Paper Title: Control charts as an informative and robust environmental monitoring tool for decision making

Authors: Aaron Gove, Jess Oates and Robert Archibald
Organisation: Astron Environmental Services
Country: Australia
Email: aaron.gove@astron.com.au

Paper:

Introduction

Due to the dynamic nature of natural systems, all environmental impacts associated with a development can not necessarily be predicted, and therefore appropriate controls are not necessarily introduced prior to development. Hence, ongoing environmental monitoring is considered an integral part of environmental management associated with many types of development. However, within such monitoring programs, criteria for determining: a) whether an impact has occurred, b) whether management intervention is required and c) whether the impact has been addressed, are often poorly developed. This is a current criticism of adaptive management where changes to management are rarely implemented because decision rules are not clearly defined and/or agreed upon (Lee 2014).

Control charts

Control charts are a simple and transparent means of displaying monitoring data within the context of clearly defined thresholds for impact detection ("control limits") and consequent need for management intervention. The visual presentation of data in control charts allows monitoring data to be clearly communicated and consensus on interpretation to be more easily reached. Control charts also provide an intuitive indication of statistical power: the more constrained the control limits, the more likely an impact may be detected (and conversely, the more likely a false positive may occur). Here we present the basic structure of control charts, and then demonstrate their utility with examples from plant health and animal population monitoring programs. We also describe some issues that need to be carefully considered when applying the approach.

Control charts were originally developed to monitor manufacturing processes, but are increasingly employed in environmental monitoring (Morrison 2008). Statistical control charts generally rely on a period of baseline data in order to establish the natural variation of the system which is then used to determine a set of control limits. Conventionally, control limits are set at 2 and 3 standard deviations from the mean of the baseline data (Figure 1; Gove et al. 2013). There are many variations on this theme, and it is possible to monitor a range of different data types including multivariate data (e.g., community composition) and cumulative sums (e.g. emissions) over time.

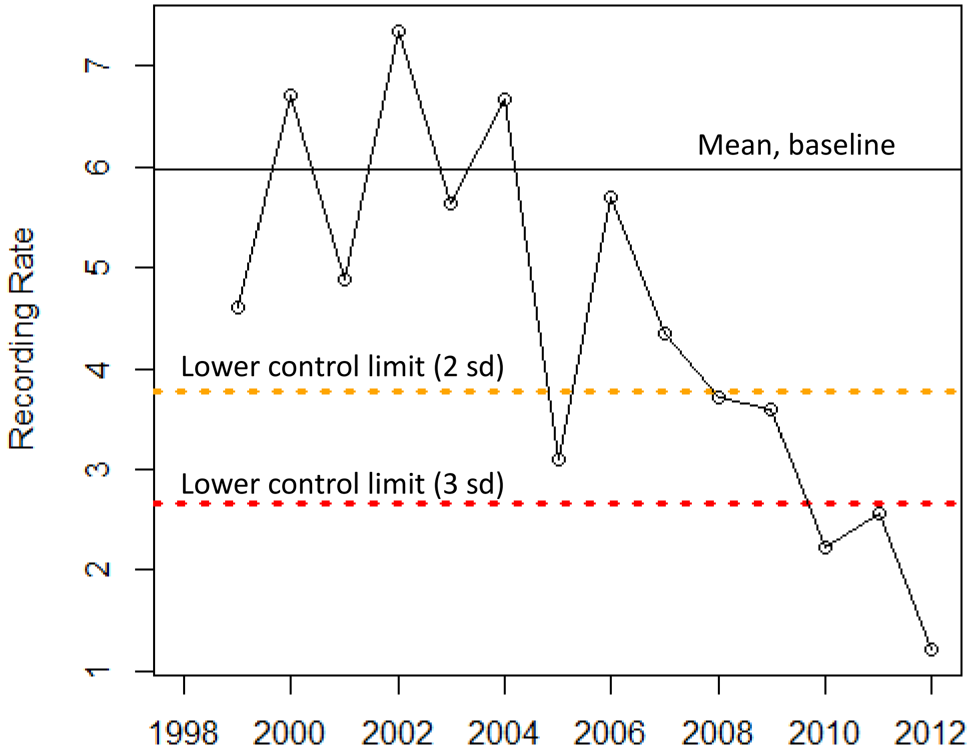

Figure 1. Example control chart, using the recording rate of a bird species. A baseline period (1999-2004) in which the system is considered to be "in control" is used to determine the natural variation in the system. This variation defines the control limits. Conventionally, the limits are set at 2 and 3 standard deviations from the mean baseline level.

