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AGGREGATE ATTRACTION MEASURES FOR DISAGGREGATE DESTINATION CHOICE MODELS

HUGH P. BROWN
Lecturer,
Department of Civil Engineering,
University of Melbourne.

ABSTRACT: *For highly discretionary travel, such as for shopping and outdoor recreation, measures of destination attractiveness are difficult to properly define or quantify. In a linked set of choice models, poor specification of the destination choice component reduce the performance of the whole set. The paper describes a way of estimating an aggregate measure of destination attractiveness from the observed flows, bypassing problems and costs of data collection, model specification and estimation. The approach is used in a case study; aggregate attration measures are estimated using a singly constrained gravity model, and included in a destination choice model. Performance was marginally superior to the usual approach.*

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INTRODUCTION

This paper is concerned with the development of a methodology for the determination of destination attractiveness, in the examples used for outdoor recreation travel, but of more general applicability to a range of travel purposes. For several travel purposes, particularly the work trip, attractiveness measures are simply the quantity of activity opportunities available at the destination, and are relatively easily determined. Other trip purposes have much less clearly defined activities associated with them, and hence measures of activity opportunities are more difficult to obtain. In these cases, individual needs and activity requirements, together with perceptions of the relative quality of alternative locations for their satisfaction, form the destination attractiveness measure. Examples of trip purposes of this type are non-essential shopping and social/recreation travel. Modelling of purposes of this type in an individual choice modelling context properly requires identification of individual measures of attractiveness for all relevant destinations, quite obviously an impossible task. The second-best approach is the exhaustive quantification of all activity opportunities potentially relevant to the particular purpose. While not impossible, this is still an enormous task; the quality of the resulting choice model will largely depend upon how well it is undertaken.

The destination choice model is extremely important in the sequence of individual choice models necessary to describe travel purposes of the above type. The inevitable errors that will result from an incomplete description of destination attractiveness can introduce significant errors into the whole sequence. Because of this problem, and because of the enormity of the data collection task necessary to otherwise overcome it, an alternative approach is proposed.

The basis of this approach is that the data sample to be used for the estimation of individual choice models will already reflect an aggregate (i.e., measured across all elements in the data set) measure of destination attraction. If this implicit measure can be extracted from the data, without detailing its composition or structure, and free of non-attraction influences on destination choice, then specification of the individual attributes of attractiveness will be unnecessary. It is suggested that this can be achieved through the direct estimation of the attraction measures in a singly constrained gravity model.

These aggregate destination-specific measures can then be used as composite attraction measures in a destination choice model estimated on individual data.

The advantages of this approach are: (i) the considerable task of detailing all relevant attraction measures for each destination is avoided; (ii) loss of model accuracy through an incomplete specification of the measures is avoided, and hence the performance of models higher in the sequence of relevant choices is maintained; (iii) technical difficulties in the estimation of the parameters of more than one "size" (quantity) variable describing attractiveness are bypassed; (iv) estimation of the parameters associated with the more important travel time, cost and socioeconomic variables influencing choice can proceed unencumbered by the foregoing problems; (v) isolation of the elements of attractiveness that might be important for policy purposes can be undertaken outside the choice modelling process.

These aspects are amplified in the paper, which describes in more detail the approach, a validation test, and an application to the modelling of outdoor recreational travel.

AN OUTLINE OF THE SUGGESTED APPROACH

The approach to obtaining aggregate measures of destination attractiveness is summarised below; before doing so, however, the destination choice model that would otherwise be necessary is presented in detail. The individual choice modelling approach on which the model is based is well known; a complete development of the theoretical basis for and properties of the multinomial logit (MNL) model used in this study is given in Hensher and Johnson (1980). The modelling of hierarchical choice structures for outdoor recreational travel is discussed in Brown et al (1979), Hensher and Johnson (1980), pps. 311-316, and in another paper at this Forum (Wisdom and Brown (1982)).

A Disaggregate Destination Choice Model

The MNL form of the destination choice model using a single measure of destination attractiveness may be written as

$$P_j = \frac{e^{U_j}}{\Sigma_j e^{U_j}} \qquad (1)$$

where P_j = probability that an individual will choose destination j from the set of available alternatives.

