Detecting change in interconnected ecosystem assets to inform indicators of condition in environmental economic accounts

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Abstract

Environmental Economic Accounts track the condition of interconnected ecosystem assets, to inform environmental decision makers about its influence on the past and current status of ecosystem services. Indicators of condition need to be analysed to determine if they lead, are coincident with or lag environmental change, so that indicators are interpreted appropriately by decision makers. Here we conduct performance testing of ecological condition indicators developed with the United Nations System of Environmental-Economic Accounting – Ecosystem Accounting (SEEA-EA) framework. We chose a case-study of a catchment-to-coast system with strongly interconnected assets and high natural variability, which likely confounds our ability to track long-term change. We first quantified covariation among ecological indicators for pasture biomass, vegetation greenness and barramundi catch per unit effort. Covariation in the indicators was driven by river flow, with higher values of all indicators occurring in years with greater river flow. Barramundi catch per unit effort was most sensitive to changes in river flow, followed by a

vegetation greenness and pasture biomass. We then defined reference bounds for each indicator that accounted for natural variation in river flow. We predicted the emergence times for each indicator, the time taken for each indicator to emerge from the background of natural variation. Emergence times were >10 years in all cases. Detecting change was more difficult where there were gaps in data. Ecosystem accounts can be used to compare ecological condition against performance objectives, but should consider natural variation in the system. National accounts are often used by decision makers to directly inform near-term actions, because economic indicators respond rapidly to new policies and the prevailing economic conditions. We found that ecological condition indicators in highly variable ecosystems are lagging indicators of change, and as such should be used to assess historical performance, not as leading indicators of future change.

Keywords: SEEA EA, Lates calcarifer, Power analysis, state-space model, catchment to coast, estuary, emergence time

Article impact statement: Ecological condition is a lagging indicator of environmental change and should only be used to inform on historical management performance.

Introduction

Accounting of ecosystem services are needed so that ecosystem services can be captured more readily in the standardized national accounts that governments use for informing decisions. Economic decisions commonly overlook, or undervalue, ecosystem services such that economic growth is promoted at the expense of environmental degradation. The objective of ecosystem accounting is to provide additional information to decision makers on the condition of ecosystem assets and their services, alongside the current national accounting headline indicators such as gross domestic products, to enable an holistic view of the current state of the economy and the environment. For instance, ecosystem accounts can be used to report on declines in condition and inform mitigative management actions, as inputs to spatial planning, or to inform about trade-offs in outcomes for competing development or conservation decisions (Keith et al. 2019; Chen et al. 2020).

Development of indicators of ecosystem condition and ecosystem services are therefore central to ecosystem accounting. The leading international framework for developing environmental economic accounts is the System of Environmental Economic Accounting - Ecosystem Accounting (SEEA-EA) which has been adopted by the UN Statistical Commission and many countries (United Nations 2021). While ecosystem extent indicators have been widely studied, there has been limited testing of how effectively condition indicators in SEEA-EA (Farrell et al. 2021), and biodiversity indicators more generally (Watermeyer et al. 2021; Nicholson et al. 2021), can inform management decisions.

There are many potential applications of SEEA-EA condition indicators in decision making (Keith et al. 2019; Chen et al. 2020), but this flexibility creates a risk that the indicators will be used in inappropriate contexts (Stevenson et al. 2021). Systematically classifying indicators for their ability be leading, coincident or lagging indicators of change is important. Ecological condition indicators can have high levels of natural variation and lags in their response to management actions that will mask long-term trends and prevent them being used as leading indicators of change, or even for timely assessment of management outcomes. Therefore, a challenge for selecting appropriate SEEA-EA condition indicators is whether they are informative about ecosystem degradation on a timescale that is relevant for management action, particularly in ecosystems with high levels of natural variation. This is an important knowledge gap, because conventional economic indicators typically respond rapidly to macroeconomic conditions and policies, making them useful as short-term guides for policy makers (Chen et al. 2020; Stevenson et al. 2021). It is not clear whether SEEA-EA condition indicators are relevant for informing policy about either the current state of the ecosystem or likely future change in condition. Context on timescales of response is needed to inform decision makers about how to use condition accounts (Stevenson et al. 2021), such as whether they can be used to monitor trade-offs among development and ecosystem service values (Chen et al. 2020), or as guides for pre-emptive management action. Therefore, a systematic approach to classifying indicators as lagging, coincident with or leading environmental change is crucial (Stevenson et al. 2021).

Classification of the appropriate applications for indicators should ideally be informed by quantitative performance evaluation, but such evaluations are rarely conducted (Fulton et al. 2005; Rowland et al. 2020; Watermeyer et al. 2021). Performance evaluations may be particularly important in ecosystems with high levels of natural variation and interconnectedness among intermediate and final ecosystem services. Many riverine, estuarine and coastal ecosystems exhibit both of these properties, with interannual variation in freshwater flows driving variation in the provision of ecosystem services, including clean water, floodplain production and fisheries production (Sheaves 2009). High levels of natural variation in indicators will mask long-term trends (Hawkins & Sutton 2012). Correlated variation in indicators, as will occur in with indicators of interconnected ecosystems, will also mask underlying trends, because they will share the same masking variation (Jakobsson et al. 2021). But this cross-indicator variation is also of primary interest, because cross-catchment management faces the issue of balancing conflicting objectives. Conflicting objectives are exemplified by many coastal fisheries, whose catches are dependent on freshwater flows to support fish life-histories, but those flows may also be reduced by upstream flow regulation for power generation or agricultural purposes (Robins et al. 2005; Broadley et al. 2020), or by the effects of climate change (Karim et al. 2015). Therefore, it is imperative that we quantify the sensitivity of condition indicators to human influences so we know if – and how quickly – such indicators can detect changes in cross-catchment processes. In particular, as SEEA EA is becoming a dominant framework for environmental economic accounts, tests of how well condition indicators in this framework can capture changes in cross-system interactions are needed (Watermeyer et al. 2021; Nicholson et al. 2021).

