AN INVESTIGATION INTO THE HIERARCHICAL PROCESSING OF SPATIAL INFORMATION

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ABSTRACT: This paper considers the way people process spatial information, particularly during a migratory move when a destination has to be chosen from a set of alternatives. It is suggested that this form of spatial choice is as a result of a hierarchical processing of information. The problems of using aspatial choice models are then mentioned when trying to measure a spatial move. The competing destination model is then used in an empirical example considering a matrix of migration flows between the 100 largest Standard Economic Areas of the United States for 1970 with the results showing that spatial information is indeed processed hierarchically and that the degree of hierarchical processing varies according to the centrality of the origin. Results from runs with modifications to the traditional competing destination model suggest that the correct model specification has yet to be used.

Gould (1975) restated an old notion that man's behavior is relatively simple, and that the complexity observed is actually the complexity of the environment within which the behavior takes place. In other words the environment in which we live in some way molds the way we represent, perceive and ultimately act upon space. This paper considers the way man migrates across that space, in this case the U.S., by using the Competing Destination model to look at migration flows between the 100 largest Standard Economic Areas of the U.S. for 1970.

There has been a plethora of work on migration flows, some concerning themselves with their explanation and modelling (Brown and Jones 1985), while others consider the prediction and directions of the flows (Rogerson 1987). Migration studies in the geographical literature have either taken an analytical approach concentrating on showing the resultant effects of migration, or they have taken a more quantative approach trying to model how people move. One such family of models used to measure these flows consist of the spatial interaction models. These models enable us to consider the relative location as opposed to actual location of components across a surface. This is obviously important as a destination ten miles away has a different significance to a farmer in the middle of Iowa as compared to a shop-keeper in The Bronx. This logically leads us to ask the question do people perceive distance and destination in different ways according to where they live? Questions such as this have led to the continuing development of the gravity and spatial interaction model structure over the last few decades. This evolution has gone beyond the original calibrations using relative distance and relative size (traditionally the two most important variables affecting a migrants moving decision) to include the present work considering a more cognitive approach to spatial choice.

A more detailed consideration of the progress in the areas of Cognition and Psychology dealing with the way people process information and in particular spatial information can be found elsewhere (Curtis 1991). In general, the move has been away from non-hierarchical theories concentrating instead on the two forms of hierarchical spatial representation (Stevens

& Coupe 1978) and the spin-off studies into border and cluster analysis (Hirtle & Jonides 1985). This is contrary to the generally accepted models of destination choice which presume that the individual evaluates all possible destinations simultaneously. Further information on this can be found in Ortuzar and Fernandez 1984; Fotheringham 1988; Haynes and Fotheringham 1989.

An individual's mental map is not only influenced by the method of representation but also by their home environment. An example of this can be found in the variations of spatial language construction found from different locations (eg, Lakoff, 1987). In this way it is suggested that the form of our language in some way mirrors the way we mentally construct our mapped environment. Consequently by studying the differences in spatial language construction we should be able to gain some insight into the way people perceive space in different ways according to their home location. One of the interesting points to be gleaned from this suggestion is that information flows consist not only of the number of people and their proximity (Gould 1975) in other words the basic components of the traditional gravity model, but also of the home environment and the way that environment affects the perception of the rest of space. Curry (1972) raised a similar point by showing how it is difficult to interpret and compare parameter values that supposedly measure the frictional effect of distance because of all the other relevant but omitted variables. Even back in 1965 Wolpert was suggesting a more behaviorally based migration model incorporating individual behaviorisms as well as the more usual physical parameters.

One of the problems is that in calibrating the gravity model for a particular information set, the results may be due to both the convoluting effects of human behavior and the effect of the map pattern or arrangement. This in turn means that the empirical estimation of the distance decay parameter will be as much a result of the population surface, and that distance alone cannot be used as a universal measure of spatial information. The distance decay parameter can be interpreted in a behavioral way whereby a highly negative parameter indicates that distance is a strong deterrent, and a small parameter shows that distance has only a weak effect. It has also been suggested that the distance decay parameter is also a function of spatial structure; that is the size and configurations of origins and destination in a spatial system.