U_j = the utility function describing the destination j, for that individual

$$= \sum_k \alpha_k X_{kj} + \ell n\, A_j \qquad (2)$$

where X_{kj} are the non-attraction attributes of destination j, such as travel time, cost, and relevant socioeconomic characteristics of the individual.

A_j = a measure of attraction.

Note that A_j must enter the utility function in logarithmic form, with a coefficient of 1.0, to ensure independence of destination choice probabilities with respect to destination size.

When multiple measures of attractiveness are necessary, as in circumstances already discussed, the form of the utility function changes to become (Daly, 1980, 1982)

$$U_j = \sum_k \alpha_k X_{kj} + \ell n \sum_{\ell}^{L-1} (\beta_\ell S_{\ell j} + 1.0 . S_{Lj}) \qquad (3)$$

where $S_{\ell j}$ are "size" variables describing quantities of activity opportunities available at the destination, or some proxy measures of these.

This form is intrinsically non-linear in the parameters, and usual maximum likelihood estimation procedures break down as this nonlinearity increases (Daly, 1982). In practice, only a few variables can be included before this occurs, severely limiting model specification even in the absence of problems with variable identification, quantification and data collection.

What is required is a means of replacing the second term in equation (3) with the second term in equation (2), enabling the parameters of equation (2) to be readily estimated. This is achieved in a two-stage process, as described below.

Estimating the Destination Choice Model: A Two Stage Approach

It is suggested that measurement and inclusion in equation (3) of disaggregate attraction variables is unnecessary, as the observed destination choices already imply aggregate measures of attractiveness. These can be recovered from the data by estimating an aggregate model of the form

$$\pi_{ij} = \frac{A_j^{\theta_j} f(C_{ij}, \tilde{\lambda})}{\sum_j A_j^{\theta_j} f(C_{ij}, \hat{\lambda})} \qquad (4)$$

where π_{ij} is the observed matrix of destination choice probabilities, T_{ij}/P_i

A_j corresponds to the second term in eqn. (3), but is estimated as a single parameter from eqn. (4).

$f(C_{ij}, \tilde{\lambda})$ is a standard impedance (generalised cost) function,

θ_j, $\tilde{\lambda}$ are other parameters to be estimated.

The estimated value of A_j can then be included in eqn (2), and the remaining parameters estimated in the second stage.

If there is interest in the component elements $S_{\ell j}$ of A_j, these can be separately determined outside the choice modelling process, as conceptually

$$A_j = \sum_\ell \gamma_\ell S_{\ell j} \qquad (5)$$

Regression analysis can be used to isolate the relevant elements $\{S_{\ell j}\}$, which can then be included in equation (3) for parameter estimation. Note that while $\tilde{\beta}_\ell$ from equation (3) will not be the same as $\tilde{\gamma}_\ell$ from equation (5), one should ideally be a monotonic transformation of the other.

The Aggregate Model and its Estimation

The aggregate model form previously suggested is a version of the well known singly constrained gravity model given familiarity in the transport field by Cesario (1973). In this version, productions and attractions are not input variables, as in the usual trip distribution model, but unknown attributes of the origin and destination to be estimated. The parameters of the non-attraction variables in the impedance function are estimated at the same time.

A variety of model estimation procedures are possible; maximum likelihood or non-linear least squares are most usual. At the time that this work was undertaken, these procedures were not available to the author, and a transformation of equation (4) enabling the use of ordinary least squares (OLS) was used instead. Subsequent work by the author has demonstrated that the parameter estimates obtained from this transformation are very close to those from the other techniques (Brown, 1982), and it is therefore considered to be adequate for the purposes of testing the validity of the suggested approach.

In order to maintain similarity of assumptions about the form of the utility function and the nature of the error terms with both the aggregate and disaggregate models (equations (4) and (1)), the deterrence function in the aggregate model was assumed to be of the form $e^{-\lambda C_{ij}}$, and an exponentially distributed random error term is included. Then

$$\pi_{ij} = \frac{A_j^{\beta_j} \, e^{-\lambda C_{ij}} \, e^{\varepsilon_{ij}}}{\sum_j A_j^{\beta_j} \, e^{-\lambda C_{ij}}} \qquad (6)$$

$$\text{Then } \ln \pi_{ij} = \beta_j \ln A_j - \lambda C_{ij} - \ln\left(\sum_j A_j^{\beta_j} e^{-\lambda C_{ij}}\right) + \varepsilon_{ij} \qquad (7)$$