Control charts can also be used to monitor changes in multivariate data, such as communities or species assemblages. Multivariate approaches still utilize a period of baseline data, however multivariate variation of this baseline is more difficult to define than univariate variation. To overcome this issue, multivariate approaches use a bootstrapping method (a form of data randomisation), to define particular percentiles as control limits (Anderson and Thompson 2004). These percentiles may be viewed simply as the likelihood of observing the current data. As seen in Figure 2, multivariate data and control limits can be displayed in a variety of ways. The natural next step in the assessment of a species assemblage would be to identify indicator species of this directional change and examine their responses in more detail.

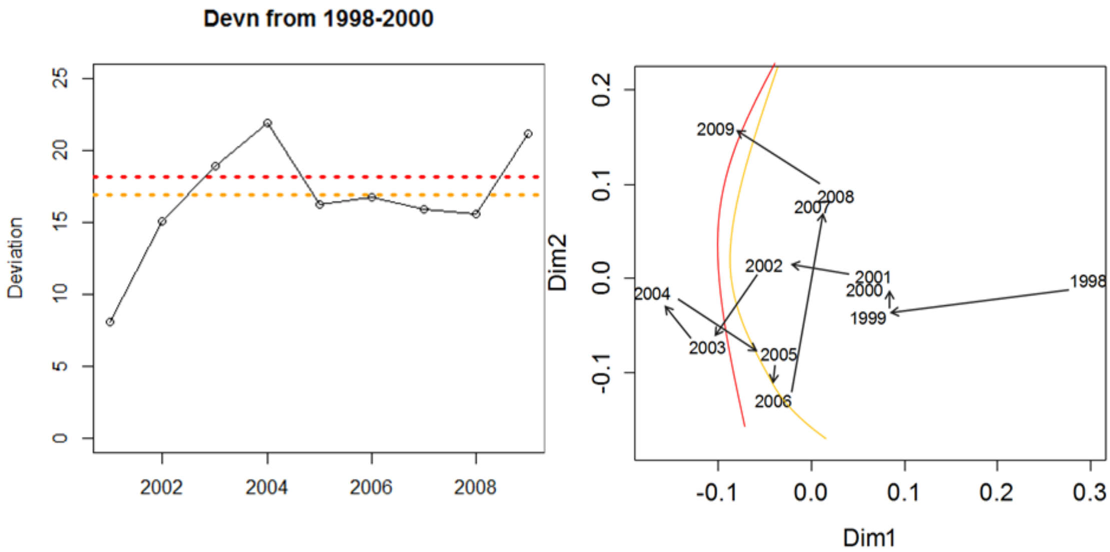

Figure 3: Multivariate bird assemblage data displayed in two different control chart formats. Left: deviation from the 1998-2000 baseline assemblage. Right: a two-dimensional ordination of the bird assemblage over time. In both cases the yellow and red lines represent control limits based on the 90th and 95th percentiles of randomized data. In 2003-2004 and 2009, the assemblage had deviated significantly from the baseline assemblage.

Probably the most significant challenge in constructing control charts is that long periods of baseline data are often not available; impact monitoring often begins concurrently with development. In these cases, several alternative approaches are available in order to establish reasonable control limits.

The establishment of control limits based on a scientific knowledge of a system (e.g., a known leaf wilting point, or minimum viable population size) can not only resolve the problem of lack of extensive baseline data, but can also be more realistic than limits derived entirely numerically (Figure 2). However, unless such control limits are developed using robust and transparent criteria, they can be criticised for being arbitary.

