Identifying good condition in native vegetation: A Bayesian regression and decision theoretic approach

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EXTENDED ABSTRACT

Vegetation condition assessment tools have been developed throughout Australia in response to vegetation management legislation and policy requirements for a metric that can be used to demonstrate duty of care. Queensland's tool BioCondition is based on the pioneering Habitat Hectares framework developed in Victoria and the Biometrics approach used in NSW. It comprises three components: (A) a standardized field methodology; (B) a set of easily measured attributes that act as surrogates or indicators of biodiversity values; and (C) a set of preliminary benchmarks that discriminate sites with undisturbed remnant vegetation from more disturbed sites, for each attribute and for each ecosystem type.

Current heuristic approaches to setting these benchmarks use the median value derived from 'Best on Offer' (BOO) sites. An expert-defined score, based on various disturbance factors and ecological maturity of the site, is used to identify BOO sites. For this project we considered statistical approaches to setting benchmarks, based on determining how sensitive a vegetation condition indicator is to various disturbance factors. In this paper we present data-driven approaches for cases where appropriate data is available. Otherwise, in the common situation with no data, expert elicitation methods were examined, but are reported elsewhere. Even when data for benchmarking is available, different benchmarks, and therefore different models for assessing sensitivity, are required for *each* ecosystem type. Indeed certain indicators may not be relevant in some ecosystems, e.g. large trees in mulga landscapes of western Queensland.

For a data-driven approach we must first assess how sensitive an indicator is to a range of different disturbance factors. This was facilitated by statistical modelling within an overall Bayesian decision analytic framework as defined by Gelman *et al* (2004). This framework was chosen since it provides (I) flexibility in selecting the statistical model to describe the sensitivity of the vegetation condition attribute to disturbance, and (II) a consistent basis for setting a benchmark. A cost function is defined to balance the need to avoid misclassifying relatively disturbed sites as being in good condition, as per the Precautionary Principle (QEPA, 1999), with the need to avoid false alarms when relatively undisturbed sites are assigned poor condition.

Different statistical modelling approaches were found useful for assessing different indicator responses to disturbance. These included regression trees, ordinary and generalized linear models (GLMs), hierarchical GLMs and mixtures of regressions. We present results for a selection of attributes in *Corymbia citriodora* (Spotted Gum) forests from southern central Queensland, for which different surrogacy models applied: a regression tree for number of large trees; a Poisson regression for fallen woody debris counts; and a hierarchical Beta-Gamma regression for average litter. Mixture of regression results are omitted for brevity.

Models used to assess sensitivity can also be used to estimate credible ranges for the effect of each disturbance and ecological maturity factor on these vegetation condition indicators. Describing uncertainty using these models helps ecosystem managers to better understand how well we can measure the indicator's response to aspects of disturbance using existing data, and therefore how to target future monitoring activities to support benchmarking.

In conclusion, we demonstrate that regression within a Bayesian decision analytic framework can be a flexible and in this case, more appropriate, alternative to existing approaches based on correlation and single heuristic scores.

1. INTRODUCTION

Monitoring vegetation condition is an essential foundation of many biodiversity protection and environmental management activities, such as adaptive management of forestry resources and implementation of tree clearing legislation (QEPA 2004). To demonstrate duty of care by landholders, several vegetation condition assessment tools have been developed in Australia: "Biometric" and "Habitat Hectares" (Oliver, 2004). Based on these methodologies, the Queensland tool "BioCondition" has three main components: (A) a standardized sampling protocol and field methodology; (B) a set of easily measured attributes that act as surrogates or indicators of biodiversity values; and (C) a set of preliminary benchmarks that discriminate sites with undisturbed remnant vegetation from more disturbed sites, by attribute and ecosystem type.

Currently, selection of indicators is based on those proposed nationally, in line with international trends, via scientific and stakeholder consultation (Oliver, 2002). The set covers several themes, primarily overstorey and understorey structure, and others such as weeds, fallen woody material and the presence of large and mature trees. In this paper we report research on assessing adequacy (B), and developing benchmarks (C), of these indicators for particular vegetation types in Queensland. Benchmarking provides a simple system with well-defined thresholds that discriminate good from poor vegetation condition.