The use of OLS requires two sets of dummy variables to be defined. The first follows from the observation that for any origin, the denominator of (6) is a constant. Hence it can be replaced by an origin - specific dummy variable and its influence captured by the estimation of an associated parameter. A set of (i-1) such dummy variables OD_k is used, where

$$OD_k = 1, \; i = k$$
$$= 0, \; i \neq k.$$

The second set of dummy variables is used to capture the attractiveness influence directly, by noting that $\ln A_j$ is constant for any destination. Hence the parameter β_j can be recovered as a measure of A_j by replacing $\{\ell n\ A_j\}$ with a set of dummy variables AD_ℓ, where

$$AD_\ell = 1 \text{ if } j = \ell$$
$$= 0 \text{ if } j \neq \ell$$

There will be (j-1) such dummy variables, which is equivalent to obtaining relative attractiveness measures, relative to the attractiveness of the zone chosen as the base, for which $A_j = 1.0$. The attractiveness measure is then given by the antilog of β_j, e^{β_j}.

The transformed model to be estimated becomes

$$\ell n\ \pi_{ij} = \beta_j\ AD_j - \lambda C_{ij} + \gamma_i OD_i \qquad (8)$$

A Validation Test of the Estimation Methodology

The estimation methodology outlined appears clumsy, and must give rise to doubts about its ability to recover consistent and unbiased estimates of A_j. To assess its performance in this regard, the data reported by Cesario (1973) was used. This data relates to travel to outdoor recreation sites in Pennsylvania; a total of 33,461 trips were reported from 10 origin counties to 5 recreation parks as destinations. Attractiveness estimates were obtained and are reported in Table 1.

Estimates of A_j from equation (8) were obtained from the data, to be compared with those estimated by Cesario. Destination 5 was taken as the base, and the results normalised to ensure comparability. These are reported in Table 1.

Table 1: Comparison of OLS Approximation Attractiveness Estimates with Cesario's Estimates

	Cesario	OLS Approximation
A_1	0.458	0.497
A_2	0.995	1.215
A_3	2.628	2.276
A_4	1.065	0.957
A_5	0.782	0.782

It is not possible to obtain a measure of the standard error of estimate of the above parameters, or confidence intervals given the transformations they have undergone. Nevertheless, the results indicate a high degree of consistency with those of Cesario, and indicate that the estimation technique can recover the parameters with reasonable precision. For the purposes of testing the validity of replacing disaggregate with aggregate attraction measures, it will be quite adequate.

AN APPLICATION OF THE APPROACH

A case study testing the proposed methodology is presented. Attractiveness measures are estimated as outlined previously, and the measures used in an MNL model of destination choice. The results are compared with a model specified on individual destination attributes. Finally, an attempt is made to develop a relationship between aggregate and individual attractiveness attributes, using regression analysis.

Case Study : Recreation Travel in Wisconsin, U.S.A.

The destination choice submodel of a set of models of destination, duration and frequency choices for weekend outdoor recreational travel developed for the Wisconsin D.O.T. by Cambridge Systematics, Inc. (Brown et al (1979)), is reproduced in Table 2. Household and travel data come from a household interview survey; 749 households were retained for analysis, representing 359 trips. Highway travel times came from a computer representation of the state highway network.

Table 2: Home-Based Weekend Recreational Trip Destination Model

Variable	Coefficient	t-Statistic
"Normal" Variables		
Population at desintation (million)	-.669	-4.0
Travel time (minutes):		
For travellers without children under 12:		
Trip duration = 2 days	-.013	-4.7
Trip duration = 3 days	-.0082	-4.0
Trip duration = 4 days	-.0076	-2.1
For travellers with children under 12:		
Trip duration = 2 days	-.0155	-7.9
Trip duration = 3 days	-.0118	-8.5
Trip duration = 4 days	-.0111	-4.3
Attraction Variables		
Area of named lakes at destination (thousands of acres) - VAR(8), App. A.	.024.	.96
Number of beaches (public and private) VAR (11)	.107	1.2
Length of trout streams at destination (miles) - VAR (24)	.68	.95
Land area of destination (acres x 10^6 - VAR (4)	1.0	*

* Coefficient constrained equal to 1: no t-value estimated.

