Downscaling
Alpine vegetation
Detrended correspondence analysis
Universal kriging
K-means

Opportunities and constraints of downscaling in environmental research

Spatial data concerning many aspects of landscape are collected at many levels of resolution, but if combined in numerical models or statistical classifications, they must be brought to a common spatial scale. This can be achieved by upscaling (fine to coarse) or downscaling (coarse to fine). This article explains how downscaling procedures using cheap, high-resolution data from digital elevation models enhance the spatial resolution of mapped vegetation patterns in the Austrian alps.

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When studying landscapes, and the biological, chemical, physical and anthropological processes operating in them, we frequently must deal simultaneously with the very small and the very large. For example, hydrogen ion concentration determines the base status (pH) of clay minerals, which are the result of rock weathering in past and present climates. The lithologic variation of clay minerals over the landscape depends on processes of erosion, transport and sedimentation that operate over many scales. In turn, these factors affect the storage and supply of nutrients to plant roots, thereby influencing the types, structures and patterns of vegetation which determine both the aesthetic and ecological qualities of the land at large (Figure 1). It is no wonder that landscape ecologists have much to discuss concerning the best way to approach their complex study object (Klijn, 2002). The signals that excite them depend very much on the tuning of their antennae to the patterns and processes they consider to be of most importance.

Because it is impossible to measure everything at all levels of resolution (in the limit, 100% sampling of soil or landform would destroy the object of interest!), landscape ecologists are forced to extend the information inherent in their samples and observations to other scales. Upscaling is the process of extending knowledge from small observation units (known in geostatistics as the support – see Burrough & McDonnell, 1998; Goovaerts, 1997) to units having larger areas; the reverse process of predicting local attributes from studies covering large areas is known as downscaling (e.g. Bierkens et al., 2000; Canon & Whitfield, 2002; Sailor & Li, 1999).

Many aspects of landscape ecology involve upscaling from data about objects smaller than people to objects that are very much larger than people. Upscaling frequently requires interpolation or the use of numerical models to extend the knowledge obtained at point or local observations to the landscape at large. In other situations, which are becoming more frequent thanks to large amounts of data in digital geographical information systems (GIS), we may have more information about the landscape over large areas and need means to extend or combine these data to make statements about local conditions. As already indicated, this is known as downscaling. The aim of this paper is to explain and illustrate how statistical methods of downscaling can enhance the value of expensive-to-measure data having a coarse (and possibly incomplete) spatial coverage through combination with cheap, readily available data having a finer spatial resolution.

Reasons for downscaling

Downscaling is the process of reconstructing fine detail from a general picture. This is a common issue in many Global Change studies, when General Circulation Models (GCMs) are used to predict climate-induced responses of local or regional hydrological conditions (Sailor & Li, 1999). Alternative means are necessary to predict local climatic changes at higher levels of spatial and temporal resolution (e.g. Cannon & Whitfield, 2002).

Although most pioneering research on downscaling comes from the Global Change community, the same

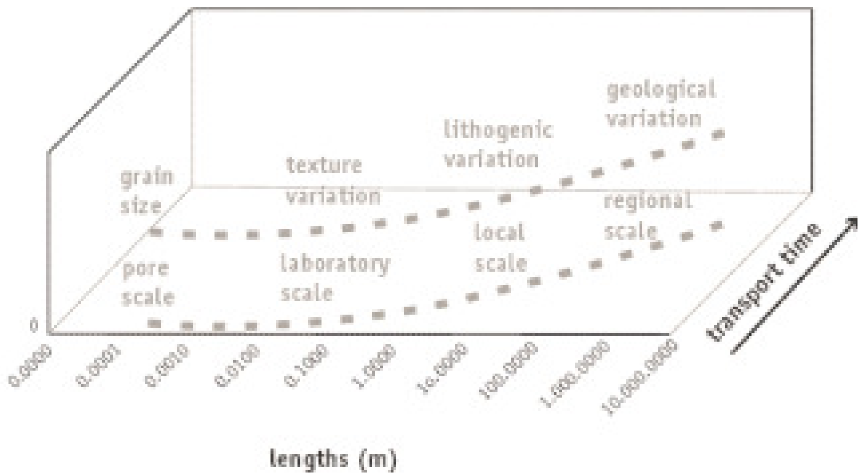


Figure 1. A schematic overview of the range of spatial scales encountered in studies of the physical landscape (adapted from Burrough 1996)