Here we test the ability of SEEA EA-compliant condition indicators to detect change across a riverine-estuarine-coastal marine system, using a case-study from a catchment in Northern Australia's Gulf of Carpentaria. The Mitchell catchment is earmarked for potential water resource development, which may provide agricultural benefits, but will also disrupt freshwater flows (CSIRO 2018) and impact the downstream ecosystems and fisheries that depend on them (Broadley et al. 2020). Similarly, climate

change is causing long-term shifts in weather patterns and flows in the region (Karim et al. 2015). We first selected variables and indicators for the interconnected assets for the Mitchell catchment, ensuring that these selections conformed to SEEA EA guidelines. We then sought to fit a process model that quantified the relationship among indicators of multiple assets' conditions and that allowed the effect of uncertainty within those indicators to be assessed (Aim 1). From this model we inferred condition bounds for each indicator based on natural variation (Aim 2). We finally quantified sensitivity of indicators as their emergence time from background variation (Aim 3). The emergence time for each indicator represents when the impacts of change will become apparent to human observers (Hawkins & Sutton 2012). Overall, addressing these aims can contribute towards ongoing development of the SEEA EA framework by testing methods for producing condition indices for interconnected ecosystems assets.

Methods

Ecosystem condition variables and indicators for the Mitchell catchment

The Mitchell catchment covers an area of over 72,000 km2 and discharges into the Gulf of Carpentaria. This catchment is subject to highly seasonal flow regimes. During the dry season many of the ephemeral rivers become disconnected water holes and in the wet season a large area becomes inundated. There is high inter-annual variability in rainfall, which drives inter-annual variation in flow and floodplain productivity (Ndehedehe et al. 2021). We therefore selected variables and indicators for the inter-connected assets where the aim was to capture variation in ecological condition related to river flow.

The SEEA-EA framework provides a methodology for producing a set of interlinked ecosystem accounts that classify relevant ecosystem types as ecosystem assets, report on asset extent and condition, and report on flows of ecosystem services from these assets to humans in biophysical and monetary terms. Ecosystem condition is thus one important component in ecosystem accounting.

The condition of ecosystem assets can be determined using variables and indicators describing the abiotic, biotic and landscape/waterscape characteristics of the different ecosystem types. Ecosystem assets refer to contiguous areas belonging to the same ecosystem type defined by its distinct abiotic, biotic and landscape (or waterscape) characteristics (SEEA EA p43). Data describing the abiotic, biotic and landscape/waterscape state of each ecosystem asset are organised in a nested hierarchy where they are aggregated per ecosystem type. The flows of ecosystem services from ecosystem assets are compiled into ecosystem service supply and use accounts that are expressed in both biophysical and monetary terms. This concept is compatible with the System of National Accounts however, measuring ecosystem service flow is considered more complex than measuring flows of manufactured goods and services and other standard economic assets, because ecosystem assets generate a variety of market and non-market services to a range of beneficiaries (Bartelmus 2015).

We focus on the provisioning ecosystem services of (i) fish biomass that supports barramundi (*Lates calcarifer*) catch in a commercial fishery and resource harvesting of barramundi by Indigenous Australians, and (ii) grazing forage growth that supports commercial livestock production. In particular, the catadromous barramundi life-cycle exemplifies cross system dependence (Barramundi migrate from freshwater to estuaries to spawn, Milton and Chenery 2005). Variability in barramundi biomass may be correlated to variability in pasture growth on flood plains which supports livestock production, because both are dependent on regional cycles in river flow.

The indicators were selected to measure the condition of the relevant inter-linked assets within the catchment. However, due to data availability not all identified variables and indicators could be compiled. Time-series data (Table S1) were collected for ecosystem service indicator, and structural state biotic indicators and landscape indicator (Discussion paper 2.3). Stream flow was used for a physical state abiotic indicator and sourced from the Northern Australia Water Resource Assessment (NAWRA).

Yearly barramundi (*Lates calcarifer*) catch data and fishing effort data were used to derive a biotic state indicator. Data were sourced from the Queensland Fisheries 'QFish' data cube (State of Queensland Department of Agriculture Fisheries and Forestry 2018) for the Mitchell region. Barramundi are an important fishery species in in northern, Australia, and they are caught in commercial, Indigenous, recreational and charter fisheries. They also play an important cultural role within the ecosystem (Jackson et al. 2012). Barramundi spawn in estuaries, with juveniles then moving upstream to freshwater habitats, returning to saltwater as adults (Robins et al. 2005). Seasonal flooplains provide connection to off-stream freshwater habitats as well as highly productive, short-term habitats. Individuals residing in upstream habitats to the estuary and saltwater, to eventually participate in spawning as adults. Barramundi are impacted by the flow regimes through changes in connectivity throughout the catchment, which benefit growth and survival (Robins et al. 2005; Balston 2009; Roberts et al. 2019; Leahy & Robins 2021). Barramundi opportunistically exploit multiple ecosystem assets (i.e., aquatic habitats) at different stages of their life cycle. Therefore, if connectivity between these different ecosystem assets is diminished, this can impact their harvestable biomass in following seasons. Barramundi catch per unit effort (CPUE) is a suitable condition indicator of the interlinked suite of assets that support barramundi production could presumably be based on the 'trophic aggregation' that barramundi provide as a near-apex predator in the system, and the fact that they depend on persistent freshwater in lagoons and waterholes to survive dry periods (Robins et al. 2005). Their life history utilises the suite of interconnected assets to which the condition indicator refers, so in any given year, their population size (proxied by CPUE) reflects the condition of that suite of assets (for the year concerned and suitably time-lagged years for assets that were utilised earlier in the life cycle).