Following the *Pressure-State-Response* ecological model for environmental reporting (QEPA, 1999) indicators are more effective if they measure the *state* or condition of vegetation in a way that is sensitive to disturbance *pressures*. Condition can then be managed through landholder or legislative *responses* addressing these pressures. Typical facets of disturbance impacting on native vegetation condition at landholder scale include grazing; fire both wild and prescribed; erosion; logging and other silvicultural treatment. These disturbance factors in isolation or combination can result in changes in the structure of the community and are generally associated with less mature overstorey. We thus require indicators that show clearly increasing response (changing vegetation condition), and so are sensitive, to increased levels of disturbance and less mature overstorey.

Current heuristic approaches to setting these benchmarks use the median value of 'Best on Offer' (BOO) sites. This score is based on an unweighted sum of expert ratings of the site on different facets of disturbance, then effectively multiplied by the site's maturity score, and categorized from A-D using expert-defined thresholds. Category A corresponds to BOO sites. This expert-defined disturbance/maturity score embodies several implicit assumptions. A single disturbance score assumes (a) *all* indicators respond to an overall level of disturbance, rather than to distinct disturbance factors. Using an unweighted sum assumes, for each indicator, that (b) *all* disturbance factors have an adverse effect, and (c) *equal* impact. The overall moderation by maturity assumes that (d) ecological maturity of a site moderates the effect of each disturbance factor in the *same* way. Thresholds defining BOO sites are set by experts, so presume (e) some *unknown* tradeoff between misclassifying good condition and poor condition, and (f) the same BOO sites represent best condition for *all* indicators.

A related problem of testing surrogacy of ecological indicators is often addressed through assessment of correlation (e.g. Moritz *et al*, 2001). Using correlation in this context would assume in addition that: (g) the indicator is at its maximum (minimum) when the underlying disturbance level is zero (maximal); and similar to (d) that all disturbance measures impact on the attribute to the same degree and do not act in concert.

In this paper we examine statistical approaches to setting benchmarks. Using regression we may investigate the pressure-state relationship, and test assumptions inherent in previous approaches. More than one covariate allows that (b) each disturbance factor may have adverse *or positive* effect and (c) may have *different* relative impact compared to other factors on each indicator. Including interactions means (d) ecological maturity of the site may moderate the effect of each disturbance factor *separately*. Separate regressions for each indicator addresses (a) and allows (f) that a *different* set of BOO sites may reflect good condition specific to an indicator. Non-zero intercept means (g) the indicator may be nonzero even for disturbed sites.

The particular regression model appropriate for any indicator is difficult to prescribe in advance. Instead we consider a spectrum of linear regression methods for data-driven assessment of an indicator's sensitivity to disturbance/maturity. The regression equation provides an alternative to the expert-defined score that effectively calibrates weights for each disturbance/maturity measure of vegetation condition to particular indicators.

Developing benchmarks is constrained by information available and accessible on each indicator. There are two levels of information which typically represent the current state of data availability on vegetation condition in Queensland. The most common *data-poor* situation is where expert knowledge is available, but with little quantitative measurement of vegetation condition. Expert elicitation methods for addressing this situation are documented elsewhere (Low Choy *et al*, 2005a). This paper focuses on the opposite *data-only* situation where moderate data is available, although this information may have arisen from a monitoring program with different objectives, such as the Regional Forest Agreement process or other similar planning processes (QEPA 1999). Here we apply Bayesian regression with non-informative priors for data-driven results.

Finally we propose a flexible Bayesian decision theoretic framework for setting benchmarks. This addresses assumption (e) by *specifying* the tradeoff between misclassifying good condition and poor condition. This framework applies equally to the data-poor situation using prior scores based on expert elicitation rather than expert-defined scores, and the data-only situation, using posterior scores.

2. DATA

Vegetation condition indicators of potential interest to environmental managers numbered over a hundred. In this paper we present a general approach suitable for all data types but to save space, give details only for counts and proportions.

Ecologists with expertise in vegetation condition followed the expert panel approach of Parkes *et al* (2003) to distil their conceptual model for major factors defining vegetation condition and derive a reduced set of indicators. This set, arrived at through consensus across nearly twenty experts, was considered to (EPA, in prep.): (i) capture the main elements of vegetation condition; (ii) be sufficiently simple and robust for use by landholders; and (iii) be sensitive to disturbance changes. A subset of these indicators was selected for further statistical investigation to (a) test their sensitivity to disturbance and (b) identify benchmarks which discriminate good from poor sites. The case study examines two examples: amount of fallen woody debris, and average litter cover.

