Quantifying uncertainty in the identification of endangered ecological communities

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Abstract
Ecological community and ecosystem “red lists” have been developed in several jurisdictions to improve ecosystem-level biodiversity protection. However, a challenge for the conservation and management of listed ecosystems is consistent identification in the field or from plot records. Ecosystem descriptions must have enough detail for positive identification but be broad enough that most instances are included. In many jurisdictions, descriptions are not supported by dichotomous keys or thresholds of ecosystem collapse and identification relies on the interpretation of trained individuals, with potential for opposing opinions. Using a structured process, we assessed the ability of experts to identify a critically endangered ecological community from vegetation plot samples. We compared the allocations made by experts with a numeric classification that underpinned the legal definition of the community. Overall, experts correctly identified the presence or absence of the community in 81% of samples although individual classification rates ranged from 63% to 94%. False positive rates varied among experts (7–50%) and experienced botanists did not necessarily perform better. Disturbance increased uncertainty and experts differed in their opinion about when the community had collapsed and was no longer recoverable. Inconsistent interpretation, in the absence of diagnostic keys and consensus models of collapse, will have implications for recovery and conservation of listed communities and ecosystems, and could impact the effectiveness of laws and policies designed to protect them.

KEYWORDS
environmental policy, expert elicitation, IUCN red list, threatened ecological communities, threatened ecosystems, vegetation communities

1 INTRODUCTION
The conservation of ecosystems and ecological communities is a critical component of multi-level approaches to biodiversity conservation planning and management (Lindenmayer et al., 2007; Noss, 1996). Ecosystem-level approaches are appealing as they are potentially efficient, can capture undescribed species which may be lost before
they are recognised, and maintain ecological processes to prevent common species becoming threatened in the future (Keith et al., 2015; LaRoe, 1993; Noss, LaRoe, & Scott, 1995).

A long-running debate in ecology has centred around whether ecosystems and ecological communities occur as deterministic types (Clements, 1916), or from chance associations and human perception (Gleason, 1926; Shipley & Keddy, 1987). Yet ecologists have formulated ecosystem and community classifications at a range of scales to support a spectrum of conservation approaches (Evans, 2006; Keith, 2009; Noss et al., 1995). In the last decade, the International Union for the Conservation of Nature (IUCN) has developed structured methods for the global prioritisation and listing of ecosystems for conservation (Red List of Ecosystems; see for example Berg et al., 2014; Keith et al., 2015). A growing number of jurisdictions have also adopted regulations to support the protection of ecosystems and communities (e.g., in Australia, Norway, South Africa) (Bland et al., 2019; Botts et al., 2020; Keith, 2009). For example, in New South Wales (NSW), Australia, at the time of writing some 114 threatened ecological communities have been listed as either vulnerable, endangered or critically endangered, and their occurrence triggers laws and regulations along with the promotion of conservation actions (Box 1). Similarly, the Habitats Directive of the European Union (Council Directive 92/43/EEC) provides a legal basis for the conservation and restoration of approximately 230 habitat types, many of which are defined by their vegetation composition (Evans, 2010).

Although criteria for the description and conservation assessment of ecological communities and ecosystems are established (Bland et al., 2017; Keith et al., 2013), we are not aware of any data that examines how reliably individual types are identified by practitioners. Accurate identification is required to assess trends in status and to ensure laws are fairly and consistently applied. However, identification of ecological communities and ecosystems is complex and challenging because boundaries between communities are often indistinct and species composition can vary in both space and time. Spatial variation arises because species are distributed individualistically along environmental gradients (Austin, 1985) and their occurrence and abundance is further influenced by stochastic events (Levin, 1976), past biogeographic processes (Cracraft, 1994), human land use (Allan et al., 2015) and invasion by exotic plant and animal species (Vilà et al., 2011). Furthermore, although the restoration of disturbed and invaded habitats can contribute to the conservation of ecological communities (Clewell & Aronson, 2006; Etter, Andrade, Nelson, Cortés, & Saavedra, 2020; Saunders, Bower, Mika, & Hunter, 2021), opinions may differ about when a collapse threshold has been crossed beyond which recovery is no longer feasible (Suding & Hobbs, 2009). In the absence of criteria to

**BOX 1 Threatened Ecological Communities in NSW, Australia**

Ecological communities can be listed under the *Biodiversity Conservation Act 2016* (the *Act*) and are described in a Final Determination that is prepared by a statutory Threatened Species Scientific Committee. The *Act* provides regulatory protection to listed communities and requires the establishment of a Biodiversity Conservation Program, the objective of which is to maximise their long-term persistence.