Normalized difference vegetation index (NDVI) is an indicator of vegetation greenness and was used for a functional biotic indicator (Pettorelli et al. 2005), obtained from the Bureau of Meteorology (Table S1). Pasture biomass was included as a structural biotic state indicator, this was also derived

from the stream flow data we used, however they also included other variables in their model therefore was not highly correlated and could be used (State of Queensland Department of Environment and Science, 2021). Pasture biomass was calculated using data on rainfall, soil types temperature and the local grazing pressure (State of Queensland Department of Environment and Science, 2021).

Aim 1: Quantify interrelations among condition indicators

It was important that the model reflected the underlying structure of the SEEA EA framework, so we could conduct a quantitative test that was consistent with the framework's specifications. We combined two common modelling approaches to develop a model of indicator interrelationships (figure 1). The first was a state-space model of barramundi catch per unit effort (CPUE) dynamics (Millar & Meyer 2000). State space models are widely applied for modelling fisheries dynamics, informing on reference points for fisheries management and for estimating environmental effects on fishery dynamics (Aeberhard et al. 2018), but have rarely been applied to model whole ecosystem change (Auger-Méthé et al. 2021). The state-space model was used to fit catches (a measure of ecosystem service flow) and estimate latent states for stock biomass (a measure of ecosystem capacity to deliver services) and environmental process variation (a condition indicator) (Fig 1).

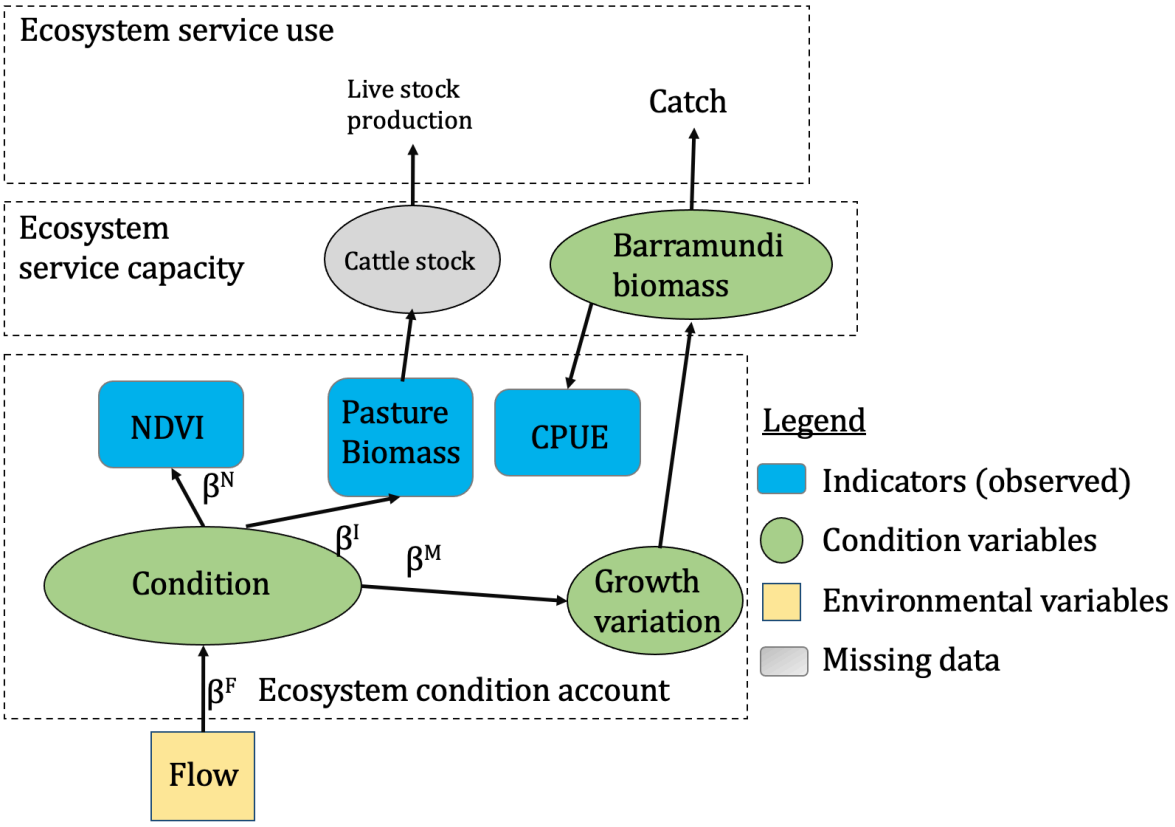

Figure 1 Overview of the approach showing the variables considered for determining linkages among indicators.

