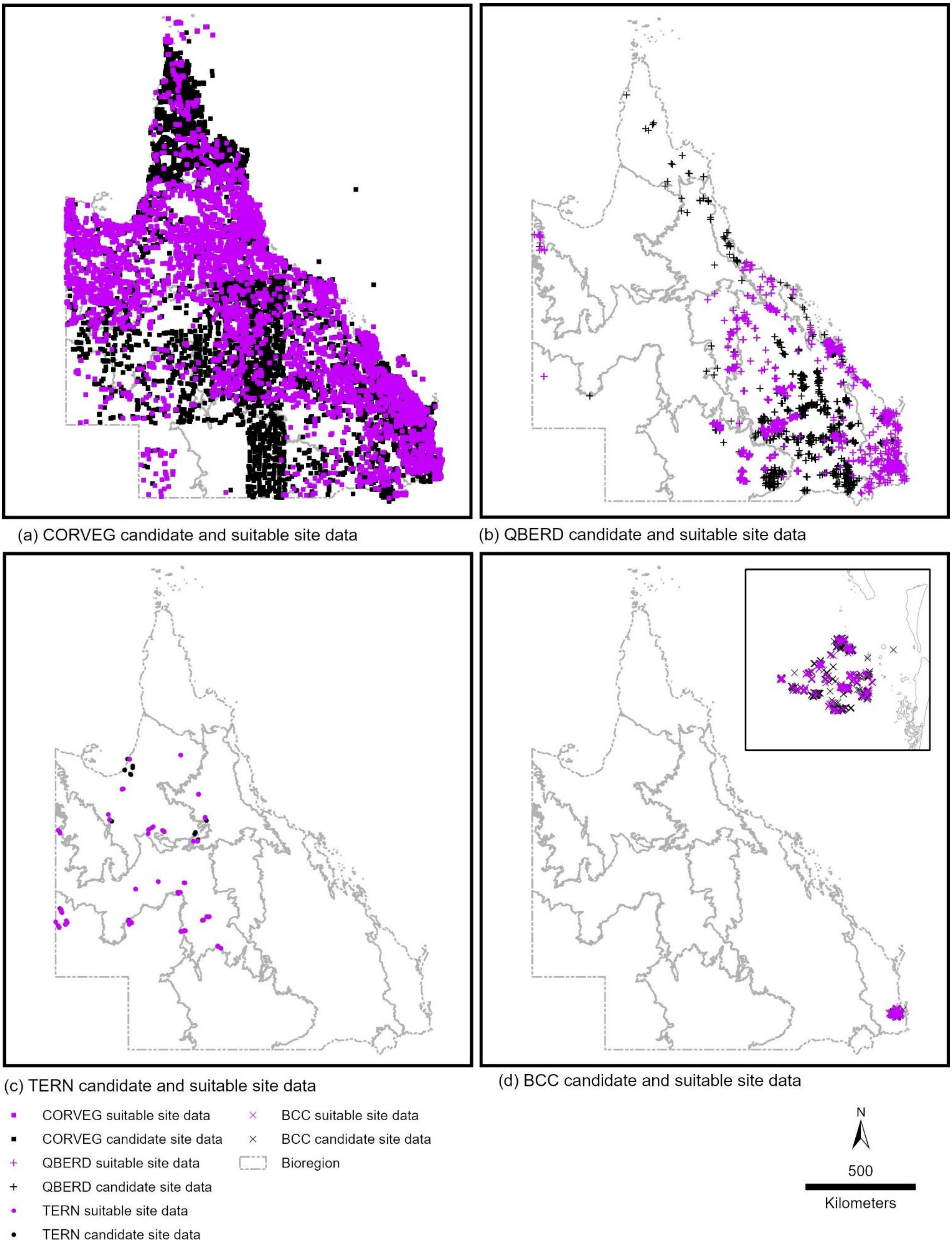

Figure 25: Distribution of collated existing site data by source dataset. Candidate sites in black and suitable (used) sites in purple.