For the purposes of the *Act* an ecological community is defined as “an assemblage of species occupying a particular area.” Each Final Determination contains four parts of which three assist identification: Part 1, description of the assemblage; Part 2, description of the particular area in which the community occurs; and Part 4 additional information to support field identification. Part 3 describes eligibility for listing including justification for status (vulnerable, endangered or critically endangered). The assemblage is restricted to native species with an emphasis on overall species composition rather than species dominance. Most assemblages are vascular plant species and are described in terms of those species that frequently occur within the community, have high fidelity and are often abundant or dominant (Preston & Adam, 2004a). The particular area in which the ecological community occurs can be specified at any spatial scale but often refers to bioregions (Thackway & Cresswell, 1995) or local government boundaries. Part 4 can include descriptions of abiotic domains (e.g., rainfall, temperature, soils), dominant species, structure (e.g., cover of growth forms and strata) and dynamics (e.g., response to disturbance). While Part 4 can assist in identification of the community, it is generally accepted that if a site meets the requirements of both assemblage and particular area, then the community is present, regardless of whether it meets Part 4 of the determination (Preston & Adam, 2004b; NSW Threatened Species Scientific Committee, 2018). In NSW, there is a clear intent to separate considerations of condition and local collapse from the description of the community in the Final Determination (Nicholson et al., 2015). Furthermore, Final Determinations lack keys or prescriptive identification tools as it is argued these might prevent the flexibility to accommodate natural ecological variability (Preston & Adam, 2004a).
support consistent assessment of condition or collapse thresholds, human-induced disturbance could increase variation among observers.

Globally, the problems associated with field identification of listed ecosystems using descriptions contained in legal determinations has forced a strong reliance on trained experts (Adam, 2009; Bunce, Bogers, Evans, & Jongman, 2013). In practical terms, this means that whether or not local evidence (abiotic environment, species composition and their relative abundance) is consistent with published descriptions is a matter of experience and opinion (Bunce et al., 2013). This is problematic because an observer's experience determines their ability to detect individual species (Garrard, McCarthy, Williams, Bekessy, & Wintle, 2013) which directly affects their capacity to identify ecological communities. Regardless of their level of expertise, individuals will also be variously subject to overconfidence, cognitive biases and reliance on heuristics to simplify the task of determining whether an assemblage of species meets a definition of a specific type (Shah & Oppenheimer, 2008; Speirs-Bridge et al., 2010; Tversky & Kahneman, 1974). Tools such as dichotomous keys or decision trees would substantially reduce variation owing to subjective judgment, however these are rarely available (Bunce et al., 2013; Preston & Adam, 2004b).

In this article, we present a case study of the diagnosis of an ecological community listed as critically endangered in NSW, Australia, under the Biodiversity Conservation Act 2016 (New South Wales Government, 2016; see Box 1). We used a structured elicitation protocol to examine variation among field ecologists and botanists in their ability to identify the community from among a set of vegetation plot samples. Specifically, we asked; (1) how well do practitioners’ opinions correspond to a quantitative reference, (2) how sensitive are their assessments to departures from typical structure and composition, and (3) do practitioners differ with respect to when they perceive individual samples have collapsed, are no longer recoverable and hence no longer form part of the ecological community? In practice, expert judgement plays an important role in identification of threatened ecological communities and variation among experts could have significant implications for the application of legislation and regulations that support them.

### 2 | METHODS

#### 2.1 | The Monaro and Werriwa tablelands cool temperate grassy woodlands

The Monaro Tablelands Cool Temperate Grassy Woodlands and the Werriwa Tablelands Cool Temperate Grassy Woodlands (CTGW) are two related grassy woodland ecological communities, restricted to south-eastern NSW, Australia (Figure 1). Both are listed as Critically Endangered under the *Biodiversity Conservation Act 2016*. An ecological community is eligible to be listed as critically endangered if it is “facing an extremely high risk of extinction in Australia in the immediate future.” The NSW Threatened Species Scientific Committee determined that both CTGW had undergone very large reductions in geographic extent, a very large degree of environmental degradation, and very large disruption of ecological processes, primarily owing to agriculture. Under current trends in land use and climate, declines are expected to continue (NSW Threatened Species Scientific Committee, 2019a, 2019b). The ecological communities have overlapping assemblages, occur as low open woodland, and with a sparse tree cover that is often, but not always, dominated by Snow gum (*Eucalyptus pauciflora*; Figure 1a). They can also occur as secondary grasslands that result from historic tree clearing (Figure 1b). The CTGW often occur in a mosaic with

![Figure 1](image-url)
other woodland and grassland communities including White Box—Yellow Box—Blakely's Red Gum Woodland and Natural Temperate Grassland of the South Eastern Highlands, which are both listed as Critically Endangered under the Australian Government's Environment Protection and Biodiversity Conservation (EPBC) Act 1999.

