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Contact CEH NORA team at
noraceh@ceh.ac.uk

1 **Clarity or confusion? – problems in attributing large-scale ecological changes to**

2 **anthropogenic drivers**

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4 Smart, S.M. [1], Henrys, P. [2], Purse, B.V. [3], Murphy, J.M. [4], Bailey, M.J. [5], Marrs, R.H.[6]

5

6 *1. NERC Centre for Ecology and Hydrology, Library Avenue, Bailrigg, Lancaster*

7 *LA1 4UP UK*

8 **email: ssma@ceh.ac.uk**

9 **author for correspondence telephone; +441524-595823, fax; +441524-61536**

10

11 *2. NERC Centre for Ecology and Hydrology, Library Avenue, Bailrigg, Lancaster*

12 *LA1 4UP UK*

13 **email: pehn@ceh.ac.uk**

14

15 *3. NERC Centre for Ecology and Hydrology, Bush Estate, Penicuik, Midlothian EH26*

16 *0QB UK*

17 **email:beth@ceh.ac.uk**

18

19 *4. Queen Mary College, University of London, Freshwater Biological*

20 *Association River Laboratory, Wareham, Dorset BH20 6BB UK*

21 **email: j.f.murphy@qmul.ac.uk**

22

23 *5. NERC Centre for Ecology and Hydrology, Maclean Building, Benson Lane,*

24 *Crowmarsh Gifford, Wallingford, Oxfordshire OX10 8BB UK*

25 **email: mjb@ceh.ac.uk**

1

2 *6. Applied Vegetation Dynamics Laboratory, School of Biological Sciences,*

3 *Biosciences Building, Crown Street, University of Liverpool, L69 7ZB, UK*

4 **email: calluna@liverpool.ac.uk**

5

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14 **Abstract**

15 Ways of reducing the drivers of global biodiversity loss and degradation of ecosystem

16 services are needed more than ever before. Policy options must be based on the best

17 evidence of the role of multiple driving forces. Increasingly, a significant part of the

18 evidence base comes from attributing signals of biological change detected in large-

19 scale analytical surveys to a range of possible causal factors. We highlight a number

20 of subtle difficulties that can beset the challenge of detecting such correlative

21 relationships. These are as follows: 1. The Modifiable Area Unit Problem. 2.

22 Incomplete explanatory variable data. 3. Lack of control over the replication and

23 crossing of driving variables. In most cases these problems can be avoided by more

24 careful specification of the scientific question and application of relatively new

25 analytical techniques. Ignoring them can lead to mis-specification of hypothesised

1   driver-state-impact relationships and flawed conclusions as to the most important

2   causes of change.

3

4   **1. Introduction**

5   On 29th October 2010, the parties to the UN Convention on Biological Diversity

6   agreed a new 10 year Strategic Plan. This followed failure to meet the Rio Earth

7   Summit goal "to achieve by 2010 a significant reduction of the current rate of

8   biodiversity loss at the global, regional and national level as a contribution to poverty

9   alleviation and to the benefit of all life on Earth" (Butchart *et al*. 2010). Action is

10   needed now more than ever to halt the direct drivers of biodiversity loss and

11   degradation of ecosystem services. This in turn means understanding how the relative

12   importance of different drivers varies across a heterogenous planet. Increasingly, this

13   understanding comes from analysis of the relationship between potential causal

14   factors, such as atmospheric pollutant deposition, climate change and land-use and

15   ecological state indicators (Sala *et al.* 2000; MA 2005). Such research takes time yet,

16   in a rapidly changing world, answers are needed quickly. Policy makers therefore find

17   themselves under pressure to infer possible causes from indicator change in the

18   absence of the evidence base that might emerge from time-consuming statistical and

19   model-based attribution analyses supported by experimentation to establish the

20   plausibility of the underlying mechanisms (Gadbury & Schreuder 2003). Sidestepping

21   the analytical attribution phase is attractive because changes in indicators can appear

22   to be superficially consistent with known changes in driving variables. This invites

23   common-sense interpretations; if on average, the ecological indicator has increased,

24   decreased or remained stable and, on average, the driver has intensified, reduced or

25   not changed, then the two are likely to be causally linked (Bellamy *et al. 2005;*

1   Butchart *et al.* 2010). While demonstrations of these simple and consistent

2   relationships are vital warning signs in the assessment of possible driver-state-impact

3   relationships, in themselves they offer incomplete evidence if the goal is to unravel

4   the relative contributions of multiple drivers across a domain of interest. Although the

5   apparent clarity and policy resonance of the message increases with the size of the

6   spatial units across which indicators are averaged, such high-level reporting can

7   obscure the existence and directions of ecosystem-specific trajectories of change

8   linked to different human-induced drivers (Jelinski & Wu 1996; Anderson *et al.*

9   2009). A step toward quantification of these relationships comes from analysis of

10   change in state indicators recorded from large-scale ecological surveillance programs.