Discussion

Existing site data is a valuable and information-rich resource for any large-scale modelling project. That more than two thirds of existing data collated as part of this project failed our selection criteria highlights the critical importance of data assessment and cleaning, as well as the requirement for projects using existing site data as training input for models to devote significant resources to the assessment of existing data. The failure of a large number of existing CORVEG sites at criteria A and B highlights the fact that the CORVEG database has historically been a data repository for a broad range of data collected using various methodologies, some of which pre-date the standardised Regional Ecosystem framework and methods, and project specified cut-off date of 1st January 1995. Some of these survey sites either lack sufficient floristic composition and abundance information to be reliably allocated to a recognised vegetation community/regional ecosystem or have been in areas considered to be transitional or ecotonal under the RE framework. Whilst such sites may contain valuable environmental, distribution and compositional data, they have limited utility to a modelling project which is endeavouring to map the vegetation condition as it is in 2017.

The numbers of sites requiring checking or excluded because of proximity to other sites or to structural edges is dependent of the resolution or scale of the modelling framework and predictor variables, which defines the assessment area. The large assessment area (90m x 90m) used in this project proved problematic for sites sampling small or narrow communities or close to structural edges. Future improvements in the resolution of remote sensing products will reduce the size of the assessment area, improving model accuracy for small or narrow communities as well as significantly reducing the number of sites that need (time consuming) further assessment and the number failing proximity related criteria.

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Appendix 6 Disturbance data to support expert elicitation of reference sites

Introduction

To assist in the expert elicitation of reference state sites for under sampled vegetation communities or regional ecosystems, a suite of datasets representing potential disturbances thought to impact on the reference vegetation condition state was compiled. Four disturbance types with suitable spatial indicators were collated/developed. These are listed along with their impact on ecosystem condition, and available mapped indicator in Table 19.

Table 19: Summary of disturbances considered, their impact to biodiversity, and their mapped indicators

Disturbance	Impact	Mapped indicator
Grazing by stock	Soil compaction Increased bare ground and associated erosion risk Change in species composition and or structure through preferential grazing Spread of naturalised non-native organisms Reduction in habitat features	Effective distance to water – Healy et al (2020)
Woody vegetation disturbance (includes broad scale and selective removal)	Reduced canopy cover Simplified structure, loss of large trees, mechanical disturbance to remaining vegetation Loss of perennial woody vegetation Reduction in habitat features and availability Soil compaction Change in species composition and/or structure Spread of naturalised non-native organisms	Statewide Landcover and Trees Study Queensland series 1988-2018 (DES 2017a, 2018a, 2019a)
Excess fire frequency	**Too frequent** Reduced canopy cover Simplified structure (including fallen woody material, hollow bearing trees) Reduced shrub and ground cover Change in species composition and/or structure, (loss of abundance of slower growing obligate seeders) **Too infrequent** Change in species composition and/or structure (increase in abundance of species adapted to less frequent fire)	Excess fire frequency dataset, derived from an analysis of: Landsat Count of Detected Fire Scars Queensland (DES 2019b); Regional ecosystem mapping (DES 2018b); Regional ecosystem fire guidelines (Queensland Herbarium 2018b)
Recent fire	**Temporary without further disturbance:** Reduced canopy cover Simplified structure Change in species composition and/or structure	Recent fire dataset, derived from an analysis of: Landsat Count of Detected Fire Scars Queensland (DES 2019b); Regional ecosystem mapping (DES 2018b); Regional ecosystem fire guidelines (Queensland Herbarium 2018b)

Grazing by stock

The BioCondition site-based assessment framework includes a surrogate of grazing pressure for intact landscapes, which is distance from permanent water (Eyre et al. 2015b). Total grazing pressure (native, feral and stock) has been shown to radiate in intensity with distance from water and this pressure surface has been termed a Piosphere (James et al. 1999). Piospheres have been shown to influence fauna and flora species assemblages (Landsberg et al. 1999; Pringle and Landsberg 2004; Fensham and Fairfax 2008).