The second modelling approach was a structural equation model that related the observed indicator variables to ecosystem condition, which was assumed to be a latent state (Fig 1). Structural equation models are widely used to develop indicators, because they can model the correlations between observed indicators and an unobserved ('latent') state that is hypothesized to be equivalent to the joint condition of different components of an ecosystem (Brown & Hamilton 2018). We linked the two modelling approaches by assuming that the observed indicators of NDVI, pasture biomass, and CPUE were all dependent on an unobserved ecosystem condition variable. Ecosystem condition, in turn, was assumed to be driven by freshwater flow, an 'environmental variable' in the SEEA EA terminology (fig 1).

The state space model had the form:

$$B_t = \left(B_{t-1} + rB_{t-1}\left(1 - \frac{B_{t-1}}{K}\right) - C_t\right)\exp(u_t)$$

$$ln\,(CPUE_t) \sim normal(ln\,(qB_t), \sigma^{CPUE})$$

where B_t was the latent estimate of biomass, r was the intrinsic growth parameter, K was the carrying capacity, C_t was catches (assumed fixed), q is the catchability coefficient, u_t were process errors and σ^{CPUE} was the standard deviation for CPUE errors (we use superscripts to demarcate parameters relating to different variables, subscripts to demarcate indices). B_1 was assumed a fixed fraction of 20% of the estimate of K (Millar & Meyer 2000; Streipert et al. 2019). We tested the effects of the assumptions that B_1 was 20% of K and that q was constant over time in additional sensitivity analyses (Supplementary material).

The state space model was linked to the structural equation model through a dependence of the process errors on ecosystem condition:

$$ln\,(u_t) \sim normal(\beta^u \gamma_t, \sigma^u)$$

where β^u was a regression coefficient and γ_t was the latent condition value. For the purposes of our model framework, the process errors were a condition indicator, though they were unobserved.

The state-space model assumed a one-year lag between flow and changes in barramundi biomass. Flow likely impacts barramundi catches and biomass at a number of different time-scales, as described above, but we assumed the single year impact for simplicity. To further verify this assumption, we confirmed that residuals from the modelled CPUE relationship had no autocorrelation. Future modelling could separate the different types of flow effects on barramundi populations. But note this would require additional data types, because biomass, productivity and catchability parameters are close to being interchangeable in unstructured surplus production models, so they are difficult to estimate simultaneously.

NDVI and pasture biomass were also related directly to the condition indictor:

$$y_t \sim normal(a^y + \beta^y \gamma_t, \sigma^y)$$

where y_t refered to either NDVI or pasture biomass and a^y is the intercept.

NDVI and pasture biomass were mean centred and standardized prior to analysis.

Finally, ecosystem condition was estimated as a regression on flow:

$$\gamma_t \sim normal(\beta^\gamma \ln(F_t), 1)$$

where the standard deviation was arbitrarily set at 1, because γ_t is scale invariant. In our regression we used the log of flow, to reflect hypothesized multiplicative effects of flow on ecological condition.

The NDVI data started in 1992, so the condition indicator was estimated only from flow, CPUE and pasture biomass in 1990 and 1991. The model also interpolated the missing NDVI values. We presented results as marginal predictions for each data type and the latent states for barramundi biomass and ecological condition.

We obtained parameter and prediction probabilities within a Bayesian estimation framework. We set priors based on prior information for each parameter and prior expectations for the variance in NDVI and CPUE. It was also important to set weakly-informative priors to aid algorithm convergence and identification of parameters. In particular, the latent state $\gamma_t$and the β coefficients can 'sign-switch' (Hui et al. 2015). Prior choices and algorithm settings are explained in the Supplementary material. The model assumptions were checked by confirming independent normally distributed residuals, where residuals were defined as the observed values of CPUE, NDVI and pasture biomass minus their posterior predicted median value. Residual independence was confirmed by plotting the auto-correlation function with the R function 'acf' (R Development Core Team 2019). Further, we calculated the cross-correlation of residuals across indicators to confirm the model had captured all dependencies between indicator values. We further verified the model through a simulation study, focussing on the model's ability to interpolate missing data (Supplementary material).

We determined the strength of the relationship between each indicator variable, ecological condition and flow as the direct effect of condition on each indicator (simply the marginal posterior distributions for β^{y}) and total effect of flow on the condition indicator $= \beta^{\gamma}.\beta^{y}$. For barramundi we calculated the direct and total effect sizes on surplus production, where surplus production was defined as the sum of change in biomass and catch (i.e. $\mathrm{SP}_t = B_t - B_{t-1} + C_t$). We then plotted the total effect of a doubling of flow on each indicator and the direct effect of a one S.D. change in ecological condition on each indicator (see Appendix for details). We also calculated one-tailed probabilities that the total effect was greater than zero. We note that given the prior choices (Table S2) the prior probability that $\beta^{\gamma}.\beta^{y}$>0 was 0.5.

Aim 2: Bounds of natural variation

We used the fitted model to define the bounds of natural variation for each indicator. The bounds were defined to represent the typical ranges of indicator values given historical variation in flow. The historical condition of flow was characterized by fitting an autoregressive moving average model to

265 the historical flow series, then simulating 1000 random flow series from the fitted model
266 (Supplementary material). Then to define conditions bounds for the indicators we simulated their
267 values for each of the 1000 flow series. For NDVI and pasture biomass, the conditions bounds were
268 then defined as the marginal probability quantiles integrating over measurement noise (also called
269 predictive intervals) and the flow simulations. The condition bounds for barramundi CPUE also
270 depended on biomass, so for simulations of barramundi we assumed a biomass fixed at the biomass
271 that gives maximum sustainable yield (B_1 = 50% of B_0). This is a common reference point used in
272 fishery management (Mace 1994), and simulations with different biomass levels gave the same
273 results. For the simulations of a conditions bounds, we also assumed that biomass was initially at the
274 biomass that gives maximum sustainable yield, doing so avoided transient dynamics affecting the
275 condition bounds.