2.2 Workshops and expert selection

A desktop structured expert elicitation, with both real and artificial samples, was undertaken within a workshop setting (e.g., Sinclair, Bruce, Griffioen, Dodd, & White, 2018) because it enabled us to: (a) control for variation in species detectability, both among observers and arising from seasonal variation; (b) maximise the range of ecological communities assessed; and (c) reduce cost and logistics. Although experts are often required to undertake assessments in the field, experts also allocate archival plot records to types and review and revise prior allocations based on sample data alone.

We identified and approached 36 ecologists and botanists with experience working in grassy woodlands of southern NSW and of these 16 were able to participate (Data S1). We ran two 1-day workshops, each with eight experts. Experts were provided with copies of the Final Determinations 1 week prior to the workshop and asked to familiarise themselves with them.

2.3 Elicitation material

2.3.1 Experiment 1

Experts were asked to provide probabilistic judgements of whether individual samples belonged to either of the CTGW communities based on data drawn from standard floristic plot surveys. Experts were provided with 30 “sites” (14 in common) drawn from a total pool of 100. Each included a complete inventory of vascular plant species within a fixed area plot (20 m × 20 m), estimated cover-abundance for each species (Braun-Blanquet, 1932), elevation, mean annual rainfall, and substrate. Satellite images showing location were also provided (Data S2). Because the two communities were similar, we simplified the task such that experts were not required to judge which of the two were present, rather they were only asked to judge the probability that either was likely.

The pool of sites included 30 previously allocated to one of the CTGW communities through quantitative analysis (see Section 2.5). Eight were CTGW that had been artificially manipulated by either removing all trees from the floristic data description (four sites) or non-native plant species were added and between 38% and 60% of native groundlayer species were removed (four sites). One of each of these was included in the 14 sites assessed by all experts. The remaining 62 included both similar and dissimilar communities from south-eastern NSW. Expert judgments were contrasted with a quantitative reference, namely the distance of each sample from centroids calculated using the member-sets of vegetation classes upon which Part 1 of the Final Determination for CTGW were derived (see Section 2.5 below).

2.3.2 Experiment 2

Artificial vegetation descriptions were used to explore the value of additional contextual information and to examine expert judgements of restoration and conservation thresholds. Experts were each provided with descriptions of 25 vegetation patches (10 in common) drawn from a total pool of 90. These descriptions were all artificially modified from a set of five reference plots that had previously been allocated to the Monaro Tableland CTGW community through numeric analysis. Descriptions were systematically modified to generate examples with and without trees, to remove characteristic groundlayer native species and add non-native species. These modifications replicated the range of degradation that result from agricultural land use including tree clearing, livestock grazing, application of fertiliser, cultivation and pasture sowing. In addition, we supplemented plots with additional information: (1) distance from the sampled vegetation patch to the nearest Snow gum in the same landscape position (0–2000 m); (2) the presence or absence of stumps and; (3) the number of trees with a diameter at breast height > 0.5 m (large trees, range from 0 to 4 within a 20 × 50 m plot; Data S2). Each of these were also systematically varied. The final set of 90 patches spanned the potential range of condition states from diverse woodland with old trees through to isolated species poor and weed dominated pastures.

Experts were told that patch descriptions were averages estimated from multiple plots within a contiguous patch of vegetation of 1 ha, patches occurred on private land managed for livestock production, and all patches occurred within a region that modelling, mapping and research indicated had a high probability of supporting both Monaro Tablelands CTGW and Natural Temperate Grassland.

