COMMUNITY ECOLOGY 4(1): 29-33, 2003
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The effect of measurement scales on estimating vegetation cover: a computer-assisted experiment

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Keywords: Artificial vegetation pattern, Estimation bias, Estimation error, Ratio scale, Visual assessment.

Abstract: We performed a computer assisted experiment to test the accuracy of different ratio scales in estimating vegetation cover. Sixteen subjects estimated the cover level of artificial vegetation patterns displayed on the screen for various levels of resolution (from presence/absence to 100 different states, each measured on the ratio scale). We found that estimation error is minimum when the range of cover is divided into ten equal parts. Finer resolution gives less precise estimation since subjects tend to divide cover level into ten or at most twenty intervals in their mind.

Introduction

The minimum requirement for characterising a community is to identify its constituting species. In addition, the measurement of density (Smith 1944) or species performance often involves the estimation of cover in vegetation science. The cover-abundance scale proposed by the Zürich-Montpellier school and its numerous variants are the most widespread in Central Europe (Becking 1957, Braun-Blanquet 1964). Due to its hybrid nature, the scale is ordinal and cannot be directly applied to conventional statistical analysis. There are some attempts to develop transformation methods to facilitate their analysis (Bannister 1966, Noy-Meir 1973, Noy-Meir et al. 1975, Londo 1976, Jensen 1978, van der Maarel 1979, Avena 1981, Peet et al. 1998). These refined methods use ten, twenty or even hundred classes for cover estimation, thus approaching the ratio scale. In addition to the statistical applicability of a given measurement scale, estimation error made by the observers is also of some concern in vegetation analysis. However, only little experience has been accumulated on observer errors inherent in field estimations (Sykes et al 1983, Gotfryd and Hansell 1985, Kennedy and Addison 1987, Lepš and Hadincová 1992, Klimeš et al 2001). These studies have pointed out that cover estimates depend not only on the characteristics of the sample, but also that observers also estimated vegetation cover in a significantly different manner. An alternative method approximates the cover level with the probability that randomly dispersed point quadrats hit a piece of vegetation rather than bare soil. There is a theoretical and a practical problem with this method, namely the size of the "point" can influence the result considerably (Aberdeen 1958, Hatton et al. 1986) and the method is time-consuming. Whereas special devices are available to help the scientist to measure cover and abundance in an objective way (at least in simple agricultural situations) and computer aided image analysis can make estimation more objective in some instances (Dietz and Steilein 1996), it is unlikely that vegetation data will ever (or at least in the near future) be free of our subjectivity. It is therefore basically important to reveal the characteristics of the assessment, and to reduce estimation error as much as possible.

Every cover estimation process starts with the definition of categories, no matter whether expressed on an ordinal or a ratio scale. The estimated values must fall into one of several categories. Evidently, the accuracy of estimation depends not only on the precision of the estimation process, but also on the size of the categories as well. If we have many small categories then we have the opportunity to measure cover more accurately. However, selecting the right category becomes increasingly difficult if more and narrower categories are used. Our main question is whether the balance of these two opposite effects can create an optimal categorization. In other words, is there a resolution level with minimum estimation error?

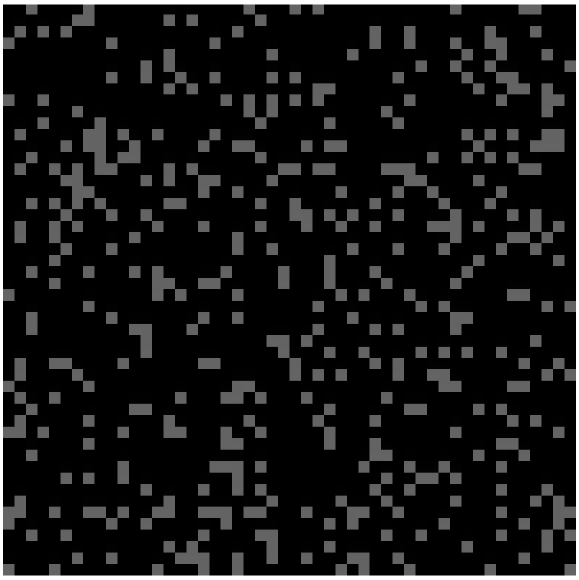

Figure 1. A simplified vegetation pattern as shown on the screen. The grey shapes were displayed originally in green, the background was black.

To answer this question, we simulated artificial vegetation patterns on computer screen and evaluated the estimation errors made by the subjects of this computer-simulated experiment.