N = 749 households, 359 trips
L(0) = -972, log likelihood with all coefficients zero.
L(*) = -876, log likelihood at estimated values.

$$\rho^2 = 1 - \frac{L(*)}{L(0)} = .10$$

The measures of destination attractiveness used were provided at the planning region level by the Wisconsin Department of Natural Resources. The data were completely homogeneous across all regions, and relatively comprehensive. The measures used in the choice model were selected by trial-and-error testing for inclusion in the model. Those available are listed in Appendix A.

Aggregate attractiveness measures were estimated as previously described. The trip data, existing at a 72 origin x 15 destination level, was recoded to a 15 x 15 matrix to reduce the number of cells with zero entries that would otherwise result from such a small data base. Zero entries were recoded to 0.1, a procedure which introduces some bias, but is considered adequate for the hypothesis-testing purpose of the exercise. The travel time matrix, also at a 72 x 15 level, was collapsed using an unweighted average of the times from the origin zones comprising the origin district, to a 15 x 15 level. Some loss of variance will necessarily result from this, reducing the precision of the time parameter estimates. This is not considered a problem, given the purposes of the study.

The attractiveness measures estimated are given in Table 3, together with actual trips recorded for each of the 15 destinations. Parameters for the dummy variables representing the accessibility influence were estimated, but are not reported, as they are of little interest to the study. They were relatively consistent across all models estimated (which included a variety of model forms) and hence it was apparent that the procedure adequately represented the accessibility influence.

Table 3: Aggregate attractiveness measures for 15 Wisconsin destinations

Destination	Aggregate attractiveness	No of trips
1	0.64	25
2	0.82	36
3	0.73	17
4	0.65	19
5	0.53	16
6	0.83	42
7	0.60	20
8	0.85	29
9	1.56	28
10	2.19	57
11	0.62	9
12	0.33	6
13	1.02	20
14	0.80	15
15	1.0	20 /359

These measures are relative to that for the base destination, for which $A_j = 1.0$, as only (j-1) parameters can be estimated. The parameter for the omitted destination is by inference zero, and as the measure of attractiveness is given by the antilog of the estimated parameter, $e^{\beta j}$, the base attraction measure is 1.00. Standard errors for these estimates cannot be calculated as such; an indication only of their confidence intervals can be obtained by taking $\exp(\beta_j \pm 1.65 * S.E.(\beta_j))$. These are not reported, but are quite wide; for destinations 12 and 10 (the lowest and highest attractions respectively) the intervals as calculated are 0.18 - 0.60, and 1.43 - 3.36. Not a great deal can be inferred from this, other than that the method used does not recover efficient estimates of attractiveness.

The Disaggregate Model With Aggregate Attraction Measures

The aggregate attraction measures reported in Table 3 were used in the destination choice model, replacing the individual attraction measures reported in Table 2. The results are given in Table 4 which includes for ease of comparison the relevant parameter estimates from Table 2, for the fully disaggregate model.

Table 4: Destination choice model using aggregate attractiveness measures

		Model with Agg(A_j)	Base model
Population		-0.32(-2.2)	-0.67(-4.0)
Travel time, without children, duration	= 2	-0.011(-4.0)	-0.013(-4.7)
	= 3	-0.006(-2.9)	-0.008(-4.0)
	= 4	-0.006(-1.6)	-0.008(-2.1)
Travel time with children, duration	= 2	-0.014(-6.9)	-0.016(-7.9)
	= 3	-0.010(-7.5)	-0.012(-8.5)
	= 4	-0.009(-3.4)	-0.011(-4.3)
Attractiveness		(1.0)	- Plus other measures as per Table 2
LLHD(0)		-972.2	-972.2
LLHD(*)		-874.7	-876.1
ρ^2		0.100	0.099

The results clearly demonstrate the ability of the aggregate attractiveness measure to capture the effects of the individual measures. Use of the aggregate attractiveness measure results in a destination choice model which is marginally superior to that obtained from a set of individual attractiveness variables, on the basis of the final value of the log-likelihood function. (It should be noted, however, that on the basis of the specification test $-2(L_U - L_R) = 2.8$, which is less than the relevant χ^2 statistic at 10% and 3 d.o.f., that the models are not significantly different). The parameter of the population variable has been significantly reduced, but while the parameters of the time variables have all decreased slightly, the differences are not significant at the 5% level. The slight decrease may be due in part to the presence of residual accessibility influences in the estimated aggregate attractiveness measures. That they are not greater attests to the ability of the OLS transformation used to capture pure attractiveness measures from the aggregate model.