principles apply in landscape ecology when one attempts to predict aspects of the short-range spatial variation of vegetation within larger areas for which only generalised maps or sample surveys are available. For example, in landscape ecological studies it is not uncommon to want to predict the ecological condition of a small vegetation plot from generalised information over a whole region. This may be necessary for many reasons. Commonly occurring situations are:

- the sources of data have fixed levels of resolution that are too coarse for the application (e.g. attempting to infer details of individual patches of vegetation from remotely sensed imagery having 1 x 1 km pixels),
- numerical models of environmental processes often require data to be brought to a common level of spatial resolution,
- it is difficult to sample an area uniformly because of varying ease of access,
- data are sparse or incomplete.

There is much interest in downscaling the coarse resolution digital data obtained by remote sensing or climate models so that they may be linked to regional or local data when required. In recent years there has also been progress in bringing together international digital data sets that can be stored, displayed, analysed and combined in Geographical Information Systems – GIS – (Burrough & McDonnell, 1998; Burrough & Masser, 1998; Longley *et al.*, 2001). Drawing on developments in the United States, Europe and international organisations, Global Spatial Data Initiatives (GSDI) have lead to the establishment of digital data sets of elevation, climate, vegetation, hydrological basins, etc. that have commensurate levels of spatial (but not temporal) resolution (Figure 2). Many of these data sources are linked to standard cartographic map scales that imply a smooth transition in resolution from one level to another.

One of the most important recent developments in GIS technology has been the improved availability of high resolution digital elevation models (DEM). Today, it is quite possible to obtain DEMs of large areas of land with a spatial resolution that is finer than 5 x 5m. To give the reader

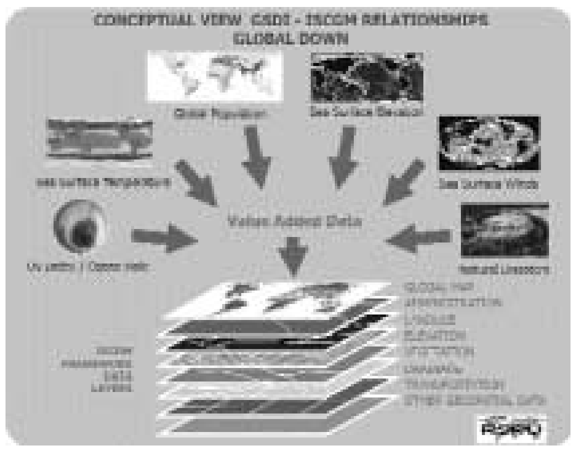


Figure 2. Shared global data may improve understanding of spatial processes affecting the planet, but only at the world scale. This figure and more details from:*http://www.iscgm.org/html4/index.html*