276 *Aim 3: Emergence time for indicators*

277 We then estimated each indicator's emergence time, given an assumed long-term trend in flow. We
278 simulated flow series and added a linear decline in flow, as an example of a situation where
279 environmental change or water resource development could put increasing constraints on
280 ecosystem services. We simulated 1000 by 30-year time-series for each indicator and each trend in
281 flow. We then defined emergence times as the time taken for the mean indicator value to cross the
282 lower 5%, 20% and 40% probability quantiles of the condition bounds. The different quantiles
283 represent different degrees of confidence for emergence, the lower the quantile the greater the
284 confidence the trend has emerged from background variation.

285 **Results**

286 *Aim 1: Interrelationships among indicators*

287 Verification of the model fits indicated that there was no autocorrelation in the residuals for the
288 fitted values for any of the condition indicators (Fig S1). Overall, the R^2 was highest for log CPUE

(0.91), moderate for NDVI (0.43) and lowest for pasture biomass (0.09) (Fig S2). Sensitivity analyses where we varied the assumptions made for constant catchability, the initial biomass ratio and higher fishing effort indicated the main results were robust to alternative assumptions (Figs S2, S3 and S4). Similarly, Therefore, below we present only the main results assuming stable catchability and an initial biomass ratio of 20%.

Model fits indicated an overall increase in CPUE from 1990 to 2012, and then a slight decrease from 2012-2015. NDVI and pasture biomass had no long-term trends, but varied year-to-year (Fig. 2). NDVI and barramundi surplus production were strongly related to river flow (Fig. 3A, pr($\beta^{\gamma}.\beta^{y}$.)>0 = 0.99 and 0.96 respectively), whereas pasture biomass had a weaker relationships with river flow (figure 3A, pr($\beta^{\gamma}.\beta^{y}$.)>0 = 0.93). Therefore, the ecological condition variable primarily captured the correlation between flow, NDVI and barramundi biomass change (Fig 2E, Fig 3B). Ecological condition showed peaks in 1991, 1998-99 and around 2010 that were driven by increased flow in those years. But overall ecological condition did not vary strongly from the long-term average (95% CIs generally overlap zero). Barramundi biomass was predicted to have increased from 0.2 to 0.5 as a fraction of B_0 over 1990-2012, and to have declined to ~0.3 in by 2015. The decline 2012-2015 corresponded to a decline in ecological condition and a decline in flow.

A simulation study where we varied the number of years of missing NDVI data suggested the model's predictions for the variables and latent condition variable were not biased by missing data, but the predictions for NDVI were less accurate with a greater amount of missing data (Fig. S5). Coverage by the 95% C.I.s was always >0.95 (Table S3). The parameter estimate for the effect of the latent condition variable on NDVI was most affected by missing data, and the parameter estimates for pasture biomass and barramundi biomass were least affected.