Computer experiment

A simple artificial pattern was generated and displayed on the screen of the computer. Cells were colored green randomly in a 50 x 50 rectangular grid whereas the background was set to black (Fig. 1). So the number of green cells was selected randomly within the interval [1, 2499], thus simulating vegetation cover ranging from 0.04% to 99.96% respectively. Although, as we mentioned above, usually 5, 10 or 100 categories are used in real estimation experiments, to evaluate the relationship between the category number (n) and the estimation error more precisely we chose categories from a wider range, (i.e., n = 2, 3, 4, 5, 6, 7, 10, 12, 14, 16, 20, and 100). The categories were of equal size for each value of n even if this is not necessarily the case in actual situations. We chose this uniform scaling method as the simplest starting point for a further, more elaborated research project. When watching the screen the subjects were informed about the actual number and size of categories used in that experiment. The subjects were asked to estimate the total area covered by the green cells, that is they had to choose the cover-level category that they thought to be the right one. Fifty random patterns were presented for every value of n for each person. We recorded the estimated category, the actual cover and the estimation time in every case. Our 16 subjects were all undergraduate or PhD students at Eötvös University.

Results

Sixteen persons estimated 50 different cover patterns for each value of n, yielding a total of 800 cover-level estimates for each category number. To calculate mean estimation error, the intervals of the categories were substituted by their centroids (that is, if the subject chose the 3rd interval on the 10-level scale, then he/she estimated 25% coverage). Mean estimation error is defined as the average of the absolute value of the differences between the actual cover and the centroid of the estimated category, that is the average of $| x-[100(\alpha-0.5)/n] |$, where x is the actual cover value, n is the category number and α denotes the category chosen.

Figure 2a depicts these errors in the function of category number. Mean estimation error decreases sharply from 2 to 10 categories, and increases moderately afterwards. As we emphasized in the Introduction, estimation error arises from two different sources: from the error proportional to the width of the category ("partition error") and from the error caused by the incorrectly estimated coverage interval ("mis-estimation error"). Since cover values were distributed evenly in this experiment, we can calculate the mean partition error easily as $100/4n$ %. Thus, after an experiment containing M estimates with L ($L \leq M$) correct ones, the mean partition error is simply $100L / (4Mn)$ (for details, see Appendix). Figure 2b plots the correct interval estimates L out of 800 estimates obtained for each value of n. Interestingly, L decreases linearly with the logarithm of n for $2 \leq n \leq 20$. L is out of this strict trend for $n = 1$ (the trivial case when merely a presence/absence decision has to be made) and for $n = 100$. Knowing L for every category number, we can compute the partition and mis-estimation errors easily (Fig. 2c). While partition error dominates estimation error for $n = 2$ and 3, its role in estimation error is negligible if there are 20 or 100 categories (Fig. 2c).

According to the Kruskal-Wallis test, the average estimation errors differ significantly for category numbers ($p < .0001$). We used this non-parametric test since the Kolmogorov-Smirnov test indicated non-normality of the data. Figure 2a suggests that mean estimation error is minimal at $n = 10$. Thus, we compare the average estimation error at $n = 10$ with the others, using Mann-Whitney test. The average estimation error at 10 categories differs significantly from every other case except n = 12, 14, 16 (Zar 1999).

Interestingly, there is a special reason why persons could not estimate cover more precisely when hundred intervals were available. As Fig. 3 demonstrates, the last digit in the estimated cover was most frequently 0 and 5 in this case, while in reality the digits are evenly distributed, except that zero has a lower expectation, since zero and 100% coverage were excluded from the simulation. It means that persons tend to divide the cover into ten, or at most, twenty intervals in their mind, even if they have the opportunity to give more precise estimates.

