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A note on vegetation monitoring approaches

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Abstract: We address issues of investigations in plant ecology with a time span exceeding the range of ordinary research projects. According to the findings in the papers of this special issue of *Community Ecology* and other related publications, long-term monitoring is faced with specific methodological challenges:

1. Since the system to be monitored as well as the objectives of monitoring may change over time, the spatial, temporal and thematic scales should be changed considerably.

2. Experience shows that monitoring results are often used for different purposes. However, there exists no sampling design that would offer a true multi-purpose application. The selection of the sampling design will therefore restrict the future use of data.

3. While the selection of sampling units is random and therefore statistical, the selection of variables is usually preferential. This may seriously hamper the results thematically and statistically.

It is concluded that combining precise ground measures with remote sensing data by appropriate mathematical models will be a most promising approach in future monitoring projects.

Introduction

In the *Merriam Webster Dictionary*, monitoring is defined as “to keep track of”, and more explicitly, “check usually for a special purpose”. In the environmental sciences, monitoring is used for long-term measurements. Long term is to be understood in an anthropocentric view: it means that measurements take place over a period exceeding the “usual” time span of a scientific project. In the context of the investigations presented in this volume, long term addresses the temporal scale adopted. One common issue is the fact that measurements are long lasting and may exceed the generation time not only of a project, but also of a person or a research group. Through this, personal experience may get lost over time and the only result persisting are the data records. In the course of this process, any undocumented part of the information is inevitably lost. On the other hand, results gain value in becoming part of the cultural heritage. Most scientists are aware of this fact and therefore tend to invest special efforts into data quality: to improve degree of freedom of error, versatility, reproducibility, and through this, credibility. Efforts of this kind were the motivation to organise a specific conference on vegetation monitoring held at WSL in 2003 and for the publication of the contributions in this issue of *Community Ecology*.

Many problems related to long term monitoring are exactly the same as in any other field investigation. Examples of many relevant issues are given, e.g., in the book of Peterson and Parker (1998) referring to the scale problem. This, as well as others, will be addressed below. One experience, however, is rather striking. Frequently, time series data are used for purposes not planned at the outset of the measurements. This fosters temptation to initialise so-called “all purpose” projects in which research questions are omitted. Although we do not support this idea in general, it happens that even data sets made just recently available were not recorded intentionally. An example is given in the article of Washington et al. (2004, this volume) informing us that the Landsat sensor has reached an age to represent a time series of considerable length. Remote sensors, initially invented as means to capture discrete states of spatial objects, are becoming a major source for the analysis of dynamic processes. And through this, time series analysis, yet another branch of science, is becoming involved in the analysis of this type of data. From this and other issues, we address some below.

Scale and continuity

Scaling is an issue that is treated in all contributions. Related to scale are the terms dimension and level. A useful clarification is given in O'Neill and King (1998). They argue that things we investigate have physical, temporal and others dimensions. Hence, scale refers to extensions measured along these dimensions. Clearly, this requires units to be assigned. The scale of observation has two parts: grain (resolution) and extent (overall size) of an observation set. For space-time processes, scale refers to the space-time index of the stochastic process. In case of time series, long-term variations versus short-term fluctuations (Percival and Wang 2004, this volume) can be of interest. Signals may occur at different frequencies and at different times, and detection of these frequencies can be relevant. As for level, O'Neill and King (1998, p. 7) argue that this "refers to level of organisation in a hierarchically organized system". According to their interpretation, there is no "ecosystem scale", but an "ecosystem level." Whether this is true or not depends on how ecosystem is defined.

The challenge of changing scales is most striking when using satellite imaginary. Schaepman et al. (2004, this volume) demonstrate how they estimate parameters like Leaf Area Index, water content, organic matter and albedo across large areas thereby spatially integrating pools and fluxes. There are no tools to measure these parameters directly, but via proxy-data only, the electromagnetic spectra, and functions derived from these. To find out the "true" values, surface-borne measurements are needed to calibrate the correlations. These take place at much smaller scales by investigations at the plot level. The results, the integration of pools and fluxes, are the outcome of a considerable variation of measurement scale. It is worth noting that the linking of large and small scales is an issue also in other sciences; one example is the modelling of the atmosphere (Nychka 2000). Thus, whenever processes operate at different scales, even if (sufficiently) complete physical descriptions are known for individual scales, combining information from varying scales is one of the upcoming challenges. In particular, suitable statistical methods need to be developed to solve these problems.