2.4 Probabilistic elicitation

Experts were asked to provide their judgement of the probability that each sample belonged to the CTGW
(Experiments 1 and 2), had crossed a low condition threshold and should not be protected as the CTGW (Experiment 2), or could be successfully restored given reasonable management inputs (Experiment 2). Judgements were elicited using a three-point probability scale (Soll and Klayman, 2004; Burgman, 2016). In each case experts were asked to assign their lowest, highest and most likely probabilities, with questions structured following the guidelines recommended by Burgman (2016) (see Data S3 for scenarios and question formats).

Subsequent to assigning their probabilities of CTGW, experts were asked to nominate a single vegetation type they thought the plot best belonged to, by selecting one of CTGW, Wet Sclerophyll Forest, Dry Sclerophyll Forest, Box-Gum Grassy Woodland, Natural Temperate Grassland, Secondary grassland but not CTGW, or Other. For analysis these data were converted to a binary classification (CTGW and Other).

Experts were given fixed timeframes to assess as many samples as possible, including the common samples. Following elicitation of CTGW probabilities, graphical summaries of the common samples were prepared after anonymising the experts (Data S4.1–S4.4). Facilitated discussion was held based on these graphical summaries, after which experts were given the option of independently revising their judgements.

### 2.5 Numeric allocation of sites

Of the 100 plots in Experiment 1, 21 represented vegetation groups unrelated to CTGW (e.g., wet sclerophyll forests and dry sclerophyll forests). For the remaining 79 plots we used noise clustering (Wiser & De Cáceres, 2013) to quantify resemblance to CTGW as the distance to relevant class centroids (Data S5). Noise clustering allows the computation of fuzzy membership coefficients for each plot in relation to each centroid and identifies which plots are apparently transitional between classes or potentially representative of new classes not included as fixed centroids. Fuzzy membership coefficients are bounded within the range 0–1 and can be thought of as vague probabilities that a given plot is drawn from a specific group (Wiser & De Cáceres, 2013). This approach reduces the problem of misallocations associated with “hard” clustering algorithms such as traditional k-means, which require each sample to be allocated to a cluster irrespective of the level of resemblance to centroids.

Class centroids were calculated using the same sample member-sets used in the circumscription of the Monaro and Werriwa CTGW and related vegetation types. The descriptions (assemblage of species, environmental characteristics) contained in the Final Determinations of the CTGW communities were based on these same member-sets and hence we argue that the derived membership coefficients reflect the intent of the legal definitions, and are an appropriate reference for quantitative comparisons.

Our data were relatively heterogeneous therefore we determined hard membership of classes using a minimum coefficient threshold of 0.2. For each sample, the highest coefficient of membership for either of the two centroids representing CTGW was treated as the estimate of the numeric relationship to the CTGW complex. The 21 sites that were a priori excluded from this analysis were all assigned a membership coefficient of 0.

### 2.6 Data analysis

We examined variation in expert allocations to CTGW (Experiments 1 & 2), expert judgment of whether patches could be restored (Experiment 2) and their estimates of whether the patch was likely to be of low condition and hence not requiring protection (Experiment 2). Our analysis utilised equally weighted average distributions, binary allocations to vegetation type (CTGW or Other) and modelling of individual estimates of most likely probabilities drawn from the 3-point elicitation. In Experiment 1, we were able to compare expert estimates and binary classifications with those of the numeric classification of plots to vegetation types.

#### 2.6.1 Model fitting

In all cases we assumed the response data were proportions and could be modelled using a beta regression with a logit link (Ferrari & Cribari-Neto, 2004). For Experiment 1, models were fitted separately to; expert most likely estimates, and the maximum membership coefficient to one of the CTGWs. Models were used to estimate parameters associated with three non-correlated variables; the cover abundance of Snow gum (“Snow Gum C/A”), the richness of characteristic species from either Final Determination (“Characteristic spp”), and the richness of non-characteristic tree species present within the plot (“Non-characteristic tree spp”). Non-characteristic tree species were any species allocated by Oliver et al. (2019) to the tree growth form and not listed in Part 1 of either Final Determination.

For Experiment 2, separate models were fitted to estimates of the probability that the patch was the CTGW, could be successfully restored, and had crossed a low condition threshold. The model for CTGW included the variables “Snow gum C/A”, “Characteristic spp”, distance to nearest Snow gum in the surrounding landscape (“Distance to snow gum”), and the presence or absence of tree stumps (“Stumps P/A”). Non-characteristic tree species were absent from all plots used in stage 2.
Models of restoration probability and probability the patch was below the low condition threshold were fit using four potential indicator variables: (1) the richness of native forb species (“Native Forb R”), (2) the log of the ratio of summed native ground cover to summed exotic plant cover (“Log N:E Cover”), (3) the number of trees with stem diameter at breast height > 50 cm (“Large Trees”), and (4) whether the site had been allocated by the expert to CTGW (binary variable, CTGW or Other). We included expert binary allocations to vegetation type in the model to allow for differences in restoration and low condition thresholds among CTGW and other vegetation types.