Different disturbance factors were investigated as detailed in Section 1. Levels of impact were based on expert-based assessment in the field on a scale from 0 to 4; increasing values indicate increased disturbance. Confidence in accuracy of scores was moderate, however, as a result of the inherent subjectivity and qualitative nature of the measures. In addition ecological maturity was used in the study as an important factor influencing vegetation condition. Its measurement was based on the proportions of growth stages in the tree layer. This ranked study sites into 4 classes of maturity from most mature, typified by older forests, to least mature, where the tree layer is dominated by regenerating trees. These disturbance scores and maturity score were used as input to the expert-defined score (Section 1).

Some indicators may respond to disturbance in different ways depending on vegetation type. An initial assessment focused on two clearly defined vegetation types for which datasets of moderate size were available. These are forests in southern central Queensland dominated by Spotted Gum (*Corymbia citriodora*) or else by Poplar Box (*Eucalyptus populnea*). Depending on vegetation type and indicator, 60–100 sites were selected for analysis. This was considered adequate representation, and did not contain replicates or other forms of pseudo-replication. Benchmarking and sensitivity modelling approaches are illustrated in Section 4, in the data-only case, on two indicators in Spotted Gum. This forms part of a larger assessment (Low Choy *et al*, 2005b).

3. METHODS

Initially it was hoped that it would be sufficient to compare the distribution (mean and variability) of an indicator across categories of the expert-defined score (Section 1), where A comprises relatively undisturbed mature sites and D relatively disturbed immature sites. This approach applies when gold standards of condition are available, e.g. trigger values for physico-chemical water quality parameters (DEH, 2000). However this score was found to give poor discrimination between good and poor sites, for all attributes, e.g. fallen woody debris (Fig. 1) does not increase or decrease consistently with this expert-defined score.

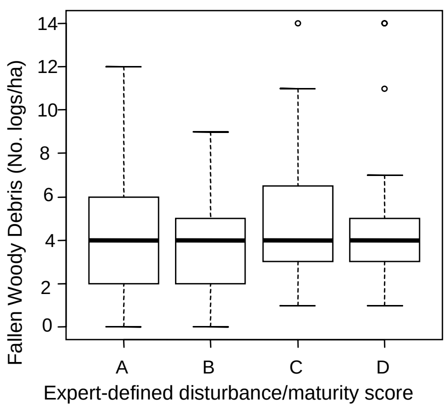

Figure 1. Distribution of fallen woody debris, for sites scored in good (A) to very poor (D) condition using the expert-defined score.

We initially assessed implicit assumptions (Section 1) behind the expert-defined score via exploratory multivariate statistics techniques (Low Choy *et al*, 2005b). Principal components and factor analysis did not confirm the assumptions (a-c) that weights in the score were all equal to one. Canonical correspondence analysis did not identify a simple way to explain variability between a set of vegetation condition indicators and disturbance/ maturity factors. Classification trees were used to test (a) whether different disturbance/maturity regimes form each category of condition. We found that, for example, a C class site could arise from high levels of logging coupled with low levels of grazing and silvicultural treatment, or equally, low levels of logging but high levels of fire. These sub-divisions of the expert-defined score still led to poor discrimination of good condition. This suggested that further modelling be based on separating the score into its constituent measures of maturity and disturbance factors.

3.1. Data-driven models assessing surrogacy

A normal regression model for condition indicator y with expected value $E[y] = \mu$ is

$$y \sim N(\mu,\sigma^2) \text{ with identity link } \mu = \eta \quad (1)$$

with score η determined by up to M disturbance factors $\{x_m\}$, weighted by coefficients $\{\beta_m\}$

$$\eta = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_M x_M \quad (2)$$

Two-way interactions were considered as additional x terms. In this case with at most 100 sites and 7 disturbance factors, and an uneven experimental design, care was required to interpret interactions among the disturbance/maturity factors, e.g. without a full factorial design, some interactions were in fact main effects or conditional. Also, since data is observational, coefficients occurring later in the score represent the additional effect of a disturbance factor after eliminating preceding ones. For Bayesian implementation uninformative priors were selected. Normal priors with zero mean and large variance were selected (Box & Tiao, 1992) for the regression coefficients. In addition to the usual conjugate Gamma prior for the precision, truncated (Normal or Uniform) priors for standard deviation were also considered (Gelman, 2005).

$$\beta_m \sim N(0,\xi_{\max}) \quad (3)$$
$$\tau = 1/\sigma^2 : \mathrm{Ga}(a,b) \text{ or}$$
$$\sigma : N(0,\varphi_{\max})(0,\infty) \text{ or } \sigma : \mathrm{Unif}(0,2\varphi_{\max}]$$

Here φ_{max} and ξ_{max} are reasonable upper limits.