Washington et al. (2004, this volume) were also forced to change scale. However, in their case information on ground properties is usually available from existing maps. Even though maps were elaborated mostly for other purposes in the past, they now serve as reference measurements. Even if they are outdated in terms of their original purpose, the remote pictures now represent an excellent source of information for establishing relationships between observations at different scale.

Whereas in the above mentioned cases the change of scale resides on technical consideration, scale-effects may also be the target of monitoring. Campetella et al. (2004, this volume) give an example of using the theory of Juhász-Nagy (1993) stating that the total information content of a data set can be partitioned into two components, "florula diversity" and "associatum" (Bartha et al. 1998). The computation of these diversity measures implies the use of relevés from varying plot size. Change over time is plotted in two dimensions with the two components as axes. Scale here is no longer a constraint, but part of the main issue of the study. If a structure is repeated at different scales, self-similarity is said to have occurred as, for instance, in the relation between number of species and their area coverage (Sizling and Storch 2004). Empirical power laws are identified in specific situations to assess the extent of self-similarity (see, for instance, Brose et al. 2003 and references therein). Estimates of the self-similarity parameter (Ghosh et al. 1997) can be used to give confidence intervals for the expected total numbers of species. If suitable power-laws can be identified, then they can be exploited to develop sampling schemes for monitoring purposes.

The simplest way to account for scale effects is to acquire data at two or more discrete levels. The choice of the levels is often arbitrary, determined by the measuring instrument used. In order to understand space-time dependence of processes, measuring should be continuous. In field investigation, sampling effort often prevents continuity in time and space. Statistical sampling is the only way to obtain an unbiased estimate of the parameters of the system. Remote sensing (Schaepman et al. 2004, this volume) is an ideal means to obtain a continuous picture of a spatial object. Spatial dependence may thus become the issue of monitoring, like change in spatial auto-correlation, spatial trend or anisotropy (Legendre and Legendre 1998, Wagner 2003). The technical limitations of digital pictures of the landscape are given by the size of the area they cover (extent) and the size of the pixels (grain). Since resolution is limited, such data are "quasi-continuous" only.

Continuity plays a similar role in time. From Washington et al. (2004, this volume) we learn that the Landsat pictures now document up to 30 yearly time steps. This is a good approximation to temporal continuity and it will allow analysis of complex temporal processes as the time series grows even longer. A typical case of temporal variable is presented by Kohler et al. (2004, this volume).

Their time step of interest is one year. To learn about the effect of variability involved in their measurements, they investigated monthly changes. This conforms with the idea of hierarchy theory (Allen and Starr 1982) where measurements are indicated one organisational level above and one level below the one of interest: "The middle level represents the scale of the investigation, and processes of slower rates act as the context and processes of faster rates reflect other mechanisms, initiating conditions or variance" (Parker and Pickett 1998).

Finally, there is thematic resolution to be considered. The latter is either the number of bands recorded on a sensor, for example, or it is the degree of differentiation, say e.g., the taxonomic list (families, genera, species, subspecies), or the number of entities recognised (forest types, land-use types, etc.). As families, genera and species are systematically related, results can be generalised *a posteriori*, i.e., by replacing species with families. Varying thematic resolution will thus depend on variable selection, as discussed below.

Statistical considerations

The objective in sampling design is to achieve "representativity". The data should offer a minimally distorted picture (estimate) of the underlying probability space. Resource limitations may force one to combine statistical principles, such as minimisation of mean squared errors, with cost constraints leading to optimal (adaptive) designs. Applications of sampling can be seen throughout this volume.

Sampling design exceeds the scope of a technical task as it will restrict the future applications of the monitoring results. If the sampling subject is a pre-defined single perimeter, then sampling may take place in space using x- and y-axis. Küchler et al. (2004, this volume) monitor a large number of mires based on a random sample. From changes in these mires (the sampling units) they expect to detect changes taking place in all mires. This is done by statistical inference.

No matter if the available data are statistical samples of populations (in case of point sampling) or representative values over large areas (in case of remote sensing), they can be subjected to pattern recognition (c.f. Legendre and Legendre 1998, Jongman et al. 1987). In this, the objective is to identify one or many patterns and to distinguish these from random variation. There are two basic approaches to data reduction: classification and ordination. While the latter is simply a reduction of dimensionality, classification is a discrete view of the sampling universe. Sanders et al. (2004, this volume) analyse their data in the form of discrete maps. The true position of borders in these maps is discussed in the context of uncertainty. Uncertainty has two sources: the variance (or even bias) introduced in sampling and the partly uncontrolled effects of classification. The examples illustrate the difficulties involved in deriving spatially explicit time series data: measurement methods and precision inevitably change over time and data analysis may reflect both the limitations of the measurements and changes of the system.