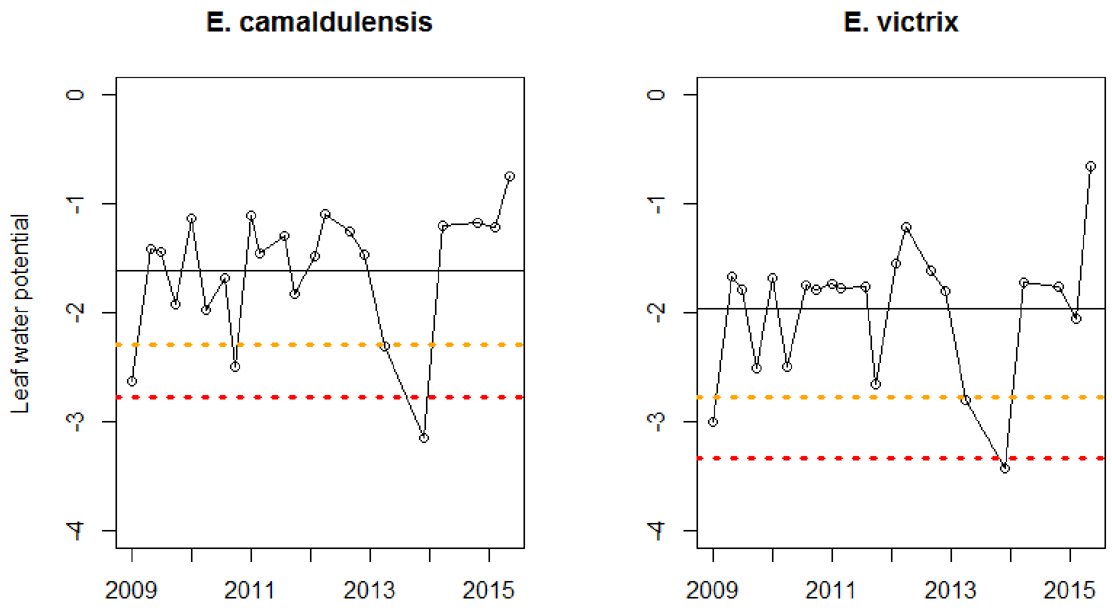

Figure 2: Examples of control charts using a biological control limit for two species of riparian tree. Critical leaf water potentials were based on observations of an independent set of trees. The lower (red) control limit was defined by the 5th percentile of leaf water potential displayed in trees independently assessed as healthy. The upper (orange) control limit is a 0.5 MPa buffer above the lower limit.

Another approach is that natural temporal variation be substituted by natural spatial variation. This spatial variation can be derived from a number of control sites. This may not be ideal where contrasts in spatial and temporal variation are not well understood. However, over time, these control sites will provide an indication of the natural variation in the system (Figure 3).

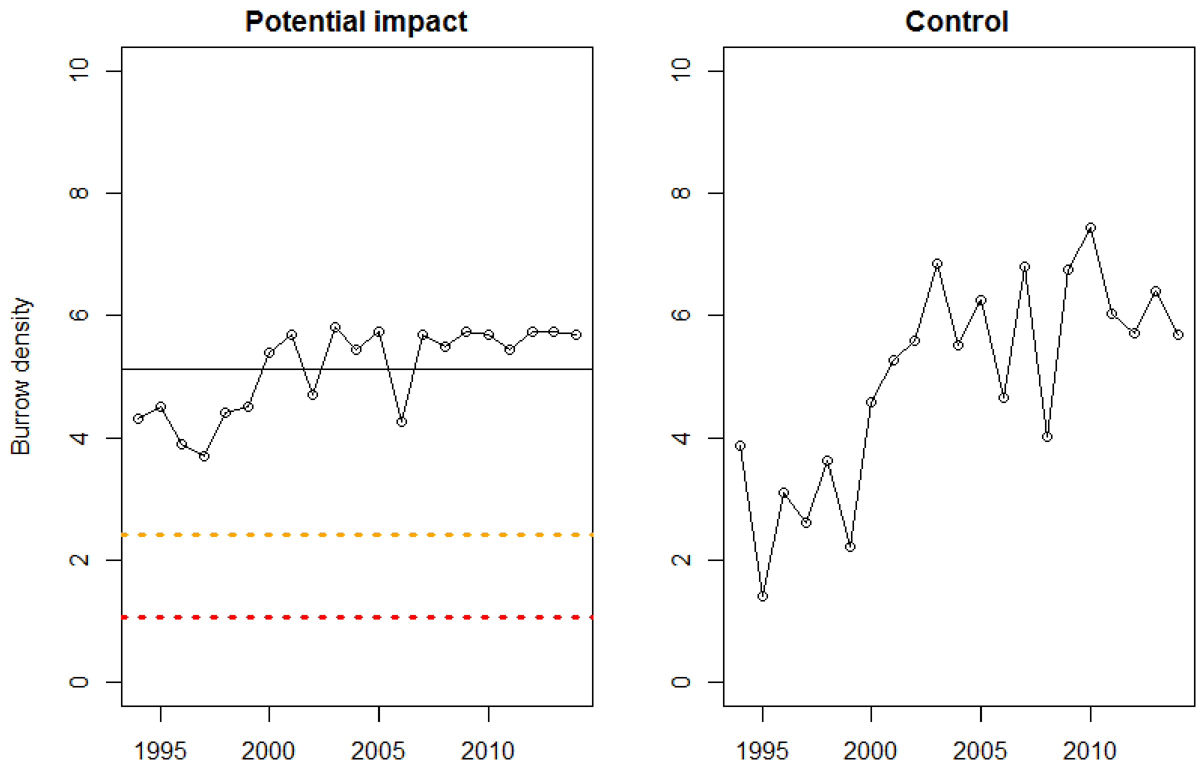

Figure 3: Seabird burrowing density on two islands. As the development begun in the early 1990s, concurrent with monitoring, there is no true historic baseline data. Over the monitoring period "control" populations have also been monitored, and these are used to derive a measure of natural temporal variation.