11   Whilst such analyses maximise the realism and policy relevance of results, they must

12   also contend with a number of problems that serve to separate the detection and

13   attribution of signals in surveillance data from partitioning of the variation in a

14   designed experiment where the observer has control over the identity and arrangement

15   of treatments and covariates (Stow *et al.* 1998; Biggs *et al.* 2009; Wintle *et al.* 2010).

16

17   Here we illustrate some of the dangers of over-simplification in the presentation,

18   interpretation and analysis of large-scale ecological change and discuss a number of

19   related problems that are particularly relevant to the identification of cause-effect

20   hypotheses in ecological surveillance data. As a new round of global target setting,

21   indicator development and monitoring begins it is timely to highlight the influence of

22   these problems on the analysis of the impacts of anthropogenic stressors on

23   biodiversity and ecosystem services. By ecological surveillance data we mean large-

24   scale surveys repeated or not, where the primary motivation of the sampling design is

25   to quantify the range of ecological or biological variation in a region and the way it

1   may change over time (Gadbury & Schreuder 2003; Haughland *et al.* 2009). We

2   exclude long-term experiments where ecological change results from designed

3   arrangements of treatments and controls (Lindenmayer & Likens 2009).

4

5   **2. Three important issues**

6   *2.1 The Modifiable Area Unit Problem*

7   Across a heterogenous sampling domain, the relationships between variables can

8   change simply by altering the orientation and size of the areal units measured. In their

9   classic demonstration, Openshaw & Taylor (1977) found that correlations between

10   proportions of elderly voters and Republican voters across the state of Iowa ranged

11   from highly positive to highly negative simply by changing the number and

12   orientation of areal units used to divide up the state. Likewise, by changing the scale

13   over which indicators are averaged, the same phenomenon can readily influence the

14   apparent direction of ecological driver-state-impact relationships (Armhein 1995;

15   Stein *et al.* 2001). We illustrate the problem using recently published ecological

16   surveillance data for Great Britain.

17

18   In Britain, national changes in a range of biodiversity indicators have been reported

19   for the 29 year period from 1978 to 2007 based on large-scale ecological surveys

20   repeated at roughly decadal intervals (Carey *et al.* 2008). Each survey collects a large

21   number of biophysical measurements and these have been published as indicators of

22   change in extent and condition of major habitats, freshwaters, soils and plant species

23   (Carey *et al.* 2008 and available on-line at www.countrysidesurvey.org.uk). Following

24   the latest survey in 2007, the results were summarised by ecosystem type and at the

25   national-scale (Carey *et al.* 2008; CEH, 2008). Particular interest focussed on changes

1   in plant species composition that could be interpreted as shifts along the nutrient

2   availability gradient and therefore as a signal of eutrophication. Attribution analyses

3   of previous surveillance data highlighted the separate impacts of intensive agriculture,

4   nutrient surpluses and atmospheric nitrogen deposition on characteristic species

5   diversity between 1978 and 1998 (Firbank *et al.* 2008; Smart *et al.* 2006a; Smart *et al.*

6   2004). Hence, key questions were whether a signal of increasing eutrophication had

7   continued across British terrestrial ecosystems up to 2007, and if so, what were the

8   likely drivers? Expressing between-survey change in the nutrient status indicator as

9   the cross-ecosystem national average gave the simplest possible answer to the first

10 question: The relative contribution of the more nutrient-demanding plant species

11 increased and then decreased over the 29 year period (Fig. 1). At this scale, the

12 indicator has maximum impact with policy makers because it is communicated as one

13 simple, spatially unified message (CEH 2008). Within-ecosystem changes were also

14 published separately (Carey *et al.* 2008). These showed overall reductions in the

15 indicator in woodland and intensive farmland, but net increases in less fertile semi-

16 natural habitats such as acid, calcareous and neutral grasslands (Fig 2). Because the

17 time series is based on a representative, stratified-random sample of land cover, the

18 national trend was a weighted average of the directions and sizes of change observed

19 across the mosaic of habitats in Britain (Fig 1). The national indicator was correct. It

20 reflected the aggregate pattern of change along the inferred nutrient availability axis

21 but did not convey the net increase in the indicator in heath & bog and the semi-

22 natural grasslands (Fig 2). The national average trend also diverted attention from the

23 fact that different drivers were likely to have impacted different ecosystems and that

24 these different ecosystems vary in conservation value and response to perturbation.