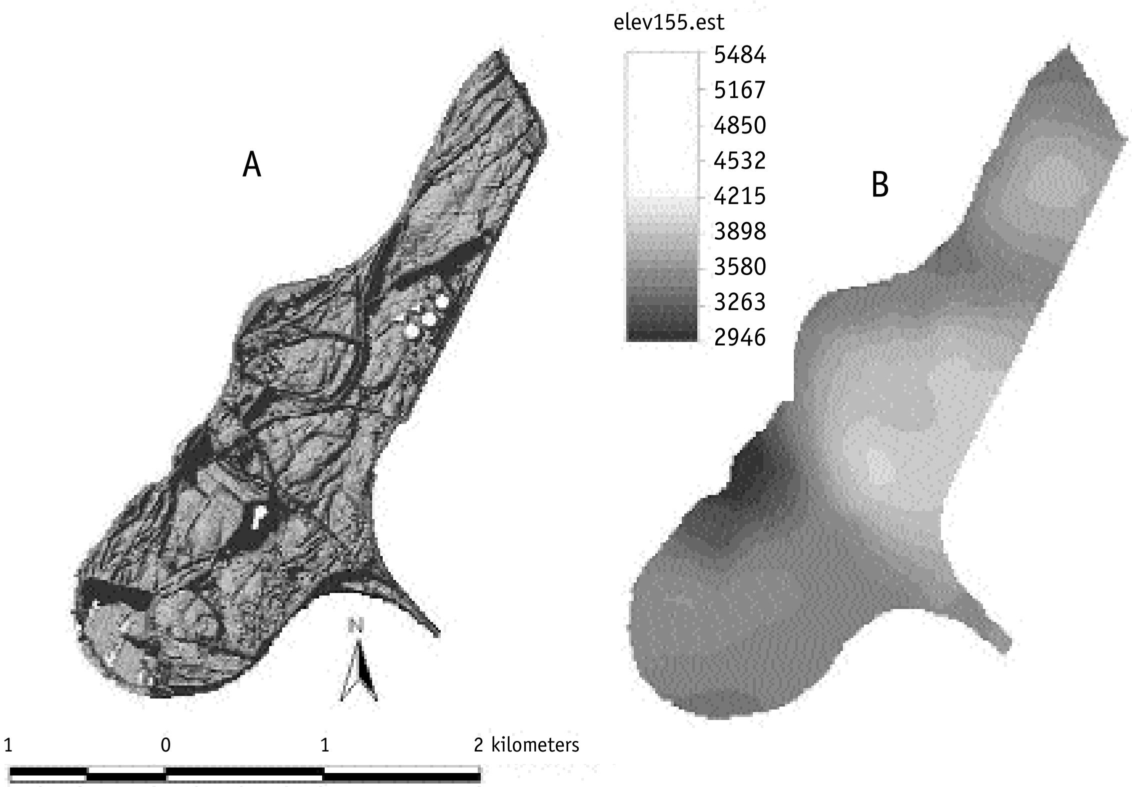


Figure 3 A comparison of elevation data (mm above local reference) obtained from Laser altimetry of part of the Maas floodplain , (courtesy Dutch Meetkundige Dienst) and interpolation by kriging. Left: 5 x 5m resolution, right: surface interpolated from 155 surface measurements to a grid of 20 x 20m. Clearly, the high resolution surface (left) gives much more information over surface structures and ecological differences than the low resolution surface (right).

an idea of the level of surface detail that is possible today, Figure 3 illustrates this for a part of the floodplain of the river Maas in a southern province(Zuid Limburg) in the Netherlands. From this figure we see that not only can elevation differences be computed directly over short distances, but also many ecologically relevant derivatives such as local slopes, aspect and direct received solar radiation and local drainage situations (Burrough & McDonnell, 1998).

As we know that many ecological processes in the landscape are moderated by differences in elevation, slope or incident solar radiation (Burrough *et al.*, 2001) a GIS can be used to calculate the derivatives of a DEM at any required level of spatial resolution, thereby providing a rich source of information on the possible short and long range spatial variation of ecological conditions. If the generalised, or expensive-to-measure attributes of vegetation types or landscape or regional climate can be linked to these detailed data, we have a means to downscale them to the fine level of detail provided by the DEM. Essentially, the global data will be modified by local variations in correlated secondary attributes to provide the more detailed downscaled picture. This can be achieved by using statistical methods and interpolation (Bierkens *et al.*, 2000; Sailor & Li, 1999).