Remote sensing now provides an extensive array of monitoring options and is frequently able to provide extensive historical libraries of imagery (e.g., Landsat), which can be used to establish baseline values and to derive levels of observed natural variation. The sensor's spectral bands can be used to derive a wide range of usually vegetation related indices, such as Normalised Difference Vegetation Index (NDVI), which is an indicator of vegetation health (Figure 4). Remote sensing also has the benefit that an entire landscape can be monitored, rather than discrete points, but is clearly limited in the types and scale of data utilized, and monitoring of animals using remote sensing for instance, is less well developed.

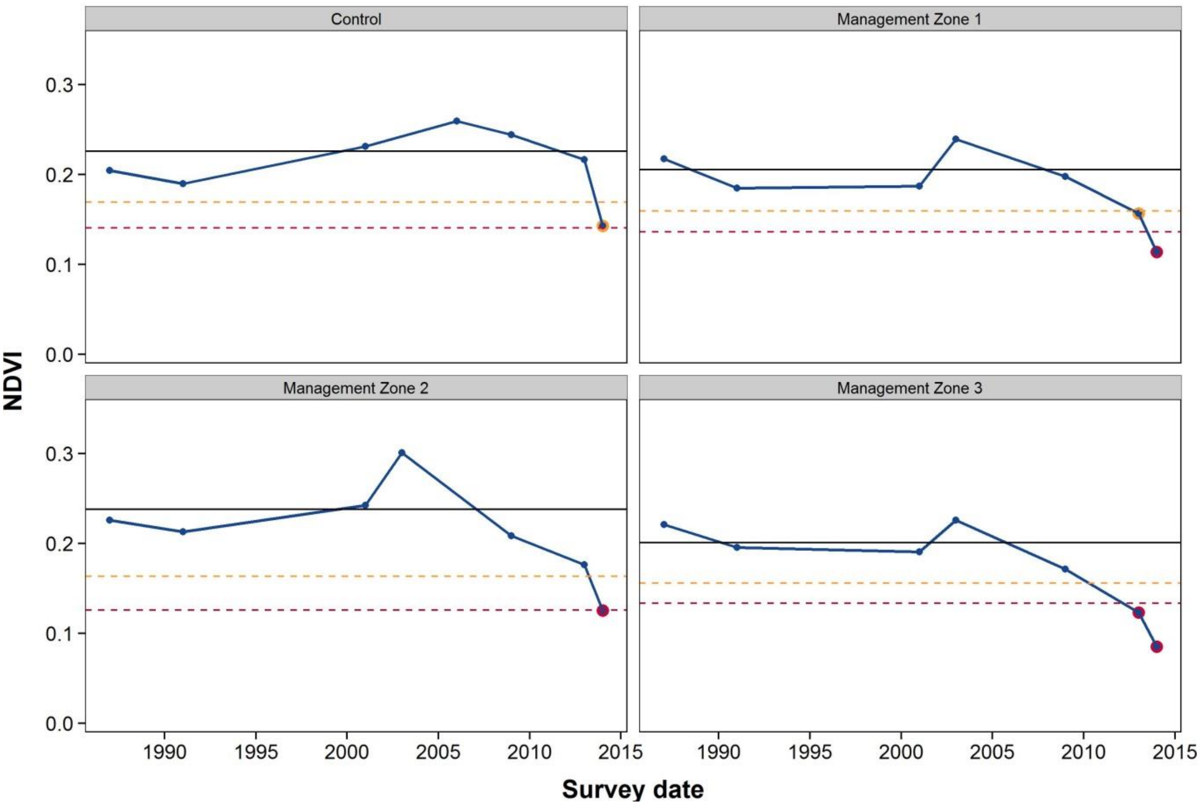

Figure 4: An example of control charts based on remotely sensed vegetation. Change in NDVI (Normalised Difference Vegetation Index) indicates a decline in vegetation condition, however, a similar result in control sites suggests that this decline is not project-related. Solid black line indicates mean NDVI between 1987 and 2014. The yellow and red lines represent the upper (2 SD) and lower (3 SD) control limits respectively.

Conclusions

Control charts are transparent and numerically robust means of processing and presenting monitoring data. Their strength is that management thresholds are clearly displayed, and that a consensus for these thresholds can be clearly established. Control charts however do not specify the intervention required, or whether this intervention is absolutely critical. True biological thresholds and the capacity for natural ecosystems to recover are still poorly understood and interventions must ultimately be determined by environmental managers.

References

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