25 For example, the extensification signal on arable land (Fig 2) appeared to reflect a

substantial transfer from cultivation to fallow in response to the domestic

implementation of Europe-wide setaside mechanisms designed to reduce crop

production (Boatman *et al.* 2009). In these highly responsive systems post-disturbance

colonisation is rapid (Critchley & Fowbert, 2000). However, the duration of any

positive ecosystem effects on soil protection, carbon sequestration and resource

availability for invertebrates and farmland birds are dependent on changes in crop

prices and can be abruptly reduced if fallow land is returned to intensive arable

cropping as happened in Britain in 2008 (DEFRA 2008; Boatman *et al.* 2009). In less

resilient semi-natural vegetation, eutrophication can be a much more persistent effect;

hard to reverse and cumulative in its impact (Strengbom *et al.* 2001; Dupouey *et al.*

2002). Only when the national trend was disaggregated was it possible to discriminate

between divergent ecosystem-specific trends, each associated with different suites of

known or possible drivers (Fig 2). Rather than concluding that the same pattern of

change occurred across the British landscape and that the most recent period saw

widespread recovery, a more detailed assessment revealed an ecosystem-specific

mixture of extensification, stability and eutrophication over the 29 year period (Fig 2).

Decisions about the definition and size of sampling units also impact greatly on the

detection and meaningfulness of patterns that purport to help understand ecosystem

service delivery and the spatial partitioning of biodiversity. Analyses that have sought

to identify trade-offs in ecosystem service provision have, for example, shown marked

scale-dependence in the direction of correlations (Anderson *et al.* 2009; Naidoo *et al.*

2008). In addition, the measurement of change in species diversity is highly scale-

dependent since increasing the size of the units censused confounds beta-diversity

with alpha-diversity (Buckland *et al.* 2005; Huston 1999). Partitioning diversity at

appropriate scales is especially important if the processes and drivers of change in

biodiversity are to be properly understood (Huston 1999; Green *et al.* 2005; Gabriel *et al.* 2010). For example, regional to larger-scale reductions in rare species (gamma

diversity) have often occurred in parallel with local increases in small-scale alpha-

diversity (Sax & Gaines 2003). While both patterns can be reconciled with the effect

of human activities that increase the range of generalists and exotics but reduce the

range of scarce specialists, (Olden & Poff 2003; Smart *et al.* 2006b) analysis is

required at more than one scale to fully characterise these inter-related trends (Weber

et al. 2004; Stohlgren *et al.* 2002). Summing changes over fewer larger areas risks

averaging out opposing directions of ecological change whose individual trajectories

may be linked to local ecosystem-specific sets of drivers and starting conditions

(Wright & Jones 2004; Smart *et al.* 2006b).

2.2 Incomplete or missing explanatory variables

Averaging across areal units of different sizes is not the only way in which important

relationships with driving variables can be concealed. Previous attribution analyses of

British data have shown that large-scale ecosystem impacts can be correlated with

spatial gradients of multiple global change phenomena (e.g. Firbank *et al.* 2008;

Maskell *et al.* 2010). Yet, if a driver has increased in one place but decreased to an

equal extent in another then a cross-ecosystem average could convey no significant

mean change in the indicator rather than significant but location-dependent

correlation. The same could potentially happen where the impacts of two drivers are

negatively correlated in their operation within an ecosystem. This is the same as the

absence of significant main effects in an experiment because of the presence of a

negative interaction between levels of those main effects (Underwood 2005; Biggs *et al.* 2009a). Such averaging problems will arise where explanatory variables have been omitted from analyses. Therefore lack of an observed change in an indicator averaged across a domain does not mean the absence of regional driver-state-impact dynamics. The challenge is to incorporate appropriate data on covariates and driving variables sufficient to isolate important interactions and main effects for example reflecting geographical variation in starting conditions, land-use and socio-economic context (Van Buskirk & Willi, 2004, 2005; Kleijn & Báldi, 2005) or across species' centres of distribution versus range margins (Oliver *et al.* 2009; Warren *et al.* 2001). An ongoing problem is that in regions where biodiversity is high yet ecosystem degradation severe, adequate explanatory variable data may be sparse or non-existent (MA, 2005).