We used a published water availability and water remoteness mapping dataset (Healy et al. 2020) to identify areas subject to high grazing pressure due to proximity to a water source, to guide the expert elicitation process. Healy et al. (2020) used a spatially explicit method to map access to water across an area of over 700,000 km^2 in areas of western Queensland with mean annual rainfall < 500mm, through mainly the western drylands. Their study area encompassed mostly the Channel Country, Mulga Lands, Mitchell Grass Downs, Northwest Highlands Bioregions, where water is a limiting resource. Our assessment of grazing pressure was also restricted to the same area.

The spatial dataset produced by Healy et al. (2020) combined existing datasets from multiple sources on the location and permanence of natural and artificial waters including springs, rockholes, boreholes, waterholes, surface waters, reservoirs and dams. Those were validated using high resolution satellite imagery. Permanence of the water sources was calculated for each cell as a percentage of the times water was detected over the total valid records derived from 27 years of Landsat data (about 600) for that pixel. Then an algorithm was applied at each pixel to produce a spatial dataset of water remoteness as a function of the distance from each water source and the permanence of that water source. This was subsequently weighted by an inverse distance raster layer, and thresholded to finally produce a spatial dataset for their study area of "effective distance from water" (EDW).

We used the EDW dataset to identify areas likely to be subjected to very high grazing pressure. A threshold of 3 km was used as effective grazing range, based on thresholds developed from empirical data in Queensland (Fensham and Fairfax 2008). This approach assumes that an animal seeking water will choose to use the closest available water source.

The extent of area with an EDW less than 3km within the western drylands is shown in Figure 27a, and encompasses approximately 387,838 km^2, which equates to 49.6% of that area.

Woody vegetation disturbance

Broadscale clearing of habitat has a significant impact on terrestrial biodiversity, leading to known decline in woodland bird, mammal and reptile species (Reside *et al*., 2017; Evans 2016; Neldner *et al*., 2017). Similarly, selective tree removal (in the form of thinning for grazing, land management, silvicultural or ecological restoration purposes, and logging for timber production purposes) can have adverse effects for biodiversity. Native vegetation managed for timber production are typically subject to a predictable suite of habitat modifications, although the degree and trajectory of change will depend upon the ecosystem type and the intensity of the activity (Eyre *et al*., 2015a).

The Statewide Landcover and Trees Study (SLATS) has been mapping and reporting on woody vegetation change in Queensland using Landsat satellite imagery which dates back to 1988 (DES, 2018a). A composite dataset produced by SLATS, representing change in foliage projected cover (FPC) between 1988-2017 including both broadscale and selective clearing, was provided to the experts as a potential indication of areas unlikely to be in reference condition, and therefore not considered suitable for locating training data points. The extent of broadscale or selective woody vegetation clearing identified using SLATS FPC change detection for the period 1988-2018 is shown in

Figure 26b and encompasses 100,973 km^2, approximately 5.6% of Queensland (Table 19).

Spatial capture of change in vegetation cover due to thinning and selective logging can be challenging due to current limitations of the Landsat imagery used by SLATS and is likely to be under-represented. For example SLATS only reported 0.1% change in vegetation cover within remnant vegetation across Queensland in the 1988 to 2018 composite. It would be useful in future to include information collected through the Queensland Department of Agriculture and Fisheries Native Forest Management Units (MUIDs), regarding detailed logging and silvicultural thinning history, to augment the data currently obtained through SLATS, which is not systematically captured.

Excess fire frequency

A large proportion of ecosystems in Queensland are adapted to fire as a periodic disturbance event. The readily measurable (using remote sensing) but *possibly* temporary disturbance to an ecosystem by fire is discussed in section 'Recent Fire Scar' below. In the current section we discuss why and how we have included areas with an excess fire frequency (burnt more often than recommended) in our disturbance dataset.