The principles of downscaling

Figure 4, (modified from Bierkens *et al.*, 2000), illustrates the geostatistical principles of downscaling. The term support is used to indicate the size of the basic spatial unit for which data for a given attribute z are available.

The horizontal axis gives the size of the support s_i while the vertical axis gives the value of the regionalised variable z_i for the whole of that support. The size of support s_2 is the smallest spatial unit for the generalised data; within this basic unit the value of z is taken to be uniform be-

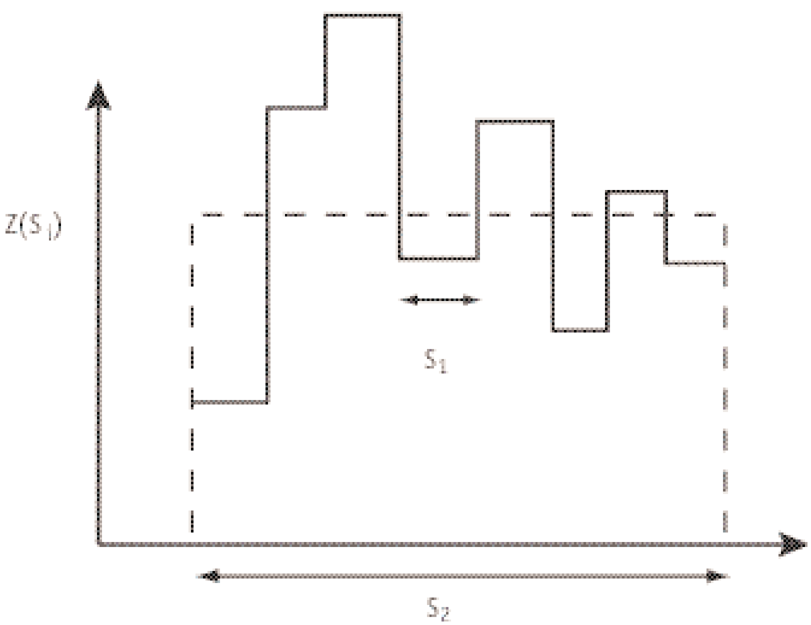


Figure 4. The principles of downscaling. Given data with the spatial resolution of s_2, reconstruct the variation of the attribute z for spatial resolution s_1

cause there is no more information. In other words, when the support is large (s_2) there is no information about the spatial variation of z within the dimensions of s_2 – only a mean value is known.

The size of the smaller support s_1 represents the desired level of spatial resolution. By downscaling we are attempting to create information about the more detailed variation of z. In this case the resolution of s_1 is eight times better than support s_2.

It is easy to generalise data from a fine to a coarse support. For a given cell there are many ways to compute the upscaled value of z_2 from the 8 data of z_1, the most obvious being the mean, or the mode, the median, the most commonly occurring value and so on. Downscaling – i.e. computing the values of the z_1 data from the z_2 is much more difficult. Because the same value of this s_2 mean can be obtained from a very large variety of, and operations on, the 8 values of the s_1 data: the variation of $z(s_1)$ shown is but one possible combination from an infinite set of possibilities based on the support s_1. This phenomenon, called equifinality, means that determining unique s_1 values from the s_2 value is impossible without extra information, so, given that we have information on z at the level of s_2, how can one predict z at the level of s_1?

There are two main approaches to downscaling that use various forms of regression:

- Have local, but sufficient amounts of empirical data on z at the level of s_1,
- Use large amounts of cheap, proxy data to predict z at the level of s_1.

Local, but sufficient amounts of empirical data on z at the level of s_1

Given sufficient amounts of data on z at the level of s_1, in principle we can use methods of spatial autocorrelation and interpolation (geostatistics) to estimate the spatial covariance of z for any required level of resolution (Burrough & McDonnell, 1998; Goovaerts, 1997; Heuvelink & Pebesma, 1999). Alternatively, through methods of conditional simulation, we may create models of the statistical nature of the spatial variation of z at the level of s_1. These models of spatial autocorrelation may be extended to areas for which we have none or very few data at the level of s_1 (e.g. Lagacherie *et al.*, 1995).