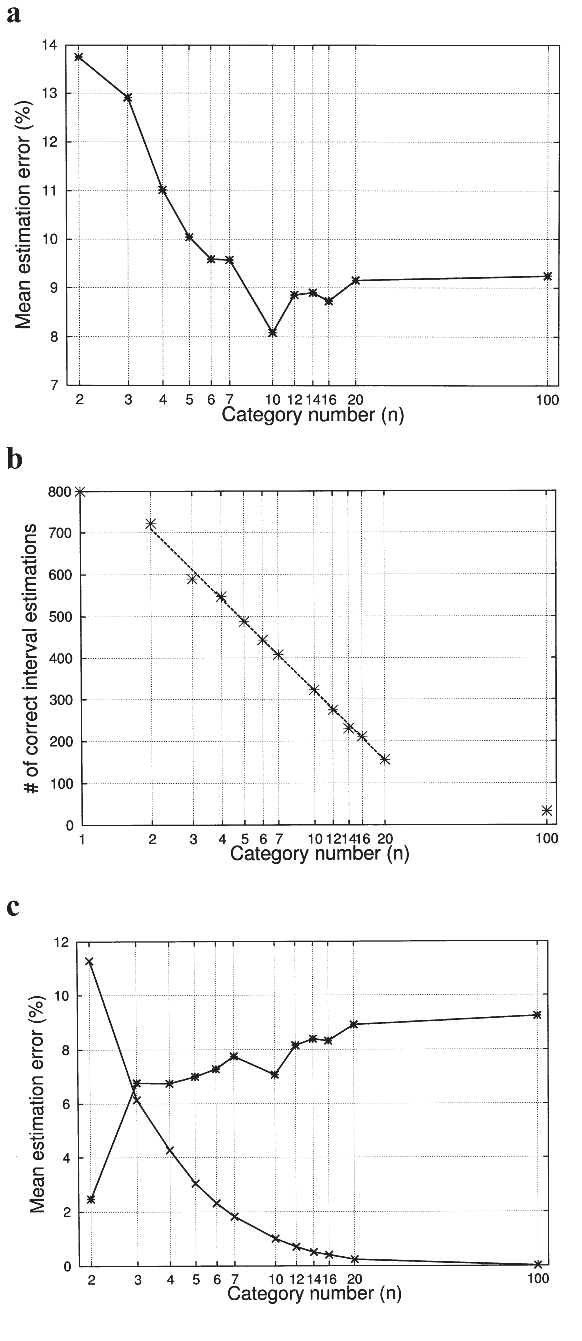

Figure 2. Estimation error in the function of category number n expressed on a log-linear scale for better visualisation. Each mean value is calculated from 800 cover values estimated by the 16 subjects. **a)** Mean estimation error. **b)** The number of correct interval estimates. The function $a - b \ln(n)$ ($a = 842$ $b = 226$) is fitted between $n = 2$ and 20 (Marquart-Levenberg algorithm used by "gnuplot" package). **c)** The average partition (x) and mis-estimation (*) error at different values of n.

Independently of category width, subjects make the greatest error when cover is estimated to lie between 25 and 75%, while this error is considerably smaller if cover is close to 0 or 100%. Similarly, estimation time is shorter at the extreme values, indicating that estimation is the least challenging task in these cases. Interestingly, subjects on average overestimate cover independently of category number, n (Fig 4).

Similarly to the field experiments (Smith 1944, Sykes et al. 1983, Gotfryd and Hansell 1985), observers do not form a homogenous group in this computer experiment. According to the Kruskal-Wallis test, the subjetcts' aver-

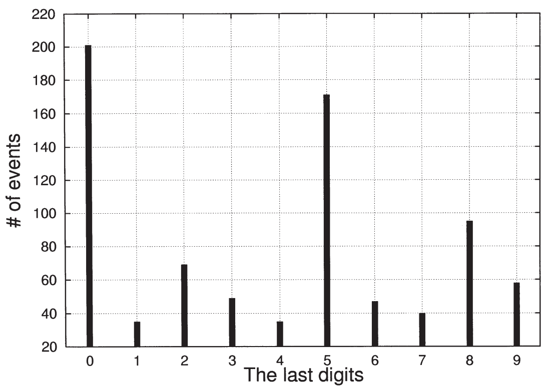

Figure 3. The frequency distribution of the last digit when subjects estimated cover in percent accuracy ($n = 100$).

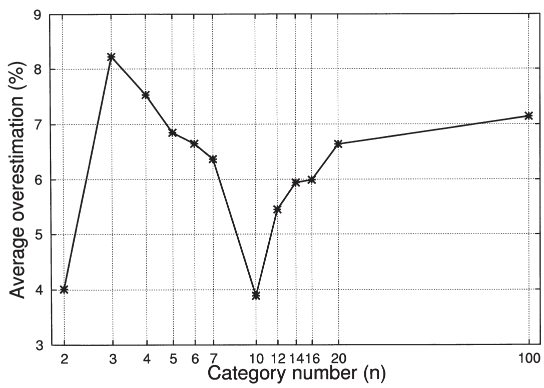

Figure 4. Average overestimation in the function of n. Here the averages are calculated from the differences between the estimated and actual cover levels.

age estimation error differs significantly for every category number. (The conditions for the ANOVA test were not fulfilled, so we used a nonparametric test.)

