

## REVIEW

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The four papers in this chapter provide illustrations of three ways in which destination attractiveness has been estimated in recreation literature and, for that matter, in a wider literature in geography. In the Juurand et al. paper on wild rivers, the estimate of a site's attractiveness is the average of subjects' stated attraction ratings. In Ross's paper on Attractivity Indices, a site's attraction is considered to be revealed through a subject's actual choices and rejections of that site when compared with alternative sites. Thus these two papers exemplify the distinction between a "stated degree of attractiveness" as opposed to what the economist calls "revealed preference" as the basis for estimating site attraction. The third estimation method is illustrated by Cheung's method, discussed in TN 9 and 28 (see also TN 1), where a site's attraction is calculated from some concatenation of the site's scores on several variables, with weighting according importance in contributing to site attraction. The variables used to calculate attraction, the score assigned to a variable at a site and the weight assigned to that variable in contributing to attraction are all based to some degree on the researcher's or planner's subjective judgment, usually bolstered to some extent by background statistics, e.g. statistics on participation rates in different activities.

The three categories of estimation can be defined as based on subject behaviour (the Ross and Cesario methods), subject opinion (the Juurand et al. method), and researcher opinion (Cheung's method). And between the subject behaviour methods of estimation there is a subtle distinction which merits note. Ross's method explicitly includes information on the circumstances under which a site is not visited by a subject, as well as those under which it is visited, whereas Cesario's model considers only data on the number of times a site is visited.

As regards the three categories, it can be argued, in a similar vein to an argument in the Supply Analysis review (see Chapter IV) that each approach reflects a conscious trade-off between validity and reliability of site attraction estimates. The method based on researcher opinion has the advantage of being standardizable. Referring for example to Cheung's formula (Equation 1 in TN 9),  $S(e)$ , the relative popularity rating of activity  $e$ , could be based on regional statistics indicating participation in that activity and in that sense a standardized set of  $S(e)$  values could be used for a region.  $R(m)$ , the relative importance rating of facility  $m$  as it relates to a particular activity, although subjective, could be a value agreed to either nationally or regionally. Only  $Q(m)$ , the quantity or quality score of facility  $m$  would be a measure dependent on the local field worker. Consequently, the test-retest reliability of the attractiveness measures so derived could be relatively high if computations were standardized. However, the validity of the measure must be in doubt if it is argued that not all the variables relevant to people's perception of site attractiveness have been included in the calculation, or if coefficients or the way they are concatenated do not accurately reflect the way users estimate site attractiveness.

Juurand et al.'s paper moves a step closer to satisfying the reservations raised above by estimating site attractiveness from statements of a sample of users. But, whilst their ratings are likely to contain more valid information about the true attractiveness of a site (since the users themselves are being polled) the test-retest reliability of the results will depend on having a sufficiently large sample, as well as depending on the ability to find a similarly stratified sample for each site. Inevitably, reliability is difficult (but not impossible) to achieve using this method.

The validity of expecting a subject to be able to give figures which accurately reflect the relative attractiveness of various sites to him has often been questioned. Given that attractiveness

is an abstract notion and that people do not necessarily "know" their subconscious evaluations of things, any statement from a subject about his inner feelings has an unknowable level of validity. The problem is well summarized by Bertrand Russell (Analysis of Mind, 1921) when he says that:

*The discovery of our own motives can only be made by the same process by which we discover other people's, namely the process of observing our actions and inferring the desire which would prompt them.*

This argument provides the philosophical basis for the paper Ross as well as Cesario's model, described in TN 9 and 28. Both researchers use information on actual recreation trips to infer estimates of site attractiveness, obviating the dependence on stated preference information. In principle such data are likely to produce valid attractiveness estimates since people's behaviour is presumably an external reflection of what they actually think about sites rather than what they say they think of sites. In practice, as will be argued below, there are certain problems in the methods used by Cesario and Ross which raise questions about the validity of these particular attractiveness estimation procedures. Moreover, the reliability of the estimates obtained is statistically undefined in the sense that it is not clear to what extent sampling from a different distribution of origins would affect the estimates of destination attractiveness.