Use proxy data to predict z at the level of s_1

Proxies are attributes that are easier to measure than those about which information is desired, but which are thought to have a strong correlation with them. A well known example is the oxygen isotope ratio in ice cores, which is thought to provide a strong indication of climate change. As noted before, detailed digital elevation models may provide useful proxies for ecological variations in a landscape. Their value may be enhanced if they can be

combined with information on the probabilities of particular relations that are known to occur.

There are many other computational tools to convert spatial data from one level to another. Besides the methods of spatial autocorrelation already mentioned, these include process models (e.g. hydrological models, crop yield models, etc.), and empirical models based on logistic regression (e.g. Barendregt *et al.*, 1993), multivariate classification (Burrough *et al.*, 2001; Pfeffer, 2003), neural networks (Cannon & Whitfield, 2002) and similar approaches. Van Horssen *et al.* (1999) combined geographical information systems, geostatistical interpolation (kriging) and logistic regression modelling to predict plant species in wetland ecosystems in the Netherlands. Bierkens *et al.* (2000) and Burrough & McDonnell (1998) provide more details of these and other methods.

In a flat landscape, the values of the attributes of interest or their proxies are usually directly linked to the support in question. In mountainous and hilly landscapes, the data collected for any given instance of the support s_j may also depend on other factors. Note that with certain kinds of proxy data (e.g. derivatives from digital elevation models and reflected electromagnetic radiation detected by remote sensors), the attributes of an instance of a given support may vary depending on the geometrical orientation of the sampling grid (Demargne, 2001). Nevertheless, we ignore this complicating issue here.

A case study: downscaling Alpine vegetation data by a factor of 10 using a digital elevation model, detrended correspondence analysis, universal kriging and k-means clustering

Although it will be clear from the foregoing that there are many ways to achieve a downscaling of environmental data from the generalised to the particular level, we will attempt to elucidate the process further using a case study taken from recent practice (see Pfeffer, 2003, Pfeffer *et al.*, 2003). The example chosen concerns the need to carry out rapid mapping of vegetation in difficult to reach, high altitude areas of the Austrian alps that are much used for skiing so that the impact of the sport has a minimal effect on the natural alpine vegetation. Local planning for optimising the location of ski runs in mountain areas requires detailed spatial information on site factors such as vegetation, which is commonly lacking in rugged terrain. The direct sampling of vegetation in high altitude alpine areas is only possible for a limited period of the year and access is difficult so systematic mapping is expensive and rarely carried out. In high altitude alpine areas the collection of data from 10 x 10m quadrats on a 100m grid would be regarded as 'detailed', though it is clear from recent research that important vegetation differences may occur over much shorter distances in the alpine environment (Guisan *et al.*, 1998; 1999; Guisan & Zimmermann, 2000; Hoersch *et al.*, 2002).

In contrast to the difficulties of visiting many sample sites, the diversity of alpine flora almost guarantees the recording of large numbers of different plants, leading to a richness of information about plant communities, but little about their spatial patterns. Therefore we may have relatively much information about the composition of different plant communities, and relatively little about their spatial distribution. In these circumstances it makes

sense to use the quadrat samples to develop an optimal (i.e. the best local) classification for the vegetation data and to use a cheap proxy for spatial mapping (c.f. van Horssen *et al.*, 1999).
As noted above, current GIS technology makes it easy to create detailed digital elevation models from large scale (1:25000) digitised contour maps or aerial photographs. These topographic attributes and their spatial derivatives (slope, slope curvature, direct received radiation and wetness indices) are realistic ecological proxies for the supply of energy, moisture and nutrients that may influence plant growth and vegetation types (Burrough *et al.*, 2001; Hoersch *et al.*, 2002): they can easily be computed from a gridded digital elevation model (DEM) at any desired resolution. As explained in the following sections, the high resolution, cheap data were combined with the vegetation classes to map the short-range spatial variations of vegetation in the terrain.