Previous studies have shown that expert judgment of condition in similar grassy ecosystems are positively correlated with richness of native forbs (Dorrough et al., 2020; Sinclair, Griffioen, Duncan, Millett-Riley, & White, 2015), a group that dominates plant diversity, includes many species sensitive to land use intensification and are challenging to restore owing to competition with exotic plant species, lack of propagule material, and imperfect knowledge of germination and establishment requirements (Clarke, 2003; Cuneo et al., 2018; Dorrough, McIntyre, & Scroggie, 2011). Dominance by non-native plant species may indicate historic disturbance and elevated soil nutrients, while non-native species can directly compete with native species and reduce probability of restoration success (Corbin & D’Antonio, 2010; Prober, Thiele, & Lunt, 2002). Large trees provide disproportionate habitat and ecosystem values in grassy woodlands and take many decades to restore (Manning, Fischer, & Lindenmayer, 2006).

All native species were allocated to primary growth forms as per Oliver et al. (2019). Individual plant species cover abundance were transformed to foliage cover as per McNellie, Dorrough, and Oliver (2019). We calculated the summed richness of native forbs, summed foliage cover of groundlayer native species (grasses and grass-like, forbs) and the summed foliage cover of non-native (exotic) plant species within each site.

Prior to fitting, continuous variables were converted to z-scores using means and standard deviations obtained from the full datasets. To ensure values fell between (0,1), response variables were transformed as:

\[ y_i = \frac{y \times (n - 1) + 0.5}{n} \]

where \( n \) is number of observations, \( y \) is the value of the response and \( y_i \) is the transformed value.

Random intercepts were estimated for expert and site for all models.

Models were fit with default weakly informative priors for the fixed effects, random intercepts and the dispersion parameter in all cases except for the Experiment 2 model of expert predictions of CTGW (Data S6). Informative priors for the intercept, richness of characteristic species and the cover abundance of Snow gum were derived from the model of expert likelihoods in Experiment 1 and used in analysis of Experiment 2 elicited probabilities of CTGW (Data S6).

Posterior simulations of the model parameters, given the observed data, were estimated using the No-U-Turn Hamiltonian Monte Carlo sampler within Stan (Carpenter et al., 2017). Models were fit using the package rstanarm (Goodrich, Gabry, Ali, & Brilleman, 2018) within R (R Core Team, 2018). Posterior distributions of the parameters were estimated from four chains, each with 1000 iterations obtained after discarding the preliminary 1000 iterations. The convergence of models was assessed using standard visual diagnostics (autocorrelation and trace plots) and inspection of effective sample sizes (min. 1000) and rhat values (<1.01). The fit of models to the observed data was visually assessed by plotting 100 samples from the posterior predicted distribution \( \hat{y} \) and the observed densities.

### 2.6.2 Unweighted average estimates and comparison with numeric allocations

Unweighted average estimates of most likely, lower and upper probabilities were estimated for each sample with three or more observations. For Experiment 1 data these were plotted against estimates of the maximum fuzzy membership coefficient. Classification rates (true positive, true negative, false positive, and false negative) were estimated across all samples and experts using the expert binary allocations to CTGW and the noise clustering allocations (converted from nine classes to CTGW or Other).

In Experiment 2, the relationships between expert binary judgments of vegetation type, the probability of restoration success and the probability that the patch was of low condition were visually examined. We expected a negative relationship between probability of restoration success and probability of low condition. However, the nature of this relationship might differ among experts and depending on whether experts considered the site to be CTGW. Experts may be unlikely to identify a patch as the CTGW if they consider it to have collapsed and be no longer recoverable.