 Analysis of recent large-scale changes in disease prevalence provide some of the best examples of how spatial disaggregation of data can reveal smaller scale trends each associated with different suites of social and ecological covariates. Increased risk of tick-borne encephalitis (TBE) to humans has occurred across parts of Europe in the last thirty years. Increased disease risk was thought to have resulted from improved conditions for natural transmission cycles resulting in higher densities of infected ticks or from changes in human behaviour resulting in greater exposure to ticks (Randolph 2008a). Since both of these factors are climate dependent, TBE is commonly listed amongst those vector-borne pathogens anticipated to become more of a threat to humans as the climate warms (e.g. Lindgren, 1998). Lindgren & Gustafson (2001) were the first to attribute the upsurge in TBE incidence over the past two decades to warming temperatures – namely milder winters and early arrival of spring (conditions favouring early development and extended autumn activity of

1   ticks). However, this study considered only climatic drivers and was restricted to

2   Stockholm county, Sweden, close to the northern range margin of this pathogen. In

3   fact, when a regional level investigation at a pan-european scale was conducted,

4   considerable variation was revealed, both within and between countries, in the timing

5   and extent of changes in TBE incidence. Though biologically-relevant climate

6   warming had indeed occurred since the early 1990s, and may have enhanced

7   transmission, the pattern of these changes was too uniform across the continent to

8   account for the extreme spatio-temporal heterogeneity in the upsurge of TBE (Sumilo

9   *et al.* 2006; 2007; Randolph 2008a; 2008b). Instead a network of interacting biotic

10   and socio-political drivers affecting both risk of infection and exposure of humans,

11   differing in force in space and time, was involved (Randolph 2008a).

12

13   A similarly comprehensive analysis invoking multiple and interacting drivers was also

14   necessary to understand the increasing incidence of American cutaneous leishmaniasis

15   (ACL), (a zoonotic vector-borne disease, caused by several species of *Leishmania* and

16   transmitted by sandflies) in the neotropics. In this example inclusion of another

17   covariate revealed an interaction with the primary driver that reversed the apparent

18   direction of the initial driver-state-impact relationship. The emergence of ACL has

19   been associated with changes in the interactions between people and forests. The

20   association between outbreaks and higher rates of infection found in populations

21   living close to forests and lower incidence in urban areas led to the proposal that

22   deforestation could reduce re-emergence of disease. These analyses ignored socio-

23   economic factors. Chaves *et al.* (2008) examined county level incidence rates as a

24   function of social and environmental variables. In common with other infectious

25   diseases, socially excluded populations were most affected by the disease. Once social

1   marginality was taken into account, living close to the forest could actually diminish

2   the risk of ACL infection. In addition, impacts of climate change on disease, due to El

3   Nino Southern Oscillation events (initially described in Chaves *et al.* 2006), interacted

4   with forest cover since resulting increases in incidence were exacerbated by higher

5   levels of deforestation. Including socio-economic covariates thus reversed the original

6   expectation. Poorer citizens were more likely to contract ACL whether in urban or

7   rural areas but were more likely to live closer to forest edges. While overall incidence

8   increased with climate effects, incidence declined with greater remaining forest cover.

9

10   Complex relationships between multiple driving variables and responses are likely to

11   be common. Unravelling them may face a simple problem of lack of data that track

12   drivers of interest at the study scale. This can be an insurmountable obstacle (e.g. MA,

13   2005) in the face of which, the identification of causal hypotheses based on those data

14   that are available, must consider the possibility that other drivers could be equally

15   important and that, if included, they may even alter the direction of the relationship

16   with the principal driver (see Supplementary Material).

17

18   *2.3 Arrangement of drivers is beyond the control of the observer*

19   A number of analytical and interpretative problems can also arise because of an

20   under-appreciation of the differences between analysis of correlative/causal

21   relationships in ecological surveillance data versus partitioning the variation in a

22   designed experiment (Stow *et al.* 1998). Unlike a designed experiment, the identity,

23   crossing, replication and interspersion of driving variables is, by definition, outside

24   the control of the observer (Stow *et al.* 1998; Gadbury & Schreuder 2003). This

25   makes attribution an analytical challenge since we must apply strong inference (*sensu*

1 Platt 1964) to weak data. That is we apply the steps involved in inductive inference

2 especially hypothesis construction and testing but to data that reflects accidental

3 arrangements of possible explanatory variables. This creates difficulties in testing

4 competing hypotheses and in gaining clear understanding from the analyses.

5

6 Analyses of large-scale survey and monitoring data face well known issues such as

7 regression to the mean (Palmer 1993; Smart & Scott 2004; Biggs *et al.* 2009), pseudo-

8 replication (Hurlbert 1984; Cottenie & De Meester 2003) and spatial autocorrelation

9 (Beale et al 2010; Hawkins et al 2007). Less widely discussed is the influence of

10 differences in the range of variation in driver intensity. This can profoundly affect the

11 conclusions drawn from analyses that seek to detect driver-state-impact relationships.