Study area

The study area is located in the Ötztal, a north-south valley in the Tyrol, on the upper western slopes of the village of Sölden, which is a popular ski area in the Austrian Alps. It covers an area of approximately 3.6 km2, and has an elevation range from the timberline, at about 1900m, up to 2650m. Figure 5a shows a general view of the upper part of the study area, while Figure 5b shows short-range vegetation across narrow (20-50m) valley heads in the lower, east-facing part. Full details of the study area are given in Pfeffer (2003).
The procedure was as follows:

Vegetation sampling

During the summer of the year 2000, plant species occurrence was recorded at 223 quadrats, each 10m x 10 m, located on a reference grid of 100m x 100m (Figure 6a). In each quadrat all species were recorded according to ordinal abundance: 1 indicates the presence of a plant species, 2 means frequent occurrence and 3 means that a certain plant species was dominant. In total 147 species were identified, neglecting some grass species and all fungi and ferns. Fifteen quadrats were rejected because they fell on tracks or other disturbed ground leaving 208 for analysis.
The vegetation data show that the study area contains many common species, known to be typical for alpine grassland and alpine heaths (Reisigl & Keller, 1987). Although each species has its own preferences, some are broadly tolerant making it difficult to identify an unambiguous correlation of species preferences and ecological attributes. Certain key species were recorded which were characteristic for sites with specific conditions like a certain elevation range, exposure or moisture content. Although these key species are important for mapping vegetation types, they frequently occurred in narrow valleys with different conditions that were too small to be resolved by the 100 x 100m sampling grid. Therefore we sought a way to downscale these vegetation data so that the vegetation types occurring in the smaller components of the landscape could be predicted.
The first step in downscaling was to reduce the 208 x 147 vegetation site/species data matrix to manageable proportions. We used detrended correspondence analysis (DCA - Canoco 4.02: Ter Braak & Smilauer, 1998), which returned four axes with a cumulative explained variance that was only 20% of the total of the complete data set (Pfeffer *et al.*, 2003). This result suggests that much of the area is indeed poorly differentiated (i.e. it is covered by a broad range of similar species with a wide range of tolerance) and that rare species, if any, occur in the less frequently sampled parts of the landscape.

Figure 5. a: (Top) view of Hoch Sölden to the north; b: (bottom) west-facing low lying gullies with large variation of vegetation over distances of 20-50m