Turning to the individual papers, Ross provided a good example of an innovative attempt to extract site attractiveness information from consumer behavioural data without having to make assumptions about what variables affect site attraction. This contrasts with trip distribution modelling which until recently had to exogenously define surrogates of destination attraction. For example, size of destination was often used as such a surrogate in shopping trip and migration studies. Ross, by contrast, directly estimates attractiveness without having to assume it to be related to specific site variables.

The basis of the estimation procedure is that if more distant site  $j$  is visited rather than a closer site  $k$ , site  $j$  is inferred to be more attractive than  $k$ ; otherwise why would the extra distance have been incurred to visit  $j$  rather than  $k$ ? The number of times  $j$  is inferred to be more attractive than  $k$  ( $C(j,k)$ ) relative to the number of times  $k$  is inferred to be more attractive than  $j$  ( $C(k,j)$ ) is the basis of subsequent site attractiveness estimates. However, spatial bias in the origin locations of respondents can bias the above figures. Specifically if there are fewer subjects for whom  $k$  is the further of the two sites than there are subjects for whom  $j$  is the further, then, ceteris paribus, the odds are in favor of  $C(k,j)$  being less than  $C(j,k)$ , since there are fewer people who choose  $k$  as a more distant destination than  $j$ , compared to the number who can choose  $j$  as a more distant destination than  $k$ . However, in practice this biasing effect can be removed, and has been in subsequent uses of Ross's procedure, by calculating:

$$(1) \quad P(j,k) = (C(j,k)/N(j,k)) / ((C(j,k)/N(j,k)) + (C(k,j)/N(k,j)))$$

WHERE

$P(j,k)$  = the proportion of times site  $j$  is inferred to be more attractive than site  $k$ ;

$C(j,k)$  = number of times  $j$  is chosen by subjects with origins further from  $j$  than from  $k$ ;

$N(j,k)$  = the number of subjects whose origins are further from  $j$  than from  $k$ .

RATHER THAN:

$$(2) \quad P(j,k) = C(j,k) / (C(j,k) + C(k,j))$$

A second, more subtle spatial bias in origin locations can also affect the estimate of  $P(j,k)$

and hence the attractiveness estimates of j and k. Consider only the set of origins, of subjects who visited site j or k, and divide the pairs of  $D(i,j)$  and  $D(i,k)$  measures into two groups. Group 1 contains all  $D(i,j)$  and their associated  $D(i,k)$  where the subject visited j when  $D(i,j) > D(i,k)$ , and group 2 contains all  $D(i,j)$  and  $D(i,k)$  where the subject visited k when  $D(i,k) > D(i,j)$ . If, to take an extreme example, the  $D(i,k)$ 's in the first group were only marginally smaller than their associated  $D(i,j)$ 's we cannot tell how much less j would have been chosen and therefore how much  $C(j,k)$  and  $C(j,k)/N(j,k)$  would decline if the  $D(i,k)$ 's in that group had been much less than the  $D(i,j)$ 's rather than just marginally less. But in general it is true that as  $D(i,k)$  diminishes relative to  $D(i,j)$ , so  $C(j,k)$  and  $C(j,k)/N(j,k)$  also decline, unless j is infinitely more attractive than k. Therefore, one can conclude that the values of  $C(j,k)$  and  $C(k,j)$  are dependent on the distances to the further, but chosen, site compared to the nearer rejected sites. Only if these pairs of distances were similarly distributed for the group of subjects choosing j when it was the more distant site and for the group choosing k when it was the more distant site, would there be no spatial bias in the estimation of  $P(j,k)$ . Whilst this condition can be tested for, it is not clear that any practical remedial action can be taken to eliminate the effect. And if the condition is common, it may well have a serious effect on estimates of site attractiveness.

Furthermore the discussion above is based on the assumption that there are no inter-personal differences in users' perceptions of a park's attractiveness, other than random differences. If the park has different attractiveness to different users (close or far, young or old, rich or poor, weekend or weekday) then the aggregate measure derived, say, for day-users is a reflection of the composition of the stream of visitors that come to the site. Actually, a site's weekday attractiveness for close by day-users may be high while its weekend activity may be nil unless users are under a time constraint. Attractiveness to whom, from where, visiting for what purpose must be a matter of major concern in future work.