12 In a large-scale analytical survey potential drivers may show considerable spatial

13 variation in their intensity. Analyses may have high realism but the apparent

14 importance of one driver versus another in driving change, maybe as much to do with

15 the fact that the severity of a driver has been consistently high in most places, while

16 the severity of another driver varies being high in some places but being absent or at

17 low severity in others. If the range of variation in a driver is relatively small despite its

18 severity being high everywhere, then variance partitioning techniques have a lesser

19 chance of detecting a significant effect of the driver over and above residual variation

20 in the response. We carried out a simulation exercise to demonstrate this effect (Fig

21 3). The driving variable ranged between 1 and 40, approximating the current range of

22 total atmospheric nitrogen deposition (Kg N ha^{-1} yr^{-1}) across Britain as a realistic

23 example of a national-scale driver of ecological change. A realistic relationship with a

24 response variable was specified and the power of detecting a significant relationship

25 tested across different ranges of variation in the driver (Fig 3). The conclusion from

1   such a test is not necessarily that the driver has not or could not induce an ecological

2   impact. If the regression slope coefficients of two driver-impact relationships were

3   equivalent, then their potential for forcing ecological change is estimated to be

4   equivalent if they were applied with equal crossing and replication. The problem can

5   be made clearer by acknowledging that two questions are involved; 1) what is the

6   inherent potency of the driver as a cause of ecological change relative to other

7   potential drivers (best answered via experiment and up-scaled via a model), and, 2)

8   which drivers happen to be most strongly correlated with observed ecological change

9   across the entirety of a region of interest? Statistical attribution relies on being able to

10 evaluate the size of a driver's impact by comparing ecological changes at high and

11 low levels of a driver; either along a gradient or by classifying the sampling domain

12 into control and impacted regions. Taking into account the relative range of variation

13 in possible drivers across the sampling domain is therefore of equal importance in

14 answering the second question as is quantifying variation in the ecological impact. If a

15 driver had operated with constant and high severity everywhere and an associated

16 magnitude of impact had occurred everywhere then the only deviations from the mean

17 of the response will be random about the mean overall level of the explanatory

18 variable. This rules out the possibility of a systematic association between the two and

19 hence a significant detected effect of the driver on the response (Fig 3). It also means

20 that a highly significant average change in a state indicator may defy statistical

21 attribution based on variance partitioning techniques even if the potential driver seems

22 very obvious. Analysis of the ecosystem impacts of reduced versus oxidised

23 atmospheric nitrogen deposition provides a topical example of the importance of

24 separating assessment of the inherent potency of two drivers from an assessment of

25 their relative importance as an additional consequence of their spatial variation in

severity. At the resolution of larger grid cells, reduced nitrogen deposits over a much

greater range of estimable values across Europe than oxidised. This means that

attribution of large-scale change in state indicators to reduced nitrogen is more likely

than to oxidised (e.g. Smart *et al.* 2004; McClean *et al.* 2011) even though the

biogeochemical mechanisms underlying their impacts, indicate that both can be

significant pollutants (Stevens *et al.* 2011). Reanalysis of datasets based on equalising

gradient lengths is possible but the constrained subsample of a large-scale survey

would no longer represent the realistic, un-designed variation in each nitrogen form as

a function of the human activities that control the deposition of each.

3. Conclusions

While the principal objective of many surveillance and monitoring programs is to

detect change, the question, why has change occurred?, inevitably follows. Yet, just

because schemes are designed to detect change across a region does not mean they are

optimised to attribute changes to potential drivers. The basic difference between

controlled experimentation and passive ecological surveillance contributes to all three

of the problems we have illustrated. We make the following recommendations:

Be wary of narratives that analyse large-scale change in indicators and then invoke

drivers operating across large areas but without quantitatively linking them: The

statistical power of such an analysis can be high leading to a powerfully simple

message but one that may conceal important local differences. High-level results

should therefore, be accompanied by an appropriate decomposition into disaggregated

trends and a health warning that the simple picture is simple at the expense of

potentially critical complexity. Techniques such as random forests (Bradter *et al.*

1   2011), locally-weighted regression and CART modelling can be used to detect and

2   characterise these variations in ecosystem response thus highlighting the locations of

3   different driver-state-impact dynamics for further hypothesis testing (Smart *et al.*

4   2003). Techniques such as hierarchical Bayesian modelling (Biggs *et al.* 2009) allow

5   joint analyses of these substrata enabling the detection of overall correlative/causal

6   relationships between drivers and state indicators but conditioned on environmental

7   heterogeneity. Such approaches help avoid excessive belief in a single simplistic

8   unified message about the causes of ecological change. Similar issues of scale-

9   dependence and aggregation or averaging effects on the clarity of higher level

10   messages have also been discussed regarding the calculation and dissemination of

11   environmental sustainability indicators (Morse & Fraser 2005; Parris & Kates 2003).