We consider the extension to the non-normal case via Generalized Linear Models (McCullagh & Nelder, 1989) for most indicators. For Poisson distributed counts such as fallen woody debris, we consider a log link to disturbance factors:

$$y \sim \mathrm{Poisson}(\mu) \text{ with } \log(\mu) = \eta \quad (4)$$

with priors for regression coefficients as in (3). This can be extended using dispersion parameter γ to relieve the Poisson constraint for equal variance and mean. This hierarchical Poisson-Gamma model has been developed to account for overdispersion (e.g. Frey & Cressie, 2003):

$$y \sim \mathrm{Poisson}(\gamma\mu) \text{ with } \gamma \sim \mathrm{Ga}(a, b) \quad (5)$$

with same link g from mean μ to regression coefficients (2). A sensible choice for Gamma hyperprior parameters is to assign the mode $(a-1)/b$ a value of one to enable assessment of whether there is under- ($\gamma < 1$) or over-dispersion ($\gamma > 1$). This leads to consideration of values $b=a+1$. Then a can be chosen to match a high though reasonable 95th percentile or variance.

Similarly a Beta-Gamma model may be applied to proportional data:

$$y \sim \mathrm{Beta}(\gamma\mu, \gamma\mu(1-\mu)) \text{ with } \gamma \sim \mathrm{Ga}(a, b) \quad (6)$$

with logit link to the regression score, $\mathrm{logit}(\mu)=\eta$ and hyperprior parameters a and b as above.

Another useful extension to regression is a mixture of regressions (Quandt & Ramsey, 1978; Hurn et al, 2003) which models different regression relationships for different groups of sites. This is useful when the factor determining the grouping has not been measured or identified so cannot be used as a predictor in the regression equation (2). In particular this approach may identify "outlier" sites that do not respond to disturbance. More details and results are provided in Low Choy *et al* (2005).

Bayesian regression models were implemented using Gibbs Sampling in the package *WinBUGS* (Spiegelhalter et al, 2002). Convergence was assessed using the *CODA* package (Plummer et al, 2005) for *R* (R Development Core Team, 2005).

Regression trees (Breiman et al, 1984) were also used to assess whether an indicator changed abruptly with respect to disturbance/maturity gradients. Fully Bayesian approaches to fitting regression trees are still under development, since their computation requires advanced techniques (Chipman et al, 2002). We therefore used a non-Bayesian optimization cost-function based approach of the recursive partitioning algorithm: *rpart* package (Therneau & Atkinson, 2005) for *R*.

3.2. Decision framework for Benchmarking

The Bayesian regression approaches outlined above define posterior distributions of parameters β. Parameter estimates alone are not sufficient for decision-making. Following Gelman *et al* (2004) we superimposed a decision analytic framework over the model, to explicitly provide a decision rule as a cost function based on these parameter estimates. The benefit of this Bayesian framework (Cooper et al, 2004) is that uncertainty in the cost is directly obtained from uncertainty, or posterior variability, in parameters. Where data is unavailable prior distributions of parameters may be used for initial estimates of costs of decisions.

Of interest here is a benchmark or threshold which separates sites in good from poor condition. One way to achieve this is to derive a cost function based on misclassification rates: a better threshold will lead to less misclassification. Using standard terminology we set negative and positive to be equivalent to poor and good condition, respectively. False Negative Rate (FNR) is the rate of misclassifying relatively undisturbed sites and occurs if they have unusually poor indicator values, whilst False Positive Rate (FPR) is the rate of misclassifying relatively disturbed sites, and occurs when they have unusually good indicator values. We can estimate these rates from the data considered representative of the vegetation type. It is impossible to minimize misclassification of both poor and good condition sites simultaneously. Instead we use a cost function to balance cost C_N of false negative (poor) sites with its opposite cost C_P of false positive (good) sites. Supposing that an indicator, e.g. No. large trees, with high values corresponds to good condition, error rates are then:

$$\begin{aligned} FPR &= p(y_i \geq B \mid \mu_i < B) \\ FNR &= p(y_i < B \mid \mu_i \geq B) \\ Cost &= C_N FNR + C_P FPR \end{aligned} \tag{7}$$