### 3 RESULTS

#### 3.1 Experiment 1

**3.1.1 Are expert and numeric allocations consistent?**

Experts each assessed between 18 and 30 sites resulting in 409 judgments. Average estimates of 14 common sites...
were reasonably consistent with the numeric classification to type (Figure 2a) and while the judgment of some experts was correlated with the fuzzy membership coefficient (e.g., expert 6), others were less so (e.g., expert 2; Data S4.5). Of the 42 sites with three or more assessments there was only one with a numeric allocation to CTGW and an average expert probability <0.5 (Figure 2b), and this site had been artificially manipulated to remove trees. Four out of a total of 28 sites a priori allocated to other vegetation types had average expert probabilities >0.5 and Snow gum was present in all cases (Figure 2b). Artificial manipulation of site descriptions through removal of trees increased the range of expert opinion (Figure 2c CTGW Secondary), while removal of characteristic species from the groundlayer had little apparent effect (Figure 2c CTGW Degraded).

Classification rates (81%) and true positive rates (88%) based on binary assignments to vegetation type were relatively high (Table S4.1). Classification rates ranged from 63% up to 94% among individual experts, primarily owing to variation in false positive rates. False positive rates among all observations were almost double that of false negatives (23% cf. 12%) and individual false positive rates were as high as 50%. Those experts who rated themselves as experienced botanists on average had higher false positive rates (Figure S4.6). Snow gum was present within 71% (42/49) of the false positive observations and was absent in 79% (15/19) of false negative observations.

Beta regression models of expert probabilities and membership coefficients provided reasonable fits to observed distributions (Data S7). The cover abundance of Snow gum was strongly positively associated with the probability of CTGW occurrence among experts but was less influential in the model of membership coefficients (Figures 3a,b and 4). In contrast, the number of characteristic species, while having a positive effect in both models, was relatively more important than either Snow gum cover abundance or the richness of non-characteristic trees in the model of membership coefficients (Figures 3a,b and 4). Both models similarly predicted low likelihoods of CTGW when Snow gum was absent and there was a diversity of noncharacteristic tree species (Figure 4).

3.2 | Experiment 2

3.2.1 | Probability the patch is CTGW

The beta regression model of expert probabilities of CTGW provided a good fit to the observed data (Data S7). Expert probabilities of CTGW were negatively correlated with distance to nearest Snow gum in the surrounding landscape.
and positively correlated with the presence of tree stumps within the vegetation patch (Figure 3c). Parameter estimates for both the richness of characteristic species and the cover abundance of Snow gum were similar in both Experiments 1 and 2 (cf Figure 3b,c). In landscapes where CTGW is expected to occur, yet have been modified through agricultural land use, the presence of relict features such as stumps or remnant Snow gum, appear to influence expert judgments of whether the community is present.

3.2.2 | Expert judgment of restoration and low condition probabilities

Pooled probabilities of restoration success and low condition were negatively correlated among the 10 common sites (Figure 5a). Those sites allocated by most experts to CTGW tended to be skewed towards the top left quadrant (high probability of successful restoration and low probability of being below the low condition threshold; Figure 5a). On average, experts tended to assume probabilities of restoration success were higher in sites they had allocated to CTGW and probabilities of low condition were higher in those allocated to other vegetation types (Figure 5b,c). Similar patterns were evident among some individual experts, although there was substantial variation (Figure 5d). Although the relationship between probabilities of restoration and low condition were approximately linear for many experts (e.g., experts 4, 6, 8, and 10), this was not always the case. In extreme cases relationships ranged from convex (risk averse, for example, expert 7) to concave (optimistic, for example, expert 2).

Variables indicative of vegetation quality; native forb richness, native: exotic cover and the number of large...
trees, were correlated with expert judgment of probabilities of restoration success and low condition (Figure 6). Sites considered likely to have high probabilities of restoration success and unlikely to be low condition had more native forb species, were dominated by native plant cover in the ground layer, and tended to support large trees. Parameter estimates confirmed sites previously allocated by the experts as CTGW on average had higher probabilities of restoration success and were more likely to be above the low condition threshold.

### 4 | DISCUSSION

Our results suggest that experts were often consistent in their diagnosis of occurrences of CTGW when it was relatively undisturbed. However, the choice of expert made a difference, especially in those cases when the community had been modified through loss of the tree canopy and changes in the ground layer. Variation among experts in their estimates of presence and probabilities of restoration success and of crossing a low condition threshold, likely reflect differences in the degree of modification that individuals will tolerate and differing belief about when an ecosystem has collapsed. Given the challenges of defining and quantifying thresholds of ecosystem collapse and degradation (Bland et al., 2018a; Cumming & Peterson, 2017), it is unlikely that these differences can be easily resolved.