In assessing the performance of this approach, and of the usefulness of the aggregate measure, one aspect of the context in which the base destination choice model was estimated must be borne in mind. This is that for the original study, a large number of measures of outdoor recreational opportunities were available. Further, these were consistent across the entire study area, which enabled all destinations to be described in terms of attractiveness by a consistent and comprehensive set of variables. This situation is highly unusual; no such parallel data set exists in Australia. As a consequence, the final set of attractiveness measures entering the model are likely to be improved upon only with difficulty. Hence it should not be expected that use of an aggregate attraction measure would significantly improve the model. If it were to provide a model of even equal performance, the suggested procedure would be validated. It in fact goes slightly beyond this.

In most applications, for which only a limited set of attraction measures would usually be available, the approach outlined and validated in this paper could be expected to provide an improved model performance.

Finally, it should be noted that even with the availability of a comprehensive and consistent set of destination descriptors, isolation of the "best" subset of attraction measures proved a lengthy process. The use of the aggregate measure represented a considerable saving in time and effort by comparison. As it enables the otherwise costly and lengthy process of data collection to be dispensed with altogether if desired, as well as reducing the time necessary for model development, it is obviously a highly worthwhile approach.

Relating Aggregate and Disaggregate Measures

A final test of the usefulness of the aggregate attraction measure remains. It was suggested earlier that the absence of detailed attraction variables from the model meant that potentially important information was not available to policy makers, particularly those concerned with the administration of recreation sites and facilities. It was noted however that this problem could be overcome outside the modelling process itself, by relating the aggregate measure to its components through a technique such as regression analysis.

This test was undertaken, using the aggregate measure previously obtained, and the set of attraction measures available, as listed in Appendix A. Regression analysis was used, with the aggregate measure as the dependent variable. The basic problem encountered was that the set of variables are all highly inter-correlated, with many measuring similar attributes in slightly different forms. A trial-and-error approach was used to overcome this problem. This involved regression analysis using a series of subsets of the variables. Those that consistently proved to be either insignificant or of the wrong (negative) sign after repeated analyses were progressively excluded. This approach worked reasonably well, and provided the following "best" relationship:

$$\underset{(3.0)}{AGG.ATT = 0.00042*VAR(24)} + \underset{(2.2)}{0.00046*VAR(22)} + \underset{(1.1)}{0.0014*VAR(11)} + \underset{(4.1)}{0.42}$$

$$\text{adj } R^2 = 0.775$$

where the variables are as described in Appendix A.

It is clear that the variables available for describing destination attractiveness explain a large amount of the aggregate attractiveness measure, but more importantly can be identified in the manner suggested. This indicates that the aggregate measure obtained does in fact represent a composite of a set of individual destination descriptors even though it is apparent that those available do not fully describe destination attractiveness. The final test is to see how well the individual measures perform in the destination choice model.

It may be observed that the above relationship includes a variable not previously used (VAR(22), but does not contain two others used in the original model (VAR(8) and VAR(4)). An attempt to include all 5 variables in the original model failed because of the non-linearity problem previously referenced. It was possible to estimate the model using 4 of the 5 variables, and the results of the resulting best model are given in Table 5

Table 5: Destination choice model using attributes identified from regression analysis using aggregate attractiveness measure

	1		2	
Population	-0.67	(-4.1)	-0.65	(-3.9)
Travel time, no children, duration = 2	-0.014	(-5.3)	-0.014	(-5.0)
= 3	-0.010	(-4.9)	-0.009	(-4.5)
= 4	-0.009	(-2.6)	-0.009	(-2.4)
Travel time, with children, duration = 2	-0.017	(-8.7)	-0.017	(-8.3)
= 3	-0.013	(-9.5)	-0.013	(-8.9)
= 4	-0.013	(-4.9)	-0.012	(-4.6)
VAR 22 (Lake area for boating)	8.395	(2.8)	11.13	(1.5)
VAR 24 (Length trout streams)	19.5	(2.7)	8.71	(2.8)
VAR 11 (Total number beaches)	(1.0)	-	(1.0)	-
VAR 08 (Area named lakes)	N.A.		0.19	(1.7)
LLHD (0)	-972.2		-972.2	
LLHD (*)	-877.1		-875.2	

In interpreting these results, it must be remembered that the analysis started with a great deal of prior information; particularly, a lengthy analysis had resulted in the isolation of what was expected to be the "best" set of attraction variables. In the event, the above analysis was able to provide further improvement. The resulting set of variables, while only containing one new variable substituted for a previous one, is such that a minor model improvement is afforded, and all variables are now significant. These results are due to the extensive correlatons between the variables referenced previously, which also give rise to some degree of parameter instability between models of different specifications.