Fire interval, intensity and seasonality act on critical life history processes of species (Whelan, 1995) and are recognised as a major determinant of plant species persistence patterns in both northern and south-eastern Australia (Williams et al., 2002; Bradstock *et al*., 2005). The key role plants play in ecosystem productivity, structure and as habitat means altered fire regimes may produce a cascade of impacts on biodiversity at all trophic levels and altered fire regimes have therefore been identified as one of six key threats to Australia's biodiversity (Natural Resource Management Ministerial Council, 2010). Ecological communities at particular risk from altered fire regimes are those dominated by fire sensitive species (e.g. rainforests, softwood scrubs, brigalow *(Acacia harpophylla*) or cypress pine (*Callitris* sp.) or ecosystems dominated by long-lived species reliant primarily on in situ recovery from seed banks (obligate seeders), many semi-arid Acacia dominated ecosystems (mulga (*Acacia aneura*), western bendee (*A. catenulata*) and lancewood (*A. shirleyii*)). The method described below identifies, from remotely sensed (RS) fire scar mapping, areas within a regional ecosystem that have been burnt more often than is recommended for that regional ecosystem, i.e. these areas are defined as having an excess fire frequency.

Available RS fire scar mapping for Queensland for a 31-year (1987-2017) period enabled an assessment of excess fire frequency as a disturbance but is not of sufficient duration to meaningfully assess for deficiency of fire for many regional ecosystems.

We derived fire regime frequency thresholds for all terrestrial vegetation communities in Queensland from published fire guidelines (Queensland Herbarium, 2018a), converting minimum recommended intervals to maximum recommended frequencies for a 31-year period; to allow for direct comparison with available fire scar mapping. We created a state-wide map of the recommended maximum fire frequency threshold using the proportionally dominant threshold value in each regional ecosystem (RE) polygon, where two or more values were equally co-dominant, we used the lowest frequency value as a conservative measure to ensure areas possibly affected by fire were included. Published fire scar mapping for Queensland - updated to include unpublished 2017 fire scars detected, was accessed to provide a RS measure of mean fire frequency (count of number of times burnt/31) for the period 1987-2017 and for the entire state except for areas of cropping and water that were masked as ‘no data’ (2.7% of state). Methods used to produce fire scar mapping and limitations of the data are described in detail by DES (2019b).

The difference between the RS measured mean fire frequency and recommended maximum fire frequency threshold was calculated for each 30m grid cell. Where measured fire frequency exceeds the recommended maximum frequency mean fire return interval (MFI) must be below the recommended interval at some point in the 31-year period and we assume that this may translate to a negative impact on condition for biodiversity and the area would be unsuitable for inclusion as a location in a reference state.

Figure 26c shows the 115,954 square kilometres (6.5%) of Queensland where RS measured fire frequency was greater than the recommended threshold for maximum fire frequency. Around 62% of the area identified using this method is mapped as remnant vegetation.

Recent fire

The potential disturbance effects of excessive fire frequency is covered in the section above. The aim of the current dataset was to identify areas recently burnt in vegetation communities or regional ecosystems not adapted to high fire frequency. Areas adapted to high fire frequency, often grasslands or grass dominated tropical savanna ecosystems are expected to show a rapid recovery in plant cover after recent fire and to display little change in structure or species composition. Areas not adapted to high fire frequency and affected by recent fire are expected to display reduced canopy cover, simplified structure and change in species composition and/or structure. These changes may be temporary or long-lasting dependent on subsequent or ongoing disturbances.

Using minimum recommended fire intervals from published fire guidelines (Queensland Herbarium, 2018a) we classified all REs into two ‘fire categories’:

- Category A – ecosystems where high frequency fire is not recommended or are fire intolerant (minimum recommended interval ≥ 3 years);
- Category B – ecosystems tolerant of high frequency fire (minimum recommended interval < 3 years).

A statewide map of categories A and B was created using lookup tables to incorporate fire category into version 11 pre-clear RE mapping (DES, 2018b) and mapped using the proportionally dominant fire category in each RE polygon, where both fire categories were equally co-dominant, we chose category A as a conservative measure.

Remotely sensed fire scar mapping for Queensland for a 3-year period from 2015-2017 (including unpublished 2017 data; DES, 2019b), was combined to provide a recent fire scar dataset for 97.3% state, excluding areas of cropping and water that were masked as ‘no data’ (DES, 2019b). We undertook a spatial analysis of the recent fire scar and fire category datasets to identify the intersection of category A and recent fire scar mapping. These identified recently burnt areas in REs not adapted to high fire frequencies were not considered suitable for locating training data points and are shown in

Figure 26d. This method identified approximately 67,572 km^2 (3.8%) of Queensland as unsuitable for inclusion as a location in a reference state, around 74% of which is mapped as remnant vegetation.