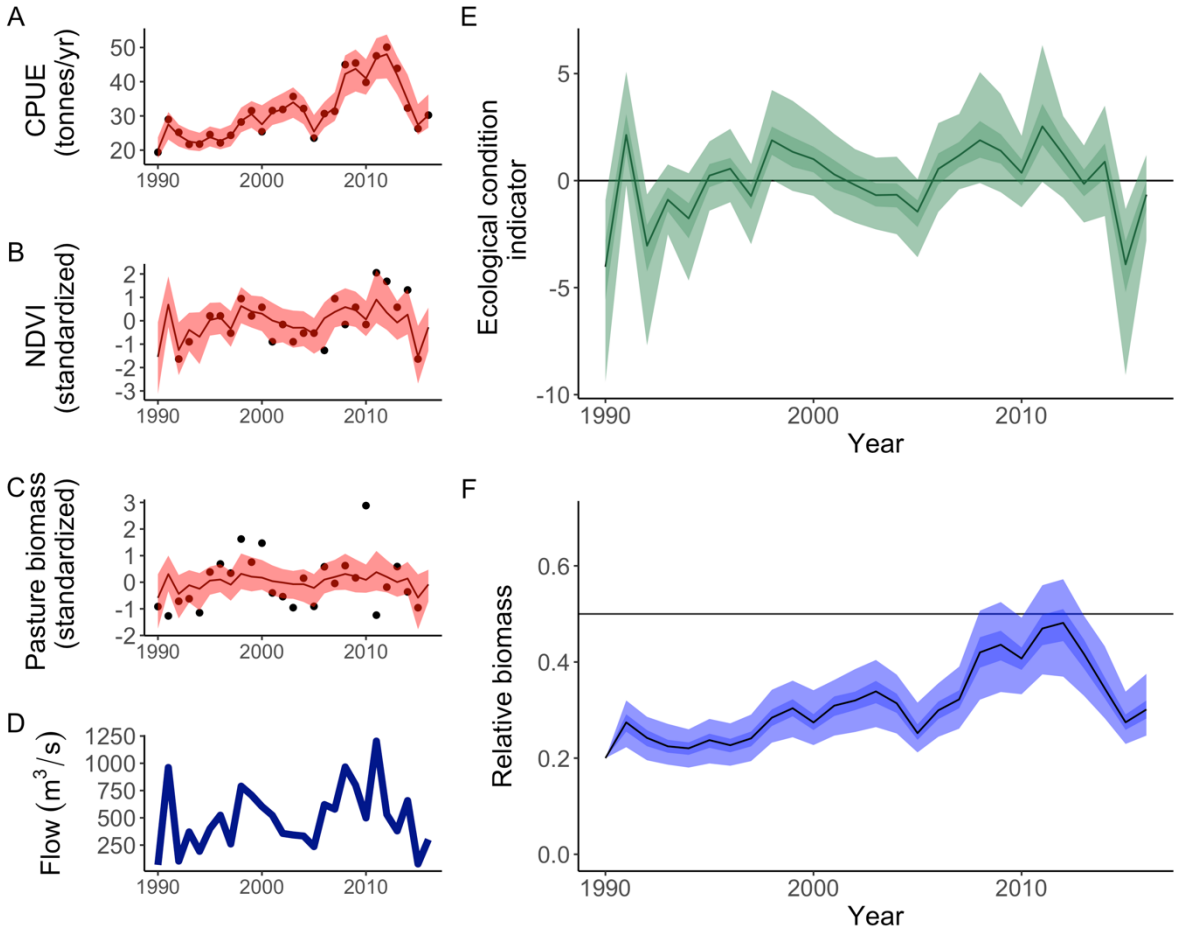

Figure 2 Model fits to data for CPUE (A), NDVI (B); pasture biomass (C); flow (D) and the estimated latent variables for ecological condition (E) and barramundi biomass relative to it's carrying capacity as estimated by the model (F). For model predictions lines show median and shaded areas show 95% CIs. Darker areas in E-F indicate 50% CIs. The solid horizontal line in (E) indicates the mean value, in (F) it indicates BMSY of 50% carrying capacity.

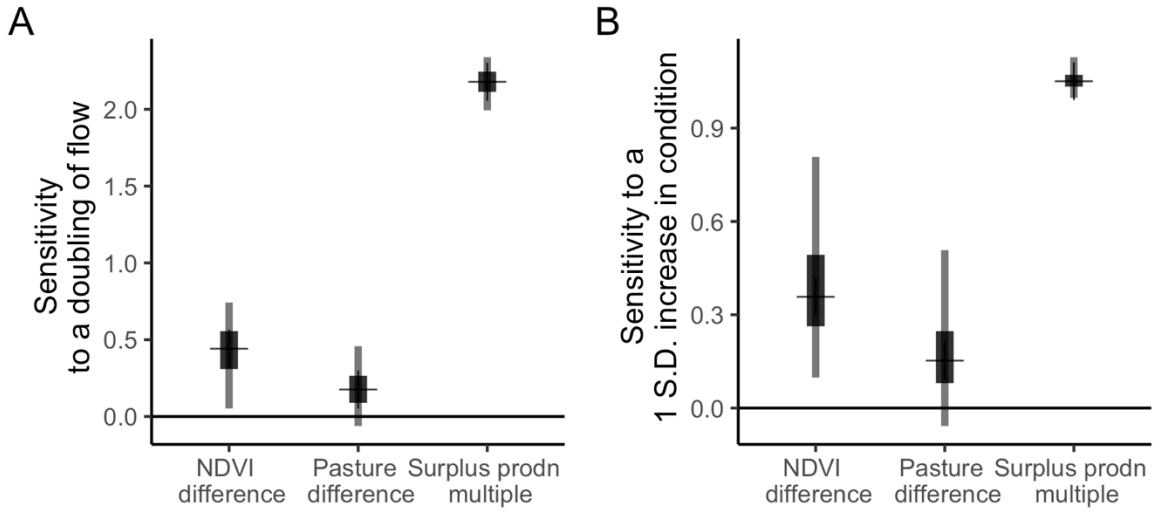

Figure 3 Strength of the relationships between each indicator and (A) a doubling of flow; and (B) a 1 S.D. increase in the ecological condition indicator. Note that NDVI are pasture are differences on a scale standardized to 1 S.D., whereas surplus production is on a multiplicative scale. Horizontal bars show median, thick solid lines show 75% probability quantiles and thin grey lines show 95% probability quantiles.

Aim 2: Bounds of natural variation

The condition bounds for each indicator had broad intervals (Fig. 4), for instance, for CPUE the 80% probability interval ranged from 39-65 tonnes per fishing year, compared to a historical range of 19-50 tonnes per fishing year. This broad variation in the condition bounds was caused by the high variation in flow year-to-year.

Aim 3: Emergence times

Emergence times were greater for pasture biomass and lowest for CPUE (Figs 4 & 5). For instance, if flow decreased by multiples of 0.9 (10% per year) the time for mean CPUE to fall below the 5% quantile of historical variation was 16 years, but >30 years for pasture biomass and NDVI. Emergence times were lower for higher quantiles, reflecting the reduced level of confidence that the trend had emerged from background variation. The differences in emergence times among indicators were

smaller as the quantiles were increased, at a quantile of 40% the indicators had similar emergence times for all trends in flow.