This analysis validates the final assertion made about the procedure, that once the aggregate measure has been obtained, a separate analysis can be undertaken to isolate the relevant variables contributing to the explanation of destination attractiveness. The resulting variables can then be input, if desired, into the destination choice model, to provide extra information that may be necessary for policy analysis. However, this step may be taken outside the main stream of model development. This reduces the labour and time associated with development but does not limit the ultimate usefulness of the model set.

CONCLUSIONS

A number of conclusions are evident from the foregoing analyses. Firstly, it is apparent that an aggregate measure of destination attractiveness can be recovered directly from observations of destination choice. This measure is sufficiently free of the accessibility influences from the remainder of the aggregate model to enable its use in a disaggregate model of individual destination choice. Its use in this way bypasses the many problems associated with the collection of a larger set of data describing all relevant attributes of the destination choice set, and associated model estimation difficulties. As well as significantly reducing labour and cost, it also has the potential of improving model performance. In a linked set of models of which the destination choice component is one of the first estimated, this may result in an overall improvement in performance.

Secondly, the aggregate measure obtained can be used at a later stage and outside the main stream of model development to assist in the isolation of a more detailed set of descriptors of destination attractiveness. This may be of use if there is interest in the effect of these measures on individual choice, for policy manipulation purposes. These measures can subsequently be used for a more refined specification of the destination choice model. The result in the case study reported was a model that was slightly worse than that including the single measure of aggregate attractiveness, but slightly better than that developed from trial and error alone.

Overall, it may be seen that the approach suggested performs well, and has the potential of considerably reducing the costs of development, and improving the performance of models of discretionary travel behaviour. The examples referenced are all of outdoor recreational travel, but more importantly the procedure may be of use for models of shopping travel. There is much to be gained from the further investigation and implementation of the procedure.

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APPENDIX A

DESTINATION ATTRACTION DATA

VAR. NO.		DESCRIPTION	UNITS
VAR	(1)	Total Population	Millions
	(2)	Population Density	#/sq. mile
	(3)	Population in Major Towns	Millions
	(4)	Total Land Area	acres x 10^6
	(5)	Total Water Area	acres x 10^3
	(6)	Total No. Named Lakes	-
	(7)	Total No. Lakes (Named and Unnamed)	-
	(8)	Area of Named Lakes	acres x 10^3
	(9)	Area of Total Lakes	acres x 10^3
	(10)	No. of Lakes with Public Access	-
	(11)	Total No. of Beaches	-
	(12)	No. of Public Beaches	-
	(13)	Total Beach Area	acres
	(14)	Area Public Beaches	acres
	(15)	Total No. Swimming Pools	-
	(16)	Total No. Public Swimming Pools	-
	(17)	Total Area Pools	acres
	(18)	Area Public Pools	acres
	(19)	Length of Canoe Streams	miles
	(20)	No. Boating Access Sites	
	(21)	Area of Great Lakes for Boating	acres c 10^3
	(22)	Lake Area for Boating	acres x 10^3
	(23)	River Area for Boating	acres x 10^3
	(24)	Length Trout Streams	miles
	(25)	Length Warmwater Streams	miles
	(26)	Area Trout Lakes	acres
	(27)	No. Public Camp Sites	
	(28)	Area Public Camp Sites	acres
	(29)	Total No. Camp Sites	
	(30)	Area Public Camp Sites	acres
	(31)	No. of Picnic Grounds	
	(32)	Area of Picnic Grounds	acres
	(33)	Public Hunting Area	acres x 10^3
	(34)	Total Hunting Area	acres x 10^3
	(35)	No. of Public Hunting Grounds	-
	(36)	No. of State, County, Fed. Rec^n Areas	-