From another perspective, given that the site attractiveness measures obtained by Ross are ordinal problems arise in either explaining ordinal scores in terms of site variable scores or using ordinal attractiveness scores as part of a trip distribution modelling effort. In the former case, if the ordinal scores are assumed to have interval properties, a procedure with weak assumptions about the distributional characteristics of variables, such as the A.I.D. technique used in the paper on wild rivers, may be used to explain attractiveness scores in terms of site variables. In the case of trip distribution modelling, however, it would be difficult to justify the assumption of interval properties, in light of the strongly metric assumptions of most trip distribution models. As a consequence, it is probable that these attractiveness scores cannot be used for that purpose.

The papers by Beaman and Cheung are concerned with the variability of site attractiveness measures that results from using different estimation techniques. Beaman compares the results obtained by Cesario, Cheung and Ross for the same set of twelve Saskatchewan parks. In observing higher correlations between Cesario and Ross's results, the suggestion is made that attractiveness measures based on behavioural data cannot help but include the influence of the surrounding area on the estimate of attractiveness of a particular park. By contrast, Cheung's measure clearly relates only to characteristics of the site in question. To test this hypothesis, a regression equation of the following form is solved:

$$(3) \quad T_c/T_f = C_0 - C_1 A(c)$$

WHERE

$T_c$  = a park's attractiveness as estimated by Cheung;

$T_f$  = the same park's attractiveness as estimated by Cesario; and

$A(c)$  = the number of alternative sites within 100 miles of the park under consideration.

A statistically significant  $R^2 = .30$  is considered to support the above hypothesis and new estimates  $\check{T}_f$ , based on the above regression solution are obtained as follows:

$$(4) \quad \check{T}_f = T_c / (27A(c) - 125)$$

The fact that the correlation between  $\check{T}_f$  and  $T_f$  turns out to be less than that between  $T_c$  and  $T_f$  occasions surprise and is left unexplained. However, it should be remarked that in Equation 4 for any particular value of  $T_c$ ,  $\check{T}_f$  is a discontinuous function of  $A(c)$ . Specifically  $\check{T}_f$  is a decreasing function of  $A(c)$  and takes on negative values for values of  $A(c)$  between 1 and 4, but takes on only positive values for  $A(c) > 5$ , although still a decreasing function of  $A(c)$ . The size of the discontinuity between  $A(c) = 4$  and  $A(c) = 5$  depends on the value of  $T_c$ . This discontinuity may explain why the correlation between  $\check{T}_f$  and  $T_f$  is poorer than between  $T_f$  and  $T(c)$ .

In Cheung's paper comparing his own and Cesario's park attractiveness estimates, the concern is to determine which set of estimates better predicts trip flow ( $V(i,j)$ ). In Cesario's original paper, attractiveness estimates  $A(j)$  were obtained by calibrating a model of the form:

$$(5) \quad V(i,j) = KE(i)A(j)f(C(i,j))e(i,j)$$

where the terms are as defined in Equation 4 of Cheung's paper. Cheung then takes the  $A(j)$  estimates obtained in one particularly specified model and uses them as an independent variable to predict  $V(i,j)$  in three models specified quite differently from Equation 5 (see Equations 8a, 9a and 10a in Cheung's paper). He offers no explanation for having done so, and the transplanted equation should be examined closely. For example, if Cesario's original equation was properly specified and the others improperly, then it would be clearly invalid to say the  $A(j)$  estimates performed poorly in terms of predicting  $V(i,j)$  by testing their performance in an improperly specified equation. If, on the other hand, Cesario's equation was not properly specified, it is difficult to see what can be proven by taking his estimates from that equation and testing their predictive ability in what may just as well be another improperly specified model. In general, it is invalid to take estimates of  $A(j)$  obtained in one equation predicting a given variable, in this case  $V(i,j)$  and to test the predictive ability of the same  $A(j)$  estimates in a differently structured equation with the same dependent variable,  $V(i,j)$ . Therefore, any inferences made from comparisons of the predictive abilities of Cheung's and Cesario's attractiveness estimates are of doubtful validity.