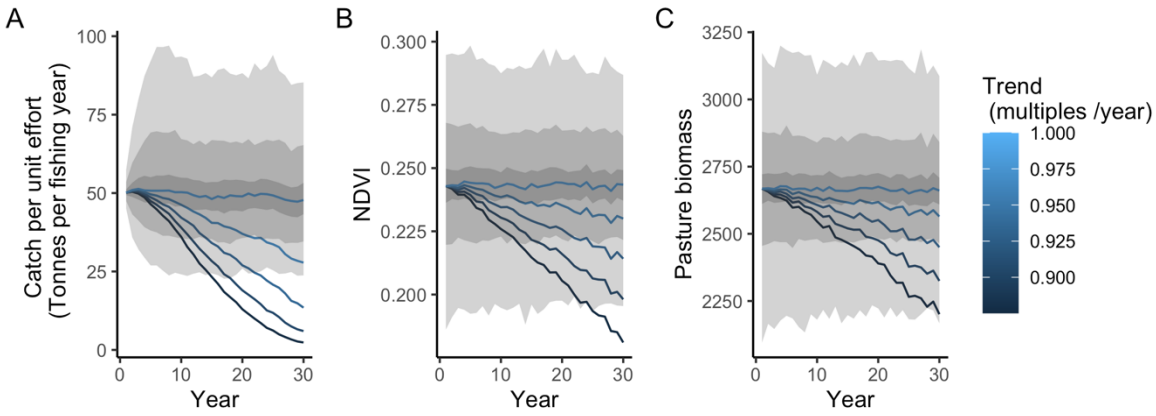

Figure 4 Condition bounds for catch per unit effort (A) NDVI (B) and pasture biomass (C). Grey zones show 20% (dark grey), 60% (medium grey) and 90% (light grey) probability intervals. Examples of trend lines shown in blue shades.

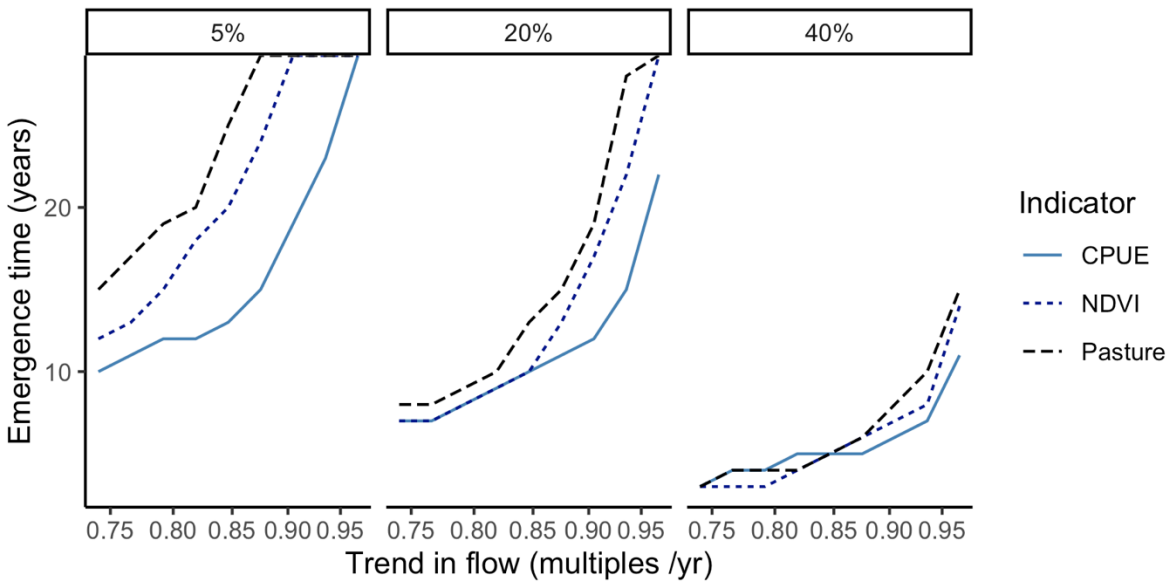

Figure 5 Emergence times for the three indicators. The different lines show emergence times for different lower quantiles.

Discussion

We identified relationships among all indicators, and particularly among flow, barramundi catch per unit effort and NDVI. There is high interannual variation in the Mitchell catchment, driven by interannual variation in rainfall. Wet years drive increased vegetation growth and barramundi production, which was reflected in correlations among river flow, NDVI and barramundi catch. Thus, ecological condition, as was defined here, largely reflected year-to-year variation in flow. This variation underscores the importance of quantifying interconnections between assets via river flow and among ecosystem services. The implication is that change in one variable (flow) can cause changes in the condition of multiple ecosystem assets, and consequent correlated changes in the annual capacity of the system to deliver different ecosystem services.

The ecological condition indicator was able to partition out environmental effects shared by all indicators from those that were unique to specific indicators. The ability to identify shared trends may be desirable in an indicator, because it enables monitoring the aspects of environmental and management change that affect just one indicator versus the overall condition of the ecosystem

366 (Sutherland et al. 2016; Kupschus et al. 2016). Over time there was an increasing trend in
367 barramundi CPUE from the 1990s to 2015. This was driven by high flows 2005-2015 and
368 management changes in the fishery in the late 1990s and early 2000s, which reduced fishing effort
369 and put increased restrictions on fishing gear (Streipert et al. 2019). NDVI had a strong correlation
370 with flow and CPUE, but in contrast to CPUE, NDVI did not show as strong a long-term trend,
371 because it is not affected by fishery management changes. Pasture biomass had the weakest
372 correlation with the other indicators, perhaps because it is more strongly driven by rainfall, which is
373 partially decoupled from flow.

374 The typical approach to defining condition indicators has been as a weighted sum of all indicator
375 values where the weights are determined by experts (Maes et al. 2020). Our approach to defining a
376 condition indicator can also be interpreted as a weighted sum of the indicators, except that the
377 weights were estimated empirically. Each approach has its own advantages and disadvantages. Our
378 approach requires time-series data, which are not available for many indicators or in some regions
379 (Dvarskas 2018). Expert weights do not require historical data and are simple to compute, but can
380 also be arbitrary. Arbitrary weights are not repeatable across different groups of experts and may
381 mis-represent management priorities (Game et al. 2013). Further, our approach partitioned variation
382 in CPUE caused by flow from changes in management of the fishery. Simply summing weighted CPUE
383 with other indicators would tend to overinflate the influence of barramundi fishery management on
384 ecological condition as a whole. Thus, a key advantage of our approach is that it can partition
385 changes unique to individual indicators, versus changes that are shared across the ecosystem.