The operational effectiveness of laws to protect threatened ecological communities will rely on the ability of individuals to make consistent and accurate judgments of when a particular community is present. In practice, in those jurisdictions where threatened ecological communities are protected by law, there is an expectation that they can be identified with reasonable certainty (Preston & Adam, 2004a). Inconsistent identification could lead to diverging regulatory outcomes and create legislative uncertainty. This is not simply speculative. In New South Wales, where CTGW is listed, expert ecological judgment is often relied upon in court to resolve matters relating to development activities and the potential occurrence of threatened ecological communities. In such cases it is not uncommon for experts to disagree on both the presence or extent of a particular ecological community (e.g., Commercial & Industrial Property Pty Ltd v Holroyd City Council, 2013; Hornsby Shire Council v Vitone Developments Pty Limited, 2003). Such uncertainty could affect assessment of potential impacts and even erode confidence in ecological community descriptions and the laws and policies that support them.

#### 4.1 | Expert classification rates

Although most experts had classification rates >80% in the first experiment, false positive rates were often high. Some experts may err on the side of caution. A
tendency to overestimate occurrence may minimise unintended loss, and is consistent with the precautionary principle (Myers, 1993). False positives can also have undesirable outcomes, including restricting management options, misdirecting conservation funding, poor selection of environmental offsets or potentially prosecution.

Experts who participated in the elicitation were field botanists with a range of experience of CTGW and similar vegetation types in south-eastern Australia. Although on average experts performed well against the numeric classification, the most experienced and confident tended to have the highest false positive rates. Other studies have found that experience is not always a good predictor of
performance (Burgman et al., 2011). Our facilitated discussions suggested that first-hand experience and prior knowledge of other vegetation classifications (Armstrong, Turner, McDougall, Rehwinkel, & Crooks, 2013; Costin, 1954; Gellie, 2005; Tozer et al., 2010) potentially contribute to individual-specific models of what constitutes CTGW, particularly among some experienced experts. While individual models are potentially valid interpretations of vegetation distribution and ecosystem processes, individuals with strongly held prior opinion may be less receptive to the detail of the Final Determinations, which may not be helpful when interpreting legally binding community descriptions.

False negatives, which could result in failure to provide adequate protection to true examples of the community, were rare and primarily limited to when Snow gum was absent, and the community occurred as a secondary grassland. Although we were not able to compare expert allocations to a numeric model in the second experiment, additional information (evidence of stumps and distance to Snow gum) contributed to expert opinions and may be particularly drawn upon when trees are absent.

For practical reasons, our study was unable to incorporate inspection of samples in the field. Although in practice experts may allocate individual plot samples to types in a desktop setting (Chytrý et al., 2020), their judgments are most often informed through field assessment. Field assessment may improve the ease with which an observer visualises species abundance and structure while also providing useful contextual information not available in desktop samples. Conversely, field assessments also bring their own sources of uncertainty with potential variation owing to timing and methods of survey, and differing ability of individuals to detect, identify and estimate the abundance of individual species (Morrison, 2015). Further studies are required to evaluate whether similar classification rates would arise in field settings.

This study considered only a limited range of vegetation communities and the classification rates we observed may not be applicable in all circumstances. In many jurisdictions there is no fixed scale at which habitats, communities or ecosystems can be defined for protection under law (Adam, 2009). Tightly described communities with a limited distribution may be more readily identified than those with both a broader distribution and more variable species composition. Similarly, where ecosystems are defined by reference to edaphic factors (e.g., geomorphology and climate) rather than vegetation composition, expert subjective judgments may be less variable. Nevertheless, our study highlights problems that are likely to be applicable to the identification of listed ecosystems generally, to a greater or lesser degree.

4.2 | Expert opinions are strongly influenced by the dominant tree species

Results suggest that experts give more weight to dominant species than overall floristic composition. NSW-listed ecological communities are based on compositional classes, and as such there is an expectation that the entire assemblage is considered, not simply the dominant species present (Keith, 2009; Preston & Adam, 2004a).

Individuals often use simple heuristics when faced with complex data (Shah & Oppenheimer, 2008; Tversky & Kahneman, 1974) and when judging whether a site conforms to a community assemblage, experts may focus on what they perceive as key attributes. The results suggest a hierarchical heuristic of decreasing importance and increasing complexity; (1) Is Snow gum abundant? (2) Are non-characteristic trees present? (3) Are many species from the listed assemblage present? Presumably if the first is satisfied, individuals may already be inclined to assign a high probability, which is a far simpler task than considering the entire assemblage.