Airline passenger interaction data from 1970 between each of the 100 largest SMSA's in the U.S. showed that interaction behavior was not constant whereas it should be in a fairly homogenous society. Some of the parameter estimates were even positive suggesting that the interaction increases with distance! It also found that the expected strong relationship between mean trip length and the distance decay parameter only turned out to be the exception and not the rule (Fotheringham 1981). From this it can be shown that the location of the origin is a strong determinant of the parameter, regardless of the constraints operating from the gravity model. Johnston (1976) shows how the estimated distance decay parameter will become less negative as the accessibility of its origin increases, which he attributes solely to variations in spatial structure where spatial structure is measured by the range of logarithmic distances. It has also been found that the production gravity formulation is an inaccurate modelling device when the choice of destination results from a hierarchical processing of information (Fotheringham 1985). This is because the hierarchical process violates the Independence from Irrelevant Alternatives (Sobel 1980, Wrigley, 1985) which is derived from the assumption that the individual considers all possible destinations simultaneously and that there is no clustering of alternatives. This Independence from Irrelevant Alternatives element is embedded in the production constrained model from its originally derived axioms of choice. Consequently a new form of the spatial interaction model was developed to include both the effects of spatial structure and the hierarchical choice process which according to the cognitive literature is the most likely means of spatial representation.

The competing destination model is such a model being more useful than the nested logit model because it is derived from purely spatial examples (Fotheringham 1983; 1986). The model assumes that an individual has a finite ability to process information which means that some sort of tree-like storage and retrieval of information takes place in a hierarchical manner. Also, because the individual's perception of what and where to cluster is unknown to the modeler, each alternative has a probability of belonging to a cluster. One problem connected with the derivation of the competing destination model is the need to find the likelihood that an alternative is in the restricted choice set. This can be done in two ways:

a) The likelihood of an alternative being in a set is a function of its dissimilarity to all the other alternatives.
b) The closer the proximity of alternatives, the more likely the chance of there being a substitution effect. Fotheringham (1983) measures this by summing the weighted distances of one alternative to all others (whereby the weight is equal to the size of the alternative).
This gives a measure of 'Potential accessibility' where large values represent clustered alternatives and low values means that the alternatives are spatially isolated. In effect it is an alternatives centrality measure. The resulting model shows by the degree the parameter varies from zero how hierarchically the information is being processed. The sign of the parameter also shows whether clustering of alternatives leads to competition or agglomeration influences.

METHODOLOGY

The next stage was to use the competing destination model to empirically prove that people process spatial information in a hierarchical way. The 1970 Census was chosen because of its detailed breakdown of migratory information at the State Economic Area level (this level of breakdown was not readily available for the 1980 census). There are 510 State Economic Areas (SEA) within the United States with each area consisting of whole or partial counties of similar social or economic characteristics. Details concerning the collection of migratory data for these areas can be found in the Census publications "Migration between State Economic Areas" (1972), and "1970 Census: State Economic Areas" (1972).

The 100 largest SEA's by population size were then taken. For each selected SEA the largest city was chosen as the centroid from which distances to all other SEA's would be calculated. The rationale for choosing this point over a geographical centroid was that, all things being equal, the largest percentage of migrants leaving any region would leave from the area of largest population. A list of the one hundred areas with their identifying SEA code can be found in table 1. The 100 cities chosen as centroids for the SEA's can be found in the results table 2 (cities in parenthesis represent the most influential city on the area even if that city falls outside the defined area. For example area "Maryland B" actually lies just outside of Washington D.C.). This can actually lead to a problem with this study as moves below 30 miles may only be capturing moves of residence and not employment moves. It will become obvious from table three that this did indeed cause a problem with certain locations around New York City. It was decided to remove these results (Newark, Camden, New Brunswick and Paterson) from the explanatory results diagrams because they were obvious outliers. However, this problem resulted from the highly disaggregated nature of the data being used. Altogether there

were 25 pairs with moves below 30 miles. It would be impossible to remove them from this study as all accessibility calculations would have to be redone for all the remaining SEA's. I would also question whether this would be the right step to take as the distances were calculated from the largest center, as explained before, which means that a large proportion of people living within the SEA but not within the identified city would be lost. The other results do not appear to suffer from their inclusion.