One choice of a benchmark B* arises naturally as the threshold which minimizes this cost. We may apply the precautionary principle (QEPA, 1999) and set high penalty C_P for mistaken classification of poor sites as good, so that sites in poor condition are unlikely to score above such a threshold. Alternatively, a landholder may be interested in placing high cost C_N on misclassifying good sites as poor. A neutral approach places equal costs on these two errors.

4. CASE STUDY

Here we illustrate two different regression modelling approaches for examining sensitivity, and derive benchmarks for two indicators.

Generalized linear model – Fallen woody debris. Sensitivity of the number of logs of fallen woody debris (FWD) to disturbance was best assessed via a Poisson generalised linear model with log link. (For details see Low Choy et al, 2005b). The resulting regression score uses posterior estimates of parameters:

$$\text{score} = 1.87 + 0.31\,S - 0.36W - 0.16W\times M$$

for silvicultural treatment (S), wildfire (W) and wildfire–ecological maturity interaction (W×M). Coefficients shown above have at least 95% probability of being away from zero (Table 1). Noting that an additive relationship with log link yields a multiplicative one on the raw counts, these results show that FWD strongly decreases with wildfire and strongly increases with silvicultural treatment. For more immature sites, more wildfire will additionally decrease FWD somewhat. There is weak evidence to suggest that for immature sites: more silviculture leads to small increase in FWD (with 84% probability) and grazing also leads to small increases in FWD (with 74% probability), perhaps since this reduces fuel load.

Table 1. Regression Coefficients (mean posterior estimates, Standard Errors) for sensitivity of FWD to disturbance and maturity variables. Uncertainty in coefficients is shown by the 95% Credible Interval and the probability that coefficients are away from zero max(p(β>0), p(β<0)).

Variable	Est	SE	95% CI	p
Intercept	1.87	0.32	(1.23, 2.5)	1.00
Grazing	0.06	0.09	(-0.12, 0.23)	0.74
Logging	0.02	0.19	(-0.36, 0.4)	0.54
P. burn	-0.02	0.22	(-0.44, 0.4)	0.52
Silvicult.	0.31	0.08	(0.14, 0.47)*	0.99
Wildfire	-0.36	0.09	(-0.54, 0.18)*	0.99
Maturity	-0.06	0.13	(-0.32, 0.2)	0.68
S×M	0.09	0.09	(-0.08, 0.27)	0.84
W×M	-0.16	0.10	(-0.36, 0.03)	0.95

Posterior mean regression scores were applied to each site, and then used to assess FPR and FNR (7) for potential benchmarks equivalent to the 10^{th}, 20^{th} through 90^{th} deciles. The marginally most successful benchmark (Fig. 3b) is set at approx. 5 logs/ha, leading to a FNR of under 20% but a FPR of 40% (Fig. 3a). Higher benchmarks would result in higher FPR (chance of indicator suggesting good condition even though badly disturbed); lower benchmarks lead to higher FNR (chance of indicator suggesting poor condition though hardly disturbed).

Regression trees generally resulted in worse FPR (22-40%) compared to Poisson-Gamma regression.