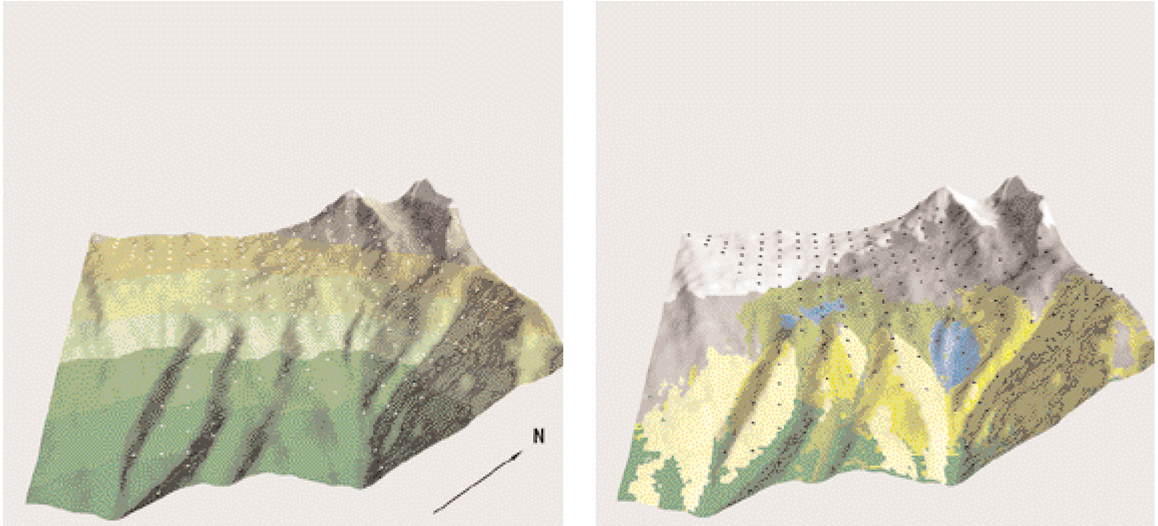


Figure 6. View from the west: a) Sampling network for 100 x 100m survey of vegetation (left): b) final vegetation classes mapped to 10m resolution by downscaling (right).

Creating high resolution proxies for mapping vegetation

We used a digital elevation model with cell sizes of 10m x 10m, (source: Bundesamt für Eich- und Vermessungswesen, Austria), which was the level of spatial resolution required for the downscaled vegetation map. The ecological proxies for vegetation namely altitude, slope, planform curvature, profile curvature, potential received annual solar radiation, distance to ridges, and mean wetness index were derived from the digital elevation model using PCRaster (PCRaster, 2002; Van Dam, 2001; Wesseling *et al.*, 1996). All results were stored in raster maps having a grid cell size of 10 m.

The downscaling procedure has four steps:

1 Compute the regressions between the dependent vegetation scores (DCA axes) and the independent proxies (elevation, slope, incident radiation, etc.) for the 208 quadrats.

2 Examine the residuals from these trends for spatial correlation using semivariogram analysis.

3 For each DCA axis, use the regressions and the semivariograms to create four DCA score maps at the resolution of the DEM.

4 Create 7 vegetation classes using a k-means classification of the original 208 DCA scores; use the k-means to allocate all points on the 10 x 10m grid to a vegetation class at the fine level of resolution desired.

Step 1 yielded the results given in Table 1, which confirm the assumed links between topographic proxies and vegetation scores, and provide the regression models (see Pfeffer, 2003).

Step 2 resulted in four spherical semivariogram models being fitted to the residuals from regression (Table 2). Parameter c0 indicates the level of non-spatial noise, c1 gives the level of spatially correlated variation, and a gives the range in metres over which that variation acts. The relations of c1 to c0 show the strong spatial dependence in all four sets of residuals, particularly for the first and third DCA axes.

Step 3 involved using the regression models and the semivariograms of residuals to interpolate each DCA score by universal kriging (Burrough & McDonnell, 1998; Goovaerts, 1997) to all cells on the 10 x 10m grid for the whole of the study area. This yielded 4 maps, one for each DCA axis.

In *step 4* k-means clustering first created 7 vegetation classes based on the DCA scores from the 208 sampled quadrats. The k-means clustering algorithm (Hastie *et al.*, 2001; MacQueen, 1967) is an iterative descent clustering technique designed to distribute multivariate data among k clusters, where k is typically less than 10 groups. For quantitative variables using a Euclidean distance metric, the total cluster variance is minimized with respect to the cluster means by assigning each observation to the closest mean. The means are recalculated and the observations are reallocated to the nearest clusters; this procedure is it-

erated until cluster memberships are stable.
Once the clustering had been carried out, all 10m x 10m grid cells were allocated to a class based on their interpolated DCA scores. The final map was displayed draped over the DEM for clarity (Figure 6b).