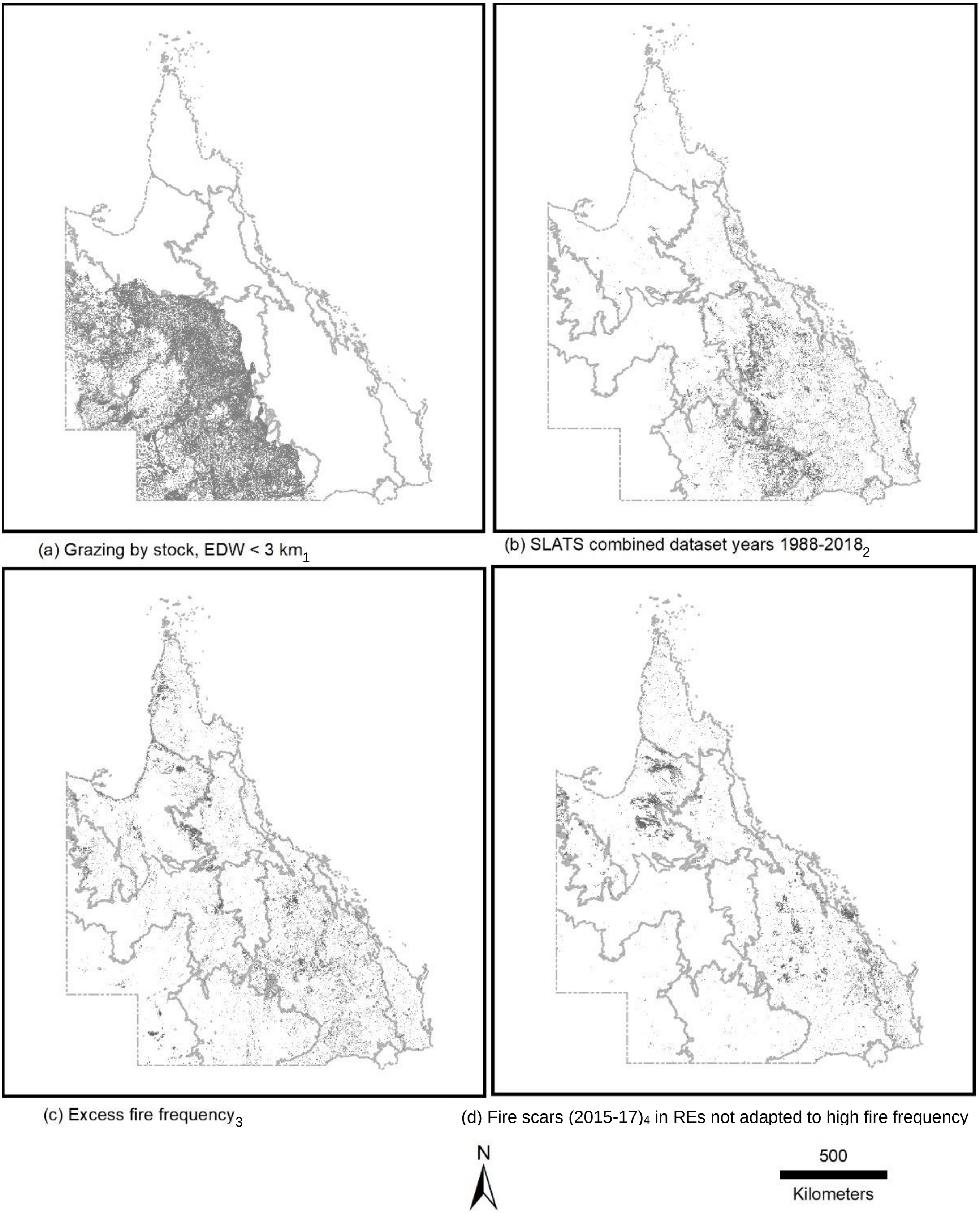

Figure 26: Four potential disturbance datasets used to guide expert elicited training data. [1] Healy *et al*., (2020), [2]DES, (2017a, 2018a; 2019b), [3]measured fire frequency > recommended fire frequency [4]intersection of fire scars (2015-2017) with REs not adapted to high fire frequency (DES, 2019b; Queensland Herbarium, 2018a).