Most systems analysed in the papers of this volume are of multivariate nature. As a consequence, variable selection took place implicitly or explicitly. The variables define the properties of the sampling universe to be monitored. The properties of interest, in turn, reflect the objective of the study. Variable selection therefore is a subjective task, often appearing in regression models (Washington et al. 2004, Schaepman et al. 2004, Waser et al. 2004, Ohlemüller et al. 2004). Generally, when remote sensing is applied, the number of variables is sufficiently small. In field surveys, variables are often the abundance of species and the number of variables may become excessive. Waser et al. (2004, this volume) and Küchler et al. (2004, this volume) build meaningful derived variables, thereby reducing the dimensionality of the data set. The success of the monitoring project will hence depend on the efficiency of the derived variables to match the objective.

One basic issue in monitoring is the question whether the measurements reflect "change" or "no change". Once the data are available, it is a statistical task to make this distinction. The answer will strongly depend on data quality in which the precision of the measurements is of importance. Careful testing of the methods to reduce measurement-induced statistical noise is addressed by the majority of papers throughout this volume; any statistical test will yield better results when undesired variance can be avoided.

Trends in monitoring

The papers presented in this volume mainly concentrate on the observation of biological variables. Some are motivated by nature conservation efforts and they are aimed at controlling the success of management measures. Others refer to the natural dynamics of systems and the possible acceleration of processes due to global change.

A related issue is an analysis of variation at different scales. For instance, it is of interest to know, how much change has occurred over time in averages of values observed at different time points. This can be answered by means of wavelet analysis of the relevant time series data. Percival and Wang (2004, this volume) perform wavelet analysis of modelled vegetation data and provide an introduction to the subject. In a similar manner, a two-dimensional wavelet analysis of images would compare co-located spatial averages (ibid.), having significant potential for analysing large scale spatial data, for instance, those obtained by remotely sensed data collection methods.

The trends we have identified have been made possible due to technical progress and the development in scientific methods, i.e., in statistics and modelling. Remote sensing gains importance as more airborne sensors with higher temporal and spatial resolution become available (Washington et al. 2004, Schaepman et al. 2004, Waser et al. 2004, Ohlemüller et al. 2004). We noticed that there exists a data pool documenting past states of the landscape not yet fully exploited. These may complement old sources of information from field surveys, such as vegetation maps. Using new tools of data analysis, there is a considerable potential remaining to learn about landscape dynamics from the past.

While past projects often concentrated on spatial pattern and for increased spatial resolution, much less effort has been spent on the analysis of temporal pattern. Changes within seasons, as shown by Kohler et al. (2004, this volume) often complicate monitoring by introducing additional variability. Seasonal change, however, is characteristic of any vegetation type. Once the frequency of satellite photographs is sufficiently high, types will be identified by their short-term temporal pattern rather than through increased spatial resolution.

The issue of global change has shown that time series data are often used for purposes not expected in the past. We are now aware that the same may happen in the future, but we still do not know the issues. Sanders et al. (2004, this volume) strongly suggest measuring raw variables, rather than derived. Vegetation maps showing the spatial distribution of vegetation types exhibit much uncertainty: while the composition of types is expected to change, species may remain the same and maps at the species level therefore represent a more robust basis for future applications. Species may of course change as well, by altering their genetic state at a slower rate. Access to these processes is given by molecular genetics (Manel et al. 2003). It can be expected that time series data of genetic composition will show up soon in vegetation and landscape monitoring.

Conclusions

Monitoring of space-time systems as shown in this volume are based on the following three elements: (i) Ground measures and point monitoring guarantee precise information of small spatial extent while the large-scale pattern is not yet known (ii). Remote assessment and monitoring offer near complete survey of large spatial entities. This allows for the identification of patterns, though their origin is as yet unknown (iii). Modern and appropriate statistical methods are the key to combine the two considerably differing approaches and to test hypotheses on the cause of observed patterns (iiii). The combination of all three elements can be seen in the majority of the papers presented.

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