12

13   Analyses of driver-state-impact relationships from large-scale ecological surveillance

14   have high realism and policy relevance. However, the 'accidental' way in which

15   drivers are spatially organised means that detection of relationships can be as much an

16   indication of the lack of equal crossing and replication of possible causal factors as of

17   the inherent potency of a driver to cause change. For example to what extent does one

18   driver emerge as more important than another just because it had operated with

19   greater variation in severity across the study region?

20

21   With sufficiently large datasets it may be possible to analyse subsets of replicated data

22   where variation in a driver is maximised along a gradient or between impacted and

23   control groups. Other drivers could be equivalently crossed and replicated or held

24   constant along with other additional covariates, such as ecosystem type. However,

25   such designed sub-sampling changes the question. Results will no longer realistically

1 represent the accidental interplay of the range of drivers across the entire sampling

2 domain. Such studies provide the basis for quantifiying the impact of a driver but over

3 a domain deliberately engineered to maximise the magnitude of the driver-state-

4 impact signal. These approaches are therefore most useful in deriving realistic

5 statistical models of driver-impact relationships (Maskell *et al.* 2010; Stevens *et al.*

6 2009). Predicted impacts can then be usefully compared with observations in other

7 parts of the sampling domain where other drivers may be operating (e.g. Diekman &

8 Falkengren-Grerup 2002; Stevens *et al.* 2004).

9

10 Finally, we should be aware that the emerging importance of a driver may simply

11 reflect data availability: If data is only available that tracks one driver but an

12 ecological impact could be more fully explained by the main or interacting effect of

13 other drivers then conclusions need to be accompanied by a qualification that analysis

14 is incomplete. Differences in data quality can also be influential. For example more

15 coarsely resolved explanatory variables cannot explain as much variation as those

16 more closely matched to the resolution of the ecological response data (Smart et al

17 2006a). Again, this may mean that some drivers appear more important in explaining

18 change in ecological state indicators than others.

19

20 Whilst the problems we have described are simple to understand, each demands a

21 cautionary perspective which may be easily overlooked in the rush to interpret

22 indicator change in the light of apparently obvious changes in the most likely drivers.

23 Reducing the decline in global biodiversity and the degradation of ecosystem services

24 is both costly and vital. If cost-effective responses are to be formulated they must be

25 based on an accurate understanding of the role of multiple drivers and the way they

1 interact to cause change. Analyses of ecological surveillance data should support the

2 elucidation of causal-correlative links between drivers and state variables. To do this

3 we believe that scientists and policy consumers need to be more aware of the

4 implications of the simple yet subtle problems we have highlighted.

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1 Figure 1. Change in the vegetation nutrient status indicator across British ecosystems

2 between the Countryside Surveys of Great Britain in 1978, 1990, 1998 and 2007. The

3 score was derived from the mean of individual indicator (Ellenberg N) values

4 assigned to species in the British flora, for species that were found in fixed sampling

5 plots in each survey year. Error bars are the 95% confidence intervals on the within-

6 year means (n=729 repeat plots). Statistically significant changes in mean score

7 occurred between all pairs of years except 1978 to 2007 and 1990 to 1998, based on

8 an autoregressive, generalised linear mixed model. An increase in the index indicates

9 greater representation of more nutrient-demanding species. The scale is such that 1