Conclusion

Overall 602,809 km^2 (34%) of Queensland was found to be impacted by at least one of the mapped indicator disturbances described. of which 74% was mapped as remnant vegetation in 2017. This represents 31% of the total remnant vegetation of QLD. Identified indicator disturbance areas were flagged during the expert elicitation process (described in section 3.3.7), as being potentially unsuitable for the location of reference state training sites.

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Appendix 7 Draft Rapid Condition Assessment (QVAL) Method

A draft rapid field condition assessment method (QVAL) was developed to facilitate the rapid assessment of vegetation condition state-wide and across all land use categories, vegetation types and condition states. The method is based on the BioCondition assessment framework (Eyre et al. 2015; 2017) and is similarly tied to the Regional Ecosystem (RE) framework (Neldner et al. 2019).

Prerequisites to the use of this method were:

(a) a thorough and detailed understanding of the BioCondition Assessment framework, (Eyre et al. 2015; 2017).
(b) a thorough understanding of the RE Framework, (Neldner et al. 2019).
(c) familiarity with the RE's for the area assessed and their presentation in a range of condition states, (Regional Ecosystem Description Database and BioCondition Benchmarks, Queensland Herbarium 2019).
(d) an understanding of the definitions of remnant, non-remnant and regrowth vegetation under the Queensland Vegetation Management Act 1999

The method aligns with the BioCondition 1, 2, 3, 4 broad condition classification, and can be used in conjunction with available Ecological Condition Profiles (DES, 2018). To reduce subjectivity, Ecological Condition Profiles for regional ecosystems are based on available BioCondition benchmarks, where Condition Class 1 represents the reference state from which benchmark values are derived.

Various iterations of this draft method have recorded a range of attributes; however, the core rapid condition assessment attributes are:

- Site location
- Regional Ecosystem/vegetation community (Version 11)
- Broad Condition Class
- Broad vegetation status

Assessment site

The area of assessment for a rapid condition site is the same as for a standard BioCondition Assessment site - 100m x 50m (0.5ha) and should be homogenous for vegetation community and condition state. The site extent is not marked out or measured with a tape but estimated by the user with all assessments made on the vegetation within that area.

Location

GPS co-ordinates representing the approximate centre point of the assessment area.

Regional Ecosystem (RE)

BioCondition assessments are relative to the reference state for the respective RE, it is therefore critical to know which RE the assessment site represents. The user will need to assign the assessment area to a valid published RE (Queensland Herbarium 2019). The assigned RE should represent the vegetation community present on the site. In most cases this will align with the most recent RE mapping but may differ in some circumstances because of scale issues or mapping errors. Assigning an RE is a complex interpretation of landscape/landform, substrate, geology, floristic composition and vegetation structure using both field and existing land resource information and satellite imagery in a GIS environment (sections 3.2.2 and 3.2.3 in Neldner et al 2019). In some cases, advice from the Bioregional Co-ordinator may be required.

Where vegetation has been significantly modified or totally removed it may be difficult to assign a RE, in such cases if no field evidence can be found, default to the dominant RE listed for the area in pre-clear RE mapping.

Broad condition class

Estimate of the overall condition of the assessment area at the time of survey relative to an inferred reference state or 'benchmark' for that ecosystem, irrespective of recovery potential. Recorded as a score 1 - 4 as per Table 20 below. The user must estimate the score for the site relative to their experience of the same RE in a reference state. These decisions are open to some interpretation. The Ecological Condition Profiles (DES, 2018) provide quantitative guidelines, but are only available for a limited number of REs:

Table 20: QVAL method - Broad condition class

Score	Definition	Detailed description
1	Good quality remnant, relatively intact	This is mature established vegetation with no or extremely minimal disturbance from weeds, fire, grazing, clearing, thinning, fodder harvesting or any other disturbance visibly altering the structure (of any layer) or species composition of the community away from the expected definition outlined by the Regional Ecosystem description.
2	Degraded remnant or advanced regrowth	Mature established vegetation impacted by disturbance(s) which have altered the structure or species composition of the vegetation community. Typically the community will still meet the remnant vegetation criteria or be high value regrowth (VMA category C) >15 years old. Examples include native woodland with a ground layer dominated by **Cenchrus ciliaris* or *Acacia aneura* open forest with minor fodder harvesting.
3	Non-remnant, some attributes missing or significantly below BM value	Non-remnant or regrowth native vegetation impacted by disturbance events and not meeting the remnant vegetation criteria. Includes young and some older regrowth. Some attributes may approach benchmark values however other attributes are either missing or significantly below benchmark value. (e.g. exotic pastures with paddock trees and coarse woody debris, grassland with high exotic cover)
4	Non-remnant, Crops, sown pastures, requires management to restore condition attributes	Non-remnant exotic dominated vegetation including crops and exotic pastures. Low biodiversity and habitat value. Includes: tree crops/orchards, exotic pastures with isolated paddock trees. Most attributes are significantly below benchmark value

Broad vegetation status categories.

The user will need to assign the assessment area to a single broad vegetation status category. These categories are based on the definitions of remnant, non-remnant in Box 4, section 3.1 of Eyre et al. (2015), but have split into further subcategories based on landuse, floristic composition or age (Table 21).

Table 21: QVAL method - Broad vegetation status categories

Code	Modified VMA category	Detailed description
Ri	Remnant – relatively intact	Mature established vegetation that meets the remnant vegetation criteria with no or extremely minimal disturbance from weeds, fire, grazing, clearing, thinning, fodder harvesting or any other disturbance visibly altering the structure (of any layer) or species composition of the community away from the expected definition outlined by the Regional Ecosystem description
Rm	Remnant – modified (disturbed)	Mature established vegetation that meets the remnant vegetation criteria that has evidence of modification/ disturbance(s) which have altered the structure or species composition of the vegetation community, but not sufficiently to alter its remnant status. If woody vegetation: includes where the understorey has been modified/altered or weedy; or where the canopy has been modified but the area still meets remnant criteria. If non-woody vegetation: includes where species composition and or dominant canopy cover have been modified but not to the extent that it would be non-remnant.
Org	Non-remnant – older native regrowth	Areas where native vegetation has been modified/disturbed to the extent that it does not meet the remnant vegetation criteria, and recovery/regrowth has occurred for a period of > 15 years. Generally these are areas where there has been significant mechanical or chemical disturbance (clearing, poisoning, etc) and native vegetation has regrown, but may also include areas of highly modified mature vegetation.

Yrg	Non-remnant – young native regrowth	Areas where native vegetation has been modified/disturbed to the extent that it does not meet the remnant vegetation criteria, and recovery/regrowth has occurred for a period of < 15 years. Generally these are areas where there has been significant mechanical or chemical disturbance (clearing, poisoning, etc) and native vegetation has regrown
P	Non-remnant – no regrowth (pasture)	Areas where native vegetation has been modified/disturbed to the extent that it does not meet the remnant vegetation criteria, and no or minimal recovery/regrowth of native vegetation observed. Includes: areas where all or most native woody vegetation has been removed leaving a native or exotic dominated pasture with no recruitment of woody species; non-woody communities which are dominated by exotic species.
C	Non-remnant – no regrowth (non-woody crops)	Areas where native vegetation has been removed and replaced with non-woody crops. e.g. grain crops, vegetable crops, cotton, fodder crops.
W	Non-remnant – native woody veg. (native plantations, macadamia)	Areas where native vegetation has been removed and replaced with woody crops - native species. Includes native timber/forestry plantations (eucalypt, hoop pine, melaleuca), Macadamia orchards
E	Non-remnant – exotic dominated woody veg. (pine plantations, weed dominated EDL) (dominated means >50% of the EDLs cover)	Areas where native vegetation has been removed and replaced with exotic woody vegetation. Includes exotic woody crops (pine plantations, fruit tree orchards, Leucaena) and areas dominated by exotic woody weeds (Lantana, Camphor laurel etc)

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