The implications of this focus on dominant species is likely to vary depending on the degree to which patterns
in species dominance correlate with overall composition across the landscape. In this study, the dominant overstorey species occurs in a wide range of vegetation communities (Armstrong et al., 2013) and assessing this species alone would over-estimate the true distribution, a pattern consistent with the higher rate of false positives among experts. In this instance a wider range of ecosystems will be protected than was intended, but in other situations the converse could be true, and such outcomes may undermine confidence in ecological community regulations.

4.3 | Indicators and thresholds of ecosystem degradation and potential for recovery

Our results suggest that simple indicators derived from vegetation survey can predict expert perceptions of vegetation condition and restoration potential. However, individuals do apply different thresholds when making decisions. Variation among experts is not surprising as they likely differ in both their experience and subjective assessment of condition, restoration success and conservation value.

While the indicators we used may be reasonable proxies for condition and potential for recovery, it would be ideal if quantitative thresholds were derived from ecological data (Bland, Rowland, et al., 2018a). Indicator variables, whose measurement identifies when an ecosystem approaches a threshold, should themselves be chosen based on their known relationships with defining ecosystem attributes and processes (Dale & Beyeler, 2001). However, in practice there may be little quantitative data to define thresholds, while choice of potential indicators can itself be subjective (Rowland et al., 2018). In the absence of appropriate data, the approach we describe here may be a useful starting point although the modelled predictions do reflect average judgments and may not resolve divergent opinions. Furthermore, in our case, it was apparent that although the experts exhibited varying degrees of specialisation, there was tendency toward vegetation survey and classification. Inclusion of additional experts with relevant experience in ecological restoration could improve the reliability of predicted thresholds.

4.4 | Should listings be more prescriptive?

Prescriptive descriptions of threatened ecological communities, supported by dichotomous keys or classification methods, would improve consistency of application. However, a consideration in the formulation of descriptions is the need for enough detail to permit confidence in identification without being so prescriptive examples are excluded (Keith, 2009). Other jurisdictions have attempted to resolve inconsistencies through use of condition thresholds that identify when a threatened community is no longer present (Beeton & McGrath, 2009). Mills (2006) suggests that excluding degraded areas minimises regulatory burden for landowners and reduces risks of overestimating current geographic distributions. However, we have shown here that opinion on condition and recovery thresholds differ among individuals. Thresholds will also vary depending on economic and social contexts, including resources available for restoration, competing land uses and land use trends. If condition or collapse thresholds are used to limit where a community is considered present, they should be identified using transparent and structured methods that explicitly describe underlying data, potential limitations and bias (Bland et al., 2018b; Drough et al., 2020).

5 | CONCLUSION

Field identification of ecological communities requires consideration of diverse and complex data. In the absence of deterministic tools to support identification there is potential for variation among observers which may impact effective protection of threatened communities. We suggest that differences among observers will be greatest when a community has been modified through past land use. These differences arise owing to varying opinion about which defining features must be present for the vegetation patch to function as part of the community. In the absence of clear quantitative data, regulatory assessment methods based on structured elicitation of expert opinion of indicators and thresholds of collapse, could reduce some uncertainties associated with the application of threatened ecological community and ecosystem descriptions.

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CONFLICT OF INTEREST
The authors declare no conflict of interest.

AUTHOR CONTRIBUTIONS
Josh Dorrough, Gregory Summerell, and Mark Tozer conceived the research. Josh Dorrough and Rob Armstrong designed the study, ran the elicitation and collected the data. Josh Dorrough processed the data and led the analyses, figure preparation and writing. Mark Tozer undertook the noise clustering analyses. Josh Dorrough, Mark Tozer, Rob Armstrong, Gregory Summerell, and Mitchell L. Scott contributed to the interpretation, writing and editing of manuscript drafts.

ETHICS STATEMENT
Research protocols were reviewed and approved by the Science Economics and Insights Division, NSW Department of Planning Industry and Environment. This manuscript describes original work, has not been published, and is not under consideration for publication elsewhere.

DATA AVAILABILITY STATEMENT
Data and R-script to run analyses are available through figshare: Model code: 10.6084/m9.figshare.13026155. Experiment 1 data: 10.6084/m9.figshare.13025147. Experiment 2 data: 10.6084/m9.figshare.13026125.

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