TABLE ONE : SEA CENSUS CODES

1	NEW YORK G	51	PENNSYLVANIA 1
2	CALIFORNIA F	52	VIRGINIA D
3	ILLINOIS C	53	TEXAS 12
4	MICHIGAN F	54	ALABAMA A
5	PENNSYLVANIA B	55	CALIFORNIA C
6	MASSACHUSETTS C	56	MASSACHUSETTS B
7	CALIFORNIA A	57	OHIO 6
8	PENNSYLVANIA D	58	FLORIDA G
9	OHIO E	59	NEW YORK C
10	NEW JERSEY B	60	INDIANA A
11	MARYLAND A	61	HAWAII H
12	MINNESOTA B	62	NEW YORK 3
13	MISSOURI B	63	NEW JERSEY H
14	TEXAS G	64	NORTH CAROLINA 4
15	NEW JERSEY 1	65	OKLAHOMA B
16	GEORGIA B	66	MASSACHUSETTS A
17	NEW JERSEY G	67	GEORGIA 4
18	CALIFORNIA G	68	FLORIDA 5
19	NEW YORK A	69	MICHIGAN 6
20	FLORIDA C	70	OHIO F
21	MARYLAND B	71	OHIO H
22	WASHINGTON A	72	WISCONSIN 7
23	CALIFORNIA H	73	ILLINOIS F
24	COLORADO A	74	CONNETICUT 2
25	CALIFORNIA B	75	FLORIDA H
26	WISCONSIN C	76	TEXAS 8
27	FLORIDA B	77	FLORIDA 6
28	LOUISIANNA B	78	CALIFORNIA 3
29	NEW JERSEY D	79	MINNESOTA 6
30	OHIO K	80	WISCONSIN 8
31	OREGON A	81	FLORIDA 4
32	OHIO B	82	OHIO 4
33	TEXAS F	83	VIRGINIA C
34	CONNETICUT C	84	OHIO A
35	OHIO C	85	MISSISSIPPI
36	CONNETICUT A	86	PENNSYLVANIA M
37	INDIANA D	87	NORTH CAROLINA 11
38	MISSOURI A	88	TENNESSE B
39	NEW YORK 9	89	NEBRASKA B
40	RHODE ISLAND	90	UTAH A
41	VIRGIN B	91	PENNSYLVANIA 6
42	DISTRICT OF COLUMBIA	92	MASSACHUSETTS E
43	TEXAS B	93	NORTH CAROLINA 3
44	ILLINOIS 6	94	MICHIGAN D
45	TENNESSEE 8	95	OKLAHOMA A
46	CONNETICUT B	96	FLORIDA E
47	NEW YORK F	97	PENNSYLVANIA 4
48	TENNESSE A	98	LOUISIANA 6
49	NEW YORK B	99	OHIO 2
50	KENTUCKY A	100	INDIANA 5

A matrix was then constructed showing migration flows from each area to every other area (thus forming a 100 x 100 matrix). Latitude and Longitude coordinates were used to calculate the straight line distance from each of the SEA cities identified to every other SEA city. Three other attributes were collected from each area.

1: Employment Status;the percentage of unemployed males aged 16 years and older (1970 Census: State Economic Areas, (1972)). It was thought that a high unemployment value would deter migrants from travelling to an area due to the perceived poor state of its economy.

2: Mean Family Income (1970 Census: State Economic Areas, (1972)). It was thought that a high mean family income used as a proxy for a destination's economic standing would be attractive to in-migrants. Conversely a low mean family income should correlate with low migrant inflows.

3: A climatic ranking. A ranking system was used as designed by the "Places rated Almanac". This system determined a score for climatic mildness including such considerations as: hot and cold months, variation in seasonal temperatures, heating- and cooling-degree days, freezing days, zero-degree days and ninety-degree days.

The final attribute calculated for inclusion in the model was the competing destinations formulation. For this particular model the following calibration was used:

$$C_{ij}=\sum_{\substack{k=1\\ k\neq j\\ k\neq i}}^{100} P_k/d_{jk}$$

Where P is the population of alternative k and d_{jk} is the distance between the two alternatives j and k. As expected, areas around the North East have higher values of this centrality index due to the clustered location of major cities in this area. Fig 1 shows a three dimensional plot of accessibility values against latitude and longitude coordinates. It is obvious from this that the North-East has the highest values, because of the clustering of major cities there, and that there is a steep falling-away to the west and the south, with the south-west recording the lowest values.