10 indicates species associated with the least, and 9, with the most productive conditions.
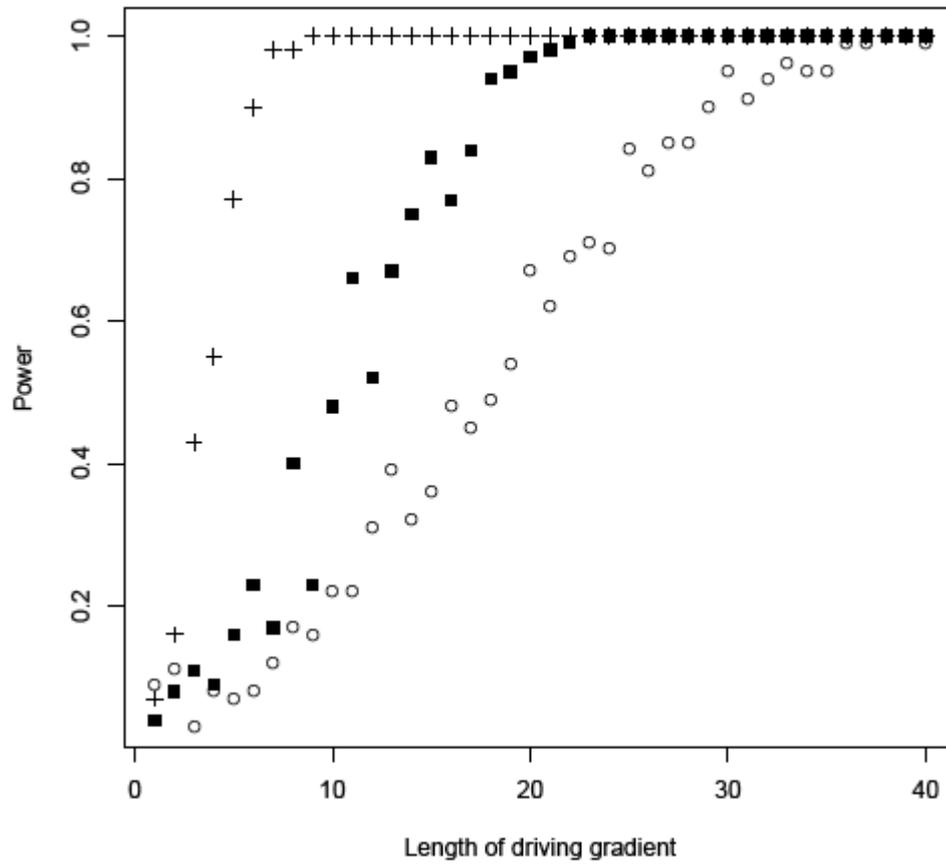
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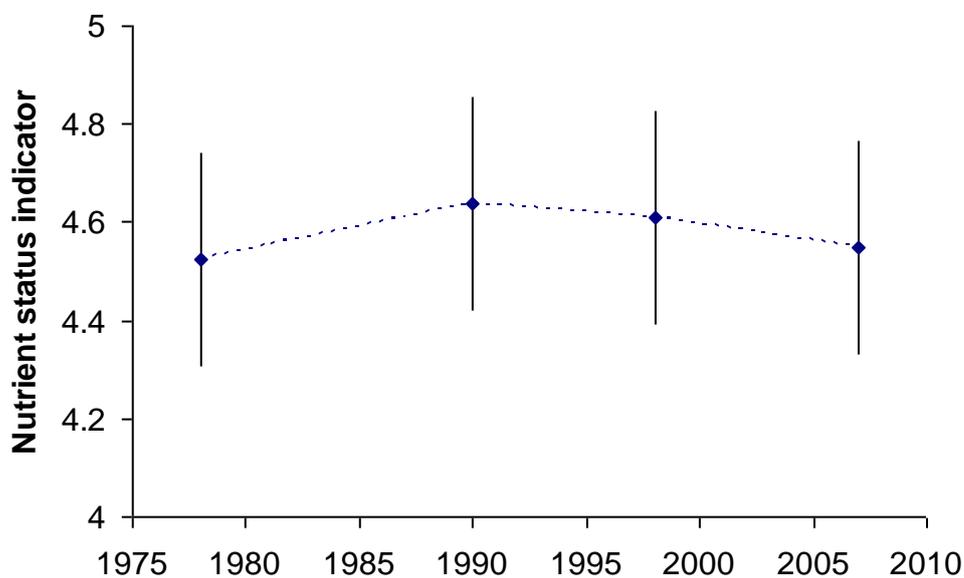
12

1   Figure 2. Change in the vegetation nutrient status indicator (see Fig 1) decomposed by ecosystem type. Values are the difference in the indicator

2   from the starting value in the 1978 survey where all ecosystem types start at zero. Letters after each ecosystem type refer to known or

3   hypothesised large-scale drivers of change in the ecosystem type over the survey period as follows; a) removal of land from production post-

4   1988 (Carey *et al.* 2008; Critchley & Fowbert 2000); b) reduced management intensity post-1990 (Carey *et al.* 2008; Smart *et al* 2005); c)

5   atmospheric nitrogen deposition (Smart *et al.* 2004; Maskell *et al.* 2010); d) abandonment (Sketch 1995); e) agricultural intensification (Smart *et*

6   *al* 2006a; Chamberlain *et al.* 2000), f) woodland succession (Kirby *et al.* 2005), g) lack of traditional management (Kirby *et al.* 2005), h) over-