Discussion

The most important practical conclusion is that estimating cover in 10 categories is the most precise method provided that the categories are of identical width. However, since estimation errors are the greatest at medium cover levels, and they are much smaller at low and high levels (as suspected by Sykes et al. 1983), a more accurate estimation can be attained if cover is divided into unequal intervals. That is, at both extremes narrower intervals are needed, and at medium sizes fewer and wider intervals should be defined to achieve smaller estimation error. (This is not a surprising result, but at least to our knowledge this is the first case tested.) Even 1% precision could be optimal at extreme cover levels. This view is supported by the fact that 11 out of 33 correct interval estimates occurred below 10% and above 90% cover level when subjects estimated cover in percent precision (n = 100). At n = 100, estimates were more frequently correct than expected from the general trend (Fig 2b).

Plants are complex three-dimensional objects, frequently having fractal-like geometry (Sugihara and May 1990). These characteristics were not taken into account in the present experiments despite their possibly significant effects on the optimal estimation strategy. For example, Sykes et al. (1983) pointed out that cover estimation is more accurate for broad-leaved species than for fine-leaved ones. Similarly, vegetation typically exhibits non-random patterns, i.e., aggregated, segregated and distinct patches appear in most real situations (Milne 1992, Haslett 1994). Further, it is highly probable, that cover level of aggregated patches can be estimated more precisely than the cover level of many segregated patches. The even distribution of cover is the other simplifying assumption. We have shown that estimation error depends on the cover level (see Fig 4a,b) and the results could therefore be different at other types of cover level distributions.

As mentioned above, subjects overestimated cover on average in the present computer experiment. Our preliminary studies reveal that this effect mainly depends on the color difference of background (now black) and estimated objects (now green). If background was changed to white, then subjects underestimated on the average the cover level. Similar observation was made by Sykes et al. (1983) in a field experiment. On the basis of these results it is likely that cover estimates depend on the color of soil and vegetation. Future experiments are necessary to examine this problem thoroughly.

Acknowledgements: The authors wish to express their thanks to the students who took part in the computer experiment. We are also grateful to Zoltán Botta-Dukát, József Garay for helpful discussions, to János Podani for linguistic comments and to the referees for their helpful criticism. This work was supported by an OTKA grant no. T037726. I. Scheuring is indebted to the Bolyai Grant and I. Hahn to the Békésy Grant for financial support.

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Appendix

Vegetation cover is divided into n equal intervals, $1/n$ wide each. Let us consider all the cases when the actual cover level is in the $(k/n, (k+1)/n)$ interval ($0 \le k \le n$). Because cover level is distributed evenly between the 0 and 100% cover level, cover is distributed evenly in every sub-interval as well. So the expected value of the correct estimates in this interval is simply $k/n + 1/(2n) = (2k+1) / (2n)$. The average Manhattan distance of the possible values from the expectation in the k-th interval is the sum of all possible distances divided by the integration interval:

$$n \int_{k/n}^{(k+1)/n} \left|\frac{2k+1}{2n} - x\right| dx = \frac{1}{4n}.$$

Consequently the estimation causes on average error of $1/4n$ if the possible cover values are distributed evenly, or $100/4n$ if this is measured in percentages.

It can be shown in a similar manner that if estimation is incorrect then the average estimation error is simply the absolute difference of the correct interval (i.e., the interval where the actual cover is) from the estimated one. So if we measure it in percent, then it is $100\Delta k/n$, where Δk is the absolute difference of the correct interval from the estimated one.

Let us assume that there are M estimates out of which L are correct and the remaining M-L are incorrect. Then, the mean error of the estimation series is

$$\frac{1}{M}\left(\sum_{i=1}^{L}\frac{1}{4n} + \sum_{j=1}^{M-L}\frac{\Delta k_j}{n}\right) = \frac{1}{Mn}\left(\frac{L}{4} + \sum_{j=1}^{M-L}\Delta k_j\right),$$

where Δk is the absolute difference of the correct interval from the estimated one at the j-th incorrect measure. So the partition error of the estimation is $L/(4Mn)$, while the mis-estimation error is

$$\frac{1}{Mn}\sum_{j=1}^{M-L}\Delta k_j .$$

(Naturally, if the error is measured in percentages, then we have to multiply these values with 100.)