386 A number of modelling toolboxes have been previously developed to quantify connections among
387 the condition of ecosystem assets and ecosystem service flows, but none of these directly address
388 the issue of how effectively one can detect trends in indicators. Examples include the soil and water
389 assessment tool (Bieger et al. 2017), the Integrated valuation of ecosystem services tradeoff
390 (INVEST) tool (Guerry et al. 2012) and globally applicable artificial intelligence tools (Martínez-López

et al. 2019). These tools have been applied for measuring connected ecosystem services across catchments, in particular regulating ecosystem services relating to water quantity, water quality and sediment erosion (Bieger et al. 2017; Hamel et al. 2017). All share a common approach, based on parameterising models of soil erosion and run-off and then analysing predicted service flows spatially in a geographic information system. However, these toolboxes are designed for making service flow projections, given sufficient information exists to parameterize their models. The utility of our approach is as a performance evaluation tool, which is an understudied aspect of biodiversity indicator development (Rowland et al. 2020; Watermeyer et al. 2021). Our state-space formulation could be extended to model multivariate change in other ecosystems, and this type of model warrants further development for assessing ecosystem level change (Auger-Méthé et al. 2021)

The high interannual variation in flow and ecological condition will create challenges for detecting change in the Mitchell catchment. Our estimates of the interannual variation for each indicator were broad and thus our model predicted that emergence times across all indicators were >10 years and sometimes >30 years for all but the most extreme trends. Further, the strong correlations among indicators suggested there would be limited ability to leverage unique information from each indicator to better detect change. These long emergence times mean the indicators will not be useful for managers aiming to use the account to pre-emptively respond to change, because the changes will not be detected on a management relevant timespan (Stevenson et al. 2021). Rather, the indicators will capture long-term low-bandwidth changes in the ecosystem. For comparison, proposed water developments in the Mitchell catchment are expected to cause much smaller reductions in flow, in order of 1-5% per year (Petheram et al. 2018), than most of the trends we explored here. Such water developments however are predicted to impact estuarine ecosystem services (Broadley et al. 2020; Leahy & Robins 2021). Thus, our findings suggest management planning will have to rely heavily on predictive modelling, and should not be guided in the short-term by trends in condition accounts.

There are some important caveats to consider in our analysis. First, there was missing data in some of the indicator time-series. Missing data in time-series is a common problem for accounts and will reduce the power to detect long-term change (Dvarskas 2018). The latent variable approach enabled interpolating missing data, on the strength of correlated variables (Hui et al. 2015). A simulation study suggested accuracy of predictions for a variable was not sensitive to missing data in other variables. Thus, we suggest our approach could have value more generally for creating indicators of ecological condition when there are gaps in time-series.

The analysis of barramundi used a simplified stock assessment model. For many fisheries additional data may be available, such as data on age structure, and this could improve the accuracy of the modelling. Our simple stock assessment did compare well with a more quantitatively complex stock assessment, with the stock status estimates being similar (Streipert et al. 2019) – this is the consequence of both assessment models being driven primarily by trends in CPUE and the assumption of an depletion of 0.2 B_0 in 1990. More importantly, the availability of barramundi to estuarine fisheries, as well as productivity, is also likely to be affected by flow (Robins et al. 2005). Future analyses could incorporate this effect if more data were available to separate catchability from productivity effects.

An important caveat is that our condition indicators are an incomplete representation of the conditions supporting ecosystem services in the Mitchell catchment. We focussed on assets that support commercial fish harvest and commercial livestock grazing, because there were sufficient time-series data for these indicators to assess emergence times. However, Indigenous uses of ecosystems are also an important component of the ecosystem services in Northern Australian catchments (Scheepers & Jackson 2012; Jackson et al. 2012, 2014), which may be particularly sensitive to development (Stoeckl et al. 2013). Our modelling did not include condition directly relating to Indigenous services, due to lack of time-series data. It is likely that our conclusions regarding emergence time would also apply to those assets supporting traditional uses, such as

water holes, given the interconnections in this catchment. Future modelling studies could integrate Indigenous knowledge to enhance the predictive power of ecosystem service models. For example, Indigenous people are aware that different assets are important to support the barramundi population at different times of year (Scheepers & Jackson 2012). This spatial information could be incorporated into ecosystem service models, like the INVEST suite of models (Guerry et al. 2012), and could enhance our ability to predict change in ecosystem services as a result of underlying change in ecosystem condition, and also predict ecosystem services for a broader range of people.

Conclusion

We analyzed change in condition indicators for interconnected ecosystem assets and found a high level of variation. This high level of variation means long time-series are required to detect change in ecosystem assets. We recommend that condition accounts are not used as leading or coincident indicators of change (Stevenson et al. 2021). We urge further caution when using condition accounts to inform policy-makers about trade-offs among development and conservation decisions – economic accounts may respond rapidly and positively to development, but the consequent degradation of ecological condition may take much longer to be noticed. Supplementing these indicators with accounts of pressures (e.g. fishing pressure, water use) may provide a greater ability for policy makers to detect and respond to ecosystem change.

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