7   grazing (Fuller & Gough 1999).
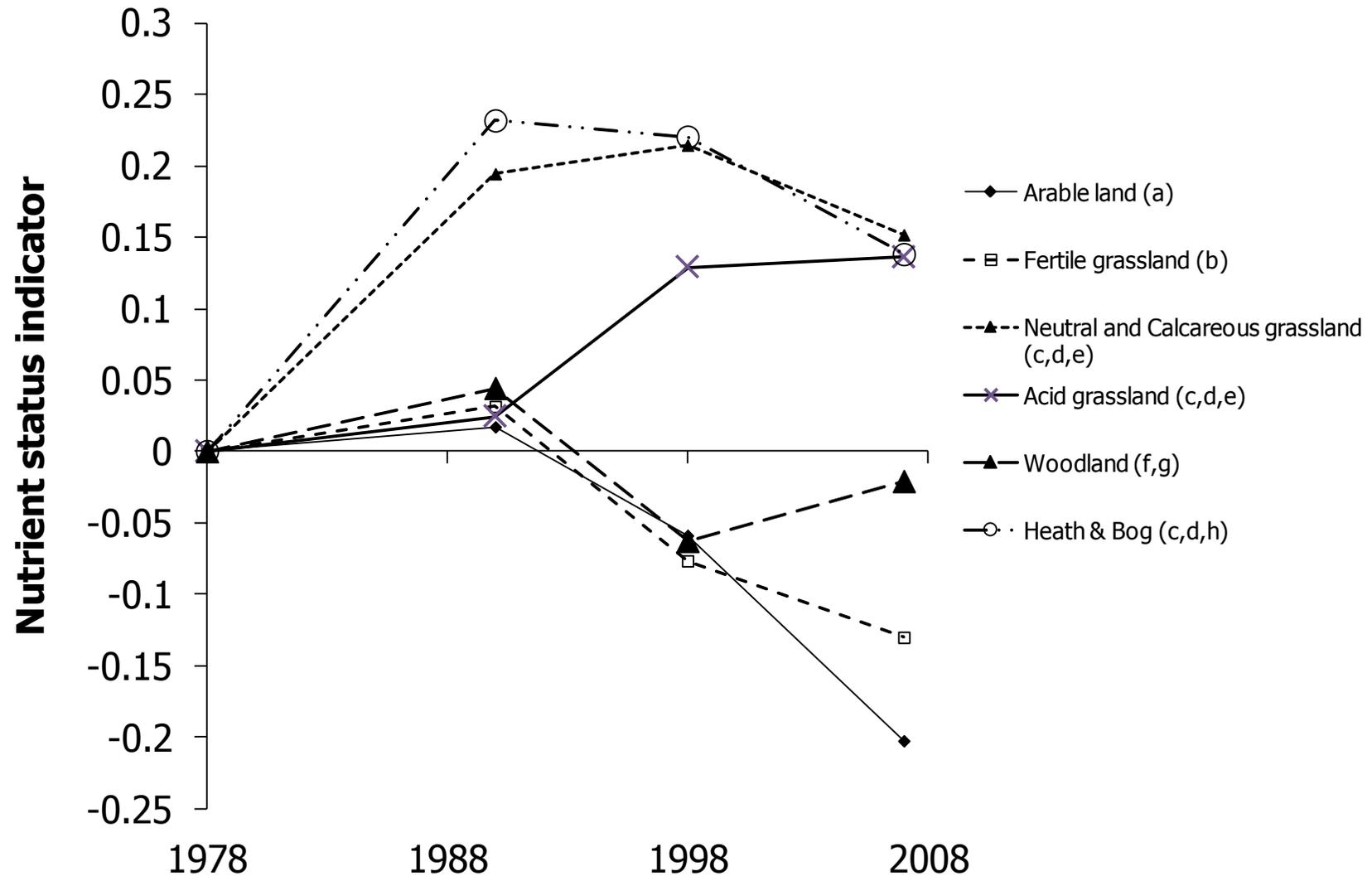
Figure 3. Effect of the range of variation in a driver of ecological change on the

2 probability of detecting a significant correlation with an ecological indicator. Data

3 were simulated based on the linear regression model $y=0.7*x$, with random residual

4 error $e \sim N(0, \sigma^2)$ where σ^2 was set to each of three values; $+ = 5$, ■ $= 15$, ○ $= 25$.

5 For each error variance, forty datasets were generated each of which consisted of 200

6 values but with x made to vary in range within each dataset between 40 and 1 but

7 always with a maximum value of 40. The slope parameter was therefore the same in

8 each dataset but the range of variation over which non-random deviations from the

9 mean response were quantified, varied from large to small. The power of detecting a

10 significant x parameter ($p<0.05$) was expressed as the number of significant linear

11 regression results out of 100 random draws from each error distribution for each

12 dataset. Power was then plotted against the range of the driving variable x. As the

13 range of x was reduced the chance of detecting a significant regression of y on x also

14 reduced. Power declined more quickly if the response variable had greater residual

15 error. Note that since the maximum value of x was always 40, low values on the X

16 axis represent situations where the driver operated with high severity everywhere.

1