Scrutiny of the least-squares estimates in regression Equations 8 through 10a in Cheung's paper also raises the question of whether the standardized regression coefficients in each pair of equations are statistically significantly different. Certainly the unstandardized coefficients provided in Tables 2 through 7 are remarkably similar, except where the scale of magnitude of  $T_c$  values relative to  $T_f$  values affects their regression coefficient values (Cheung identifies Cesario's  $A(j)$  estimates as  $T_f$  and his own as  $T_c$ ). In addition, it is really only in Equations 10 and 10a that the independent effects of  $T_c$  and  $T_f$  can be judged. In Equations 8 and 8a the explanation of variance in  $V(i,j)$  is dominated by the effect of origin population ( $P(i)$ , and  $T_f/g(D(i,j))$  and  $T_c/g(D(i,j))$  contribute only .4% and .2% respectively to the total variance explained. In Equations 9 and 9a the independent variables both have distance components embedded within them, so that it is impossible to tell how much of the 68.6% of variance in  $V(i,j)/Pop(i)$  explained by  $T_f/g(D(i,j))$  is attributable to  $g(D(i,j))$  and how much to  $T_f$ . Only in Equations 10 and 10a are the

independent effects of  $\log(T_c)$  and  $\log(T_f)$  on  $\log(V(i,j)/Pop(i))$  measurable and it is notable that in both equations,  $\log D(i,j)$  dominates in explaining 64% of variance and  $\log(T_f)$  and  $\log(T_c)$  explain only .2% and 1.1% of variance respectively. This suggests that in Equations 9 and 3a perhaps  $g(D(i,j))$  is the main explanatory variable and that the  $T_c$  and  $T_f$  terms have only a small random effect on the level of prediction of  $V(i,j)/Pop(i)$ .

It is difficult to conclude from the above either that  $T_f$  and  $T_c$  have any appreciable effect on the variance of the three dependent variables or that the small influence they may have differs markedly between  $T_f$  and  $T_c$ . Given this and the question of whether the procedure used to test the predictive ability of the  $T_f$  values is valid, one is led to conclude that nothing meaningful has been said about the relative predictive capacities of the Cheung and Cesario attractiveness measures.

Turning to the question of whether there is any effective way to compare the predictive abilities of two differently derived sets of attractiveness scores, it is difficult to see how an effective comparison could be made in this case. Cesario's set of estimates are parameters estimated by fitting an equation to the very interaction data to be predicted, whilst Cheung's estimates have much less flexibility in the sense that they are based on a predetermined formula with no free parameters. It would therefore be invalid to take Cheung's  $T(c)$  values and use them in Cesario's model (Equation 5) since there would be fewer free parameters in this case than in Cesario's case where the  $T_f$  values are free parameters to be estimated. The conclusion is that it is perhaps a vain oversimplification to hope to make direct comparisons of this kind, where the estimating procedures are so radically different.

The final paper in Chapter III on the perception of the quality of wild rivers, unlike the others, is not so much concerned with methods of estimating site attractiveness as with the explanation of these estimates, however obtained, in terms of site characteristics. In particular, it illustrates three different mathematical models which explain perceived site attractiveness scores in terms of perceived site characteristics. The less rigid the assumptions of the model, the more variance in the dependent variable is explained. The multiple regression model assumes the dependent variable to be a linear and additive function of the independent site characteristic variables and achieves an  $R^2$  of .38. By contrast, a generalized analysis of variance model, though additive, allows independent variables to be defined categorically rather than continuously and obtain an  $R^2$  of .59. Finally, A.I.D. with the added facility of allowing interaction effects between independent variables, gives an  $R^2$  of 0.84. The latter would seem particularly useful for planning in cases where as weak assumptions as possible must be made about data, and where subtle relationships between variables are thought to exist. Inevitably the price of this greater flexibility is a reduction in the ease of interpreting results in the form of an A.I.D. tree diagram.