The list of destination attributes to be included within the multiple regression included; Distance between i and j, Population of j, Unemployment of j, Mean Family Income of j, Climate of j, and the centrality of j. The logged value for all these attributes were then calibrated against the migration flow for each individual area using the multiple regression option in SAS. This meant that altogether 100 separate models were calibrated. All the models were then re-calibrated with the accessibility variable removed from the equation. This was done in order to compare the model with and without the competing destination formulation.

RESULTS

Two areas were omitted from the models due to the unusual and spurious nature of their

results. These two areas were numbers 79 (Minneapolis) and 89 Omaha. The reason for their exclusion was in both cases an unacceptably low significance value of the distance parameter in the model. Further investigation into the data sets for these two SEA revealed no immediate reason for the spurious result. Further investigation is needed to identify the problem, but until such a time, it was decided to leave the two SEA's out of the model. Table 2 shows each of the remaining 98 models calibrated with the inclusion of the accessibility variable and showing which variables are significant at the 95% confidence level.

Before we consider the results in more detail, it is important to note that the R-squares for these models are lower than in most other similar studies. This is because the data used is far more disaggregated than usual, and the smaller size of the S.E.A. (most other studies use either regions or whole states), means that outlier flows have more impact on the area in question. For example, a large outlier flow, such as the closing of General Motors assembly plants will affect the results for the area surrounding Flint far more than a study concerning the whole of Michigan. The same affect can be seen within the 100 chosen S.E.A. as the first few (like New York) will have populations large enough to mask outlier flows to a certain degree. This explains why the R-squares appear to become progressively worse. Indeed a simple regression of population size against R-square shows a significant relationship between the two (a probability of T of 0.002), but with an R-square of only 0.10. This suggests that the model does a poor job of explaining the variance but that there is indeed a relationship between population size and R-square.

TABLE 2 : SIGNIFICANT VARIABLES AT 95% CONFIDENCE

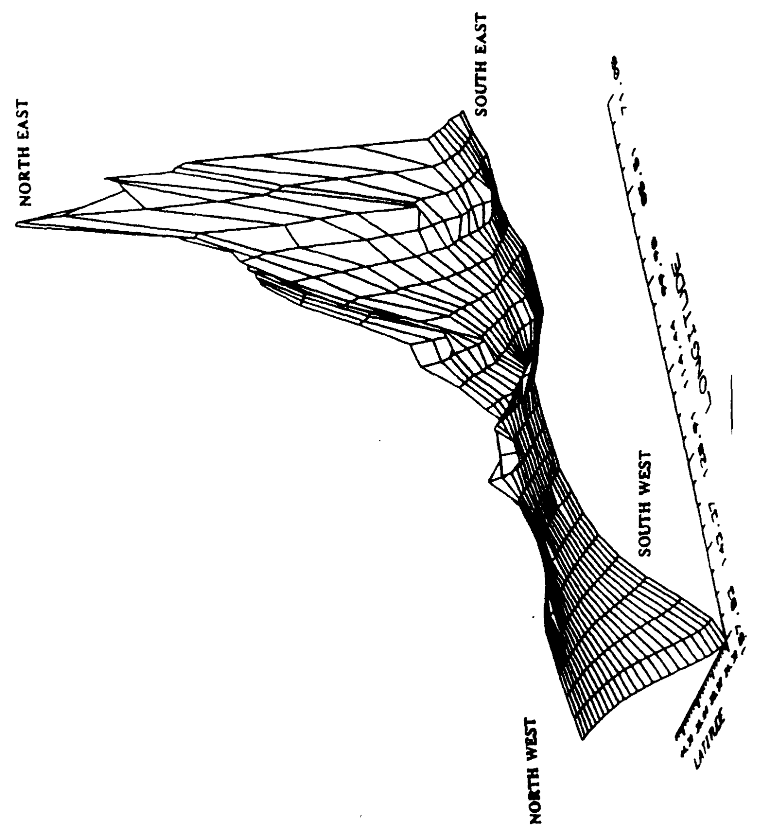
1 New York	(-) dist	(+) pop	(-) accs		(+) inc
2 Los Angeles	(-) dist	(+) pop	(-) accs		(+) inc
3 Chicago	(-) dist	(+) pop	(-) accs		(+) inc
4 Detroit	(-) dist	(+) pop	(-) accs		(+) inc
5 Philadelphia	(-) dist	(+) pop	(-) accs		
6 Boston	(-) dist	(+) pop	(-) accs		(+) inc
7 San Francisco	(-) dist	(+) pop	(-) accs		
8 Pittsburgh	(-) dist	(+) pop			(+) inc
9 Cleveland	(-) dist	(+) pop	(-) accs		(+) inc
10 Newark	(-) dist	(+) pop			
11 Baltimore	(-) dist	(+) pop	(-) accs		
12 Minneapolis	(-) dist	(+) pop	(-) accs		(+) inc
13 St Louis	(-) dist	(+) pop	(-) accs		(+) inc
14 Houston	(-) dist	(+) pop	(-) accs		(+) inc
15 NewBrunswick	(-) dist	(+) pop			
16 Atlanta	(-) dist	(+) pop	(-) accs		
17 Paterson	(-) dist	(+) pop			(+) inc
18 San Diego	(-) dist	(+) pop	(-) accs		(+) inc
19 Buffalo	(-) dist	(+) pop			(+) inc
20 Miami	(-) dist	(+) pop	(-) accs	(+) clim	(+) inc
21 (Washington)	(-) dist	(+) pop	(-) accs		(+) inc
22 Seattle	(-) dist	(+) pop	(-) accs		(+) inc
23 SanBernadino	(-) dist	(+) pop	(-) accs		(+) inc
24 Denver	(-) dist	(+) pop	(-) accs		(+) inc
25 Santa Clara	(-) dist	(+) pop	(-) accs		(+) inc
26 Milwaukee	(-) dist	(+) pop	(-) accs	(+) clim	(+) inc
27 Tampa	(-) dist	(+) pop	(-) accs	(+) clim	(+) inc
28 New Orleans	(-) dist	(+) pop	(-) accs	(+) clim	(+) inc
29 Camden	(-) dist	(+) pop			
30 Cincinnati	(-) dist	(+) pop	(-) accs		(+) inc
31 Portland	(-) dist	(+) pop	(-) accs		(+) inc
32 Columbus	(-) dist	(+) pop	(-) accs		(+) inc
33 San Antonio	(-) dist	(+) pop	(-) accs		(+) inc
34 Hartford	(-) dist	(+) pop	(-) accs		(+) inc
35 Dayton	(-) dist	(+) pop	(-) accs		(+) inc

36	Bridgeport	(-) dist	(+) pop	(-) accs			
37	Indianapolis	(-) dist	(+) pop	(-) accs		(+) inc	
38	(KansasCity)	(-) dist	(+) pop	(-) accs		(+) inc	
39	Kingston	(-) dist	(+) pop	(-) accs			
40	Providence	(-) dist	(+) pop	(-) accs			
41	(Washington)	(-) dist	(+) pop	(-) accs	(+) clim		
42	Washington	(-) dist	(+) pop	(-) accs	(+) clim		
43	Dallas	(-) dist	(+) pop	(-) accs		(+) inc	
44	Bloomington	(-) dist	(+) pop	(-) accs		(+) inc	
45	Chattanooga	(-) dist	(+) pop	(-) accs			
46	New Haven	(-) dist	(+) pop	(-) accs		(+) inc	
47	Albany	(-) dist	(+) pop	(-) accs			
48	Memphis	(-) dist	(+) pop	(-) accs		(+) inc	
49	Rochester	(-) dist	(+) pop			(+) inc	
50	Louisville	(-) dist	(+) pop	(-) accs			(-)UE
51	New Castle	(-) dist	(+) pop				
52	Norfolk	(-) dist	(+) pop	(-) accs	(+) clim		(-)UE
53	Longview	(-) dist	(+) pop	(-) accs	(+) clim	(+) inc	
54	Birmingham	(-) dist	(+) pop	(-) accs		(+) inc	
55	Sacremento	(-) dist	(+) pop	(-) accs		(+) inc	
56	Worcester	(-) dist	(+) pop	(-) accs		(+) inc	
57	Newark	(-) dist	(+) pop	(-) accs			
58	Fort Lauderd	(-) dist	(+) pop		(+) clim	(+) inc	
59	Syracuse	(-) dist	(+) pop	(-) accs		(+) inc	
60	(Chicago)	(-) dist	(+) pop	(-) accs			
61	Honolulu		(+) pop	(-) accs			
62	Elmira	(-) dist	(+) pop	(-) accs			
63	Jersey City	(-) dist	(+) pop	(-) accs			
64	Winston	(-) dist	(+) pop	(-) accs	(+) clim	(-) inc	(-)UE
65	OklahomaCity	(-) dist	(+) pop	(-) accs		(+) inc	(-)UE
66	Springfiled	(-) dist	(+) pop	(-) accs		(+) inc	
67	Macon	(-) dist	(+) pop	(-) accs			(-)UE
68	Orlando	(-) dist	(+) pop		(+) clim		(-)UE
69	Grand Rapids	(-) dist	(+) pop	(-) accs		(+) inc	
70	Akron	(-) dist	(+) pop	(-) accs			
71	Youngstown	(-) dist	(+) pop	(-) accs			
72	Green Bay	(-) dist	(+) pop	(-) accs		(+) inc	
73	St Louis	(-) dist	(+) pop	(-) accs		(+) inc	
74	Norwich	(-) dist	(+) pop	(-) accs	(+) clim		
75	Jacksonville	(-) dist	(+) pop	(-) accs	(+) clim	(+) inc	
76	Waco	(-) dist	(+) pop	(-) accs			
77	Fort Myers	(-) dist	(+) pop	(-) accs	(+) clim	(+) inc	
78	Santa Cruz	(-) dist	(+) pop	(-) accs		(+) inc	
80	Madison	(-) dist	(+) pop	(-) accs		(+) inc	
81	DaytonaBeach	(-) dist	(+) pop	(-) accs	(+) clim	(+) inc	
82	Mansfield	(-) dist	(+) pop	(-) accs			
83	Richmond	(-) dist	(+) pop	(-) accs			
84	Toledo	(-) dist	(+) pop	(-) accs			
85	Jackson	(-) dist	(+) pop	(-) accs			
86	Allentown	(-) dist	(+) pop	(-) accs			
87	Wilmington	(-) dist	(+) pop	(-) accs	(+) clim		(-)UE
88	Nashville	(-) dist	(+) pop	(-) accs			
90	SaltLakeCity	(-) dist	(+) pop	(-) accs	(+) clim	(+) inc	
91	Hazleton	(-) dist	(+) Pop	(-) Accs			
92	Taunton	(-) dist	(+) pop	(-) accs		(+) inc	
93	Greensboro	(-) dist	(+) pop	(-) accs			(-)UE
94	Flint	(-) dist	(+) pop	(-) accs			
95	Tulsa	(-) dist	(+) pop	(-) accs		(+) inc	
96	Orlando	(-) dist	(+) pop	(-) accs	(+) clim		
97	(Pittsburgh)	(-) dist	(+) pop				
98	Baton Rouge	(-) dist	(+) pop	(-) accs	(+) clim		
99	Findlay	(-) dist	(+) pop	(-) accs			
100	(Indinapolis	(-) dist	(+) pop	(-) accs			

(Cities in Brackets denotes influential city outside of area.)

FIG 1: DIFFERENCES IN THE COMPUTED ACCESSIBILITY VALUE FOR ALL THE DIFFERENT SEA

(With Patterson, Newark, New Brunswick & Camden removed)



We can see from these tables that, ceteris paribus migrants select destinations by population size (possibly due to the increased perception of opportunities); those destinations that are closer; destinations that are relatively isolated; and destinations that appear to be more affluent. The parameter estimates for population are significant in every one of the 98 calibrated models. There is also a remarkable consistency to this parameter with its value being around 1 suggesting this parameter is the most consistent and stable predictor of migration. The distance parameter is also significant in every case except one, that being Honolulu (because it is a non-contiguous area with the rest of the U.S. and probably has its own individual selection criteria for interested migrants). The accessibility parameter is also significant in all but 11 cases. Its significantly negative parameter estimate seems to support the hypothesis that spatial information is processed in a hierarchical way with the individual placing possible destinations into clusters. It also suggests that individuals tend to underestimate individual destination potential from within large clusters. These three results are by far the most striking, although Mean Family Income is also significant in 55 cases suggesting that a healthy economic destination is also important. However the reverse economic measure, that of unemployment is only significant in eight cases. The final variable, that of Climate, is significant in nineteen cases. Those areas with a positive climatic parameter tend to be the traditionally 'good' climatic regions, such as Tampa or Daytona Beach, where one would suspect that a native would be more concerned about a destination's climate.

It is interesting to note that there is an apparent spatial trend to the accessibility parameter as can be seen in Fig 2 with more accessible areas having more negative parameters. This suggests that people from more central locations process spatial information in a more hierarchical way than do those from the periphery. This finding supports our earlier suggestion that a hierarchical processing of information is an efficient means of dealing with large volumes of information, and that people from more central locations will have more contact with people from other places and subsequently more information to process, thus they are more likely to process information hierarchically.

There were however eleven calibrations where the accessibility parameter was not significant. Table 3 shows these eleven, and it can be seen that some of the non-significant results were from very central areas, particularly with Newark. It was suggested that this could be as a result of a misspecification of the centrality equation due to the very large population of New York City, and the very small distance between the area and New York City (the equation could tend towards infinity). In order to test if this is true or not, the competing destination formulation was modified in three different ways, with the distance component being raised to the powers 0.8; 0.9; and 1.1. In this way we can see what sort of effect distance has upon the equation. Hence the new formulation is (with 0.9 or 1.1 also being used as the exponent in different versions):

$$C_{ij} = \sum_{\substack{k=1 \\ k \neq i \\ k \neq j}}^{98} P_k / d_{jk}^{0.8}$$

Table 3 shows the old parameter estimates for the non-significant areas and compares them to the new parameters as estimated by using the above formulation (which proved to be the most successful of the three modifications). It can be seen that for those areas close to New York, the parameter became significant, and the parameter size became far more negative as would be expected from our theory about hierarchical processing (Paterson is a good example of this). Newark remained non-significant which tends to suggest that the optimum formulation of the competing destination model has yet to be found. As has been discussed before, many geographers would dismiss any recorded move of less than 30 miles as only a change of residence and not employment. One suggestion for further research would be to combine certain SEA's together, especially if under the influence of one major city.

Other areas such as Pittsburgh remain a mystery as to why they are non-significant, while the value of Orlando and Fort Lauderdale remains relatively unchanged as would be expected due to their peripheral location. In all cases, the inclusion of the competing destination formulation provides a better fit than the model without the formulation. The model becomes progressively better as the value of distance was decreased within the formulation. This is still a trial and error approach to finding the correct competing destination formulation and a

TABLE THREE : NON-SIGNIFICANT ACCESSIBILITY VALUES

CENTER	DIST FROM N.Y.	(ACCS=1) OLD VALUE	(ACCS=0.8) NEW VALUE
PITTSBURGH	330	-0.164 (0.466)	-0.289 (0.359)
NEWARK	12	-0.095 (0.828)	-0.386 (0.513)
NEW BRUNSWICK	29	-0.550 (0.104)	-1.069 (0.021)
PATERSON	20	-0.589 (0.132)	-1.114 (0.036)
BUFFALO	308	-0.241 (0.348)	-0.435 (0.235)
CAMDEN	80	-0.535 (0.064)	-0.930 (0.020)
ROCHESTER	266	-0.430 (0.226)	-0.726 (0.153)
NEW CASTLE	353	-0.420 (0.090)	-0.660 (0.055)
FORT LAUDERDALE	1060	-0.112 (0.386)	-0.157 (0.362)
ORLANDO	930	-0.274 (0.089)	-0.380 (0.078)
(PITTSBURGH)	330	-0.444 (0.237)	-0.702 (0.185)

more systematic approach is needed to find what is the correct form of the model. None of the other parameters either became or lost their significance.

The final step was to re-run the model with the accessibility value removed. As has been mentioned before, the R-square drops in all cases as compared to the results of the model calibrated with the accessibility variable included. The parameter estimate for Population remains consistent and significant, however the parameter estimate for distance begins to fluctuate and in some cases becomes non-significant (such as Detroit). The results here follow similar results from other studies (Fotheringham 1989) whereby the parameter results show the degree of misspecification bias present in a spatial choice model with the accessibility variable removed. Those areas around the North East, that is the more central locations, appear to have lower parameter estimates than those on the periphery (New York = -0.512, Los Angeles = -1.261). These results, as can be seen in Fig 3, suggest a spatial trend where people from more central locations seem to be less deterred by distance in destination choice than those on the periphery. This is probably a spurious result due to model misspecification as no such spatial trend appears in Fig 4 with the distance parameters when the accessibility variable is included.

CONCLUSION

The results from this investigation into migration between the 100 largest SEA of the United States have shown that the competing destination model is an important and necessary component of modelling destination choice. It has been shown that people do seem to process spatial information in a hierarchical way, and that people from more clustered locations tend to process this information more hierarchically than those in the periphery. The model calibrated without such a method for representing hierarchical spatial choice proved to produce spurious spatial results suggesting that people from clustered locations were less likely to be deterred by distance.

This paper, in line with Fotheringham's (1987) suggestion to further investigate the competing destination model by using more disaggregated data sets suggested a few further areas of study into the model's formulation. The problems associated with rival destinations being to close to one another led to some spurious accessibility values. Variations on how these problems can be rectified in the model were tried with increasingly successful results. However it became obvious that this trial and error method did not produce the optimum model, if indeed one exists. I would suggest areas of future research would include further investigations into what is the correct form of the model, and that this investigation be attempted by a more systematic approach than the iterative process of trial and error, and finally, an explanation is needed as to why there are differences within the models with a justification for choosing the new correct competing destination model.

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FIG 2: A PLOT OF ACCESSIBILITY AGAINST THE ACCESSIBILITY PARAMETER
(With Paterson, Newark, New Brunswick & Camden removed)

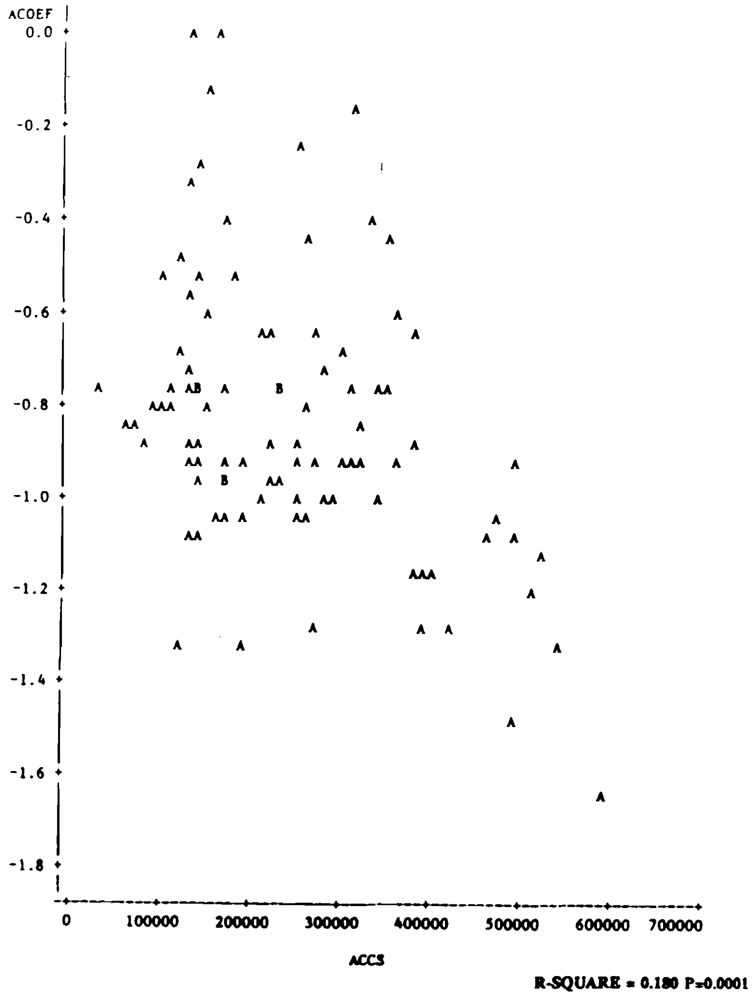


FIG 3: A PLOT OF THE DISTANCE PARAMETER FROM THE MODEL WITHOUT ACCESSIBILITY AGAINST CENTRALITY
(With Paterson, Newark, New Brunswick & Camden removed)