Discussion and conclusions

The exercise reported in this paper demonstrates that even with noisy data and many plant species tolerant of a wide range of conditions, it was possible to downscale information from a relatively coarse vegetation survey to a much finer spatial resolution. This was thanks to the extra information obtained from geostatistical interpolation aided by simple proxies derived from a high resolution DEM. Field checking, particularly in the narrow valleys to the east of the study area, showed that in these limited areas the mapped vegetation, which was based on a very sparse sample of less than 10 quadrats, corresponded with the impression of the vegetation obtained in the field. The consistency analysis indicated that it was essential to include all kinds of vegetation type in the initial sample, especially if the vegetation type represented was not common.
We conclude that although downscaling has many limitations, the availability of cheap, spatially well-correlated proxies supported by regression and spatial autocovariance studies (i.e. universal kriging) may make it possible to create useful and detailed maps of vegetation types from sparse, expensive data.

Downscaling: opportunities and constraints

As the case study shows, downscaling is not simple and requires considerable understanding of the methods of data processing being undertaken. There are both opportunities and constraints, however. The opportunities include:

- the extension of knowledge from general levels to local detailed areas,
- methods can be automated,
- enables quick and reproducible coverage of large areas if properties are similar,
- downscaling makes good use of the available ancillary data and proxies, whether in mechanistic models or empirical functions.

The constraints include:

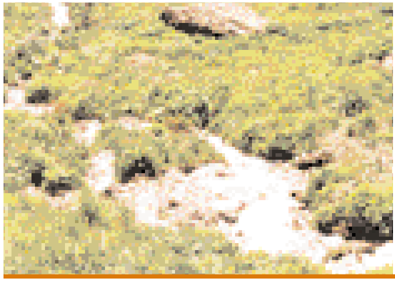
- an almost total lack of unique solutions,
- information that has been lost cannot be created from nothing – if a particular vegetation type has not been sampled then there is no information to link to fine scale proxies,
- many predictions will be based on stochastic relations that may be poorly understood,
- any single means of downscaling may not apply over all levels of the phenomena hierarchy (atoms to oceans),
- non-linearity and feedback loops may obfuscate the relations between emergent properties and details, or complexity and simple interactions,

Dependent variable	Independent variables (proxies)	Multiple R^2
DCA1	Elevation, slope, incident solar radiation	0.7466
DCA2	Mean wetness index, elevation, slope	0.1095
DCA3	Incident solar radiation	0.2733
DCA4	Profile curvature	0.0221

Table 1. Main dependent variables contributing to each vegetation axis

Dependent variable/Parameter	c0	c1	a
DCA1	0.11	1.33	10823
DCA2	0.42	0.80	612
DCA3	0.48	3.49	12779
DCA4	0.58	1.23	2522

Table 2. Parameters of spherical model semivariograms fitted to the residuals of each DCA axis



- the quality of the regression models used in downscaling may be quite sensitive to relatively small variations in the size and composition of the data set. For example, omitting only a few sample sites from critical narrow valley sites resulted in a much poorer performance when downscaling the vegetation patterns of the case study area.

Abstract

Sizes of discernible spatial units in landscapes (called the support in geostatistics) range from very small ($<10^{-6}$ m²) for soil particles and bacteria to very large ($>10^9$ m²) for geological formations and climatic zones. Many environmental models require data at common levels of spatial resolution but it is clearly impossible to measure everything at either one, or all scales. Therefore, people attempt to link data collected at different scales either by predicting the attributes of large areas from sets of local, high resolution data (upscaling), or by inferring the attributes of small areas from generalised data on large areas (downscaling). Downscaling attempts to reconstruct the fine picture from regional patterns, but this may be achieved in an infinite number of ways.

Successful downscaling is only possible through the use of ancillary fine detail (e.g. high resolution remote sensing or digital elevation models), and process-based and empirical modelling (e.g. logistic regression or neural networks) based on substantial data sets of useful proxies or mechanistic, physically-based models. In this paper, downscaling is illustrated by an example from the Austrian alps in which detailed digital elevation models, universal kriging and multivariate clustering were used to improve the spatial resolution of high altitude, sparsely sampled vegetation patterns.

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