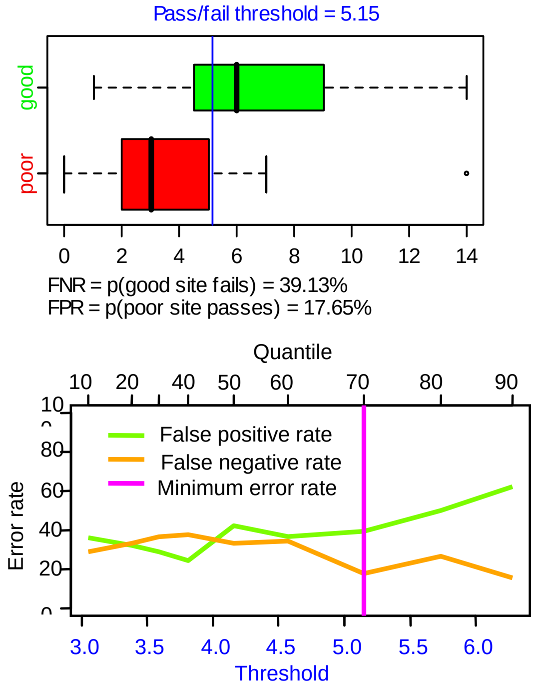

Figure 3. FWD: (a) Boxplot showing distribution of FWD (x-axis) for sites in "good" and "poor" condition (y-axis). "Good" (green) sites have disturbance-maturity regression score exceeding benchmark, whereas "poor" sites fall below. (b) Both FNR and FPR misclassification error rates are shown when the benchmark is set at 10th, 20th, through 90th percentiles of sites ordered by disturbance/maturity score.

Model assessment via posterior predictive checks showed that very few sites did not fit the overall disturbance-condition relationship at all (Fig 3, left) whereas most others did (Fig 3, right).

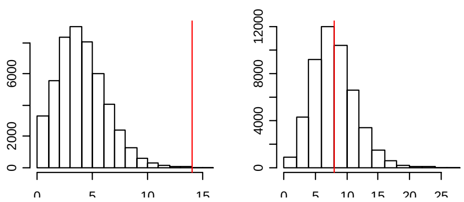

Figure 3. Posterior predictions for FWD given disturbance/maturity: predicted distribution (black) and observed (red) value for 2 typical sites.

Beta-Gamma regression – Average litter. Average litter is defined as the sum of average coverage of coarse and of fine litter across the site, estimated using quadrat sampling. A beta-gamma hierarchical GLM was selected using model diagnostics. The gamma-distributed dispersion parameter estimated beta parameters were magnified 5-fold (Fig. 4). The fitted regression (Table 2) found that average litter in spotted gum increased with logging and other silviculture practices, and was lowest for more mature ecosystems (higher maturity scores for less mature forests). Wildfires decreased average litter. A benchmark of 0.56, corresponding to the 40th percentile of scores, corresponded to minimal joint error rate, with FNR of 20%, and FPR of 42%.

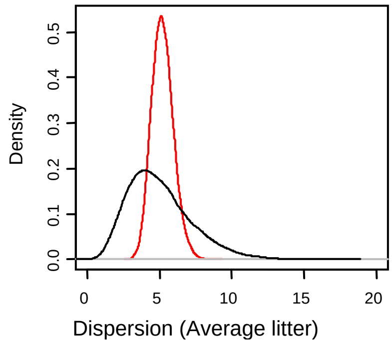

Figure 4. Prior (black) and posterior (red) distributions of dispersion parameter for hierarchical beta-gamma model for average %cover litter.

Table 2. Most important regression coefficients for sensitivity of average litter (%) to disturbance and maturity (with same columns as Table 1).

Variable	Est	SE	95% CI	p
Logging	0.35	0.36	(-0.35, 1.06)	0.84
Silvicult.	0.26	0.18	(-0.09, 0.62)	0.93
Wildfire	-0.32	0.16	(-0.63, -0.01)	0.98
Maturity	0.29	0.23	(-0.18, 0.75)	0.89

5. DISCUSSION

For both attributes benchmarks could be proposed by first isolating which aspects of disturbance were most closely linked to condition, and then minimizing the rate of misclassifying a disturbed site as being in good condition (FPR).

Attribute	Benchmark	FPR	FNR
FWD (no. logs)	5	18%	40%
Av%Litter	0.56	20%	42%

Analyses of condition-disturbance relationships also help select a set of vegetation condition indicators that are sensitive to many aspects of disturbance. In spotted gum forests, indicators were sensitive to similar disturbances, but to different degrees: logging and ecological maturity (number of large trees, results not shown); silviculture, wildfire and maturity (both FWD and average litter); and logging (average litter).

6. CONCLUSIONS

In summary the difficult problem of assessing sensitivity of vegetation indicators to disturbance and using this assessment to set benchmarks for vegetation condition (when data is available) can be facilitated by a Bayesian decision analytic framework. This can be supported by common regression models implemented in accessible statistical modelling environments. The focus on finding the best possible calibration model and benchmarks, as supported by a Bayesian modelling approach encourages a continuing cycle of improvement. Future models may use these posterior estimates of disturbance/maturity impacts on vegetation condition as prior information that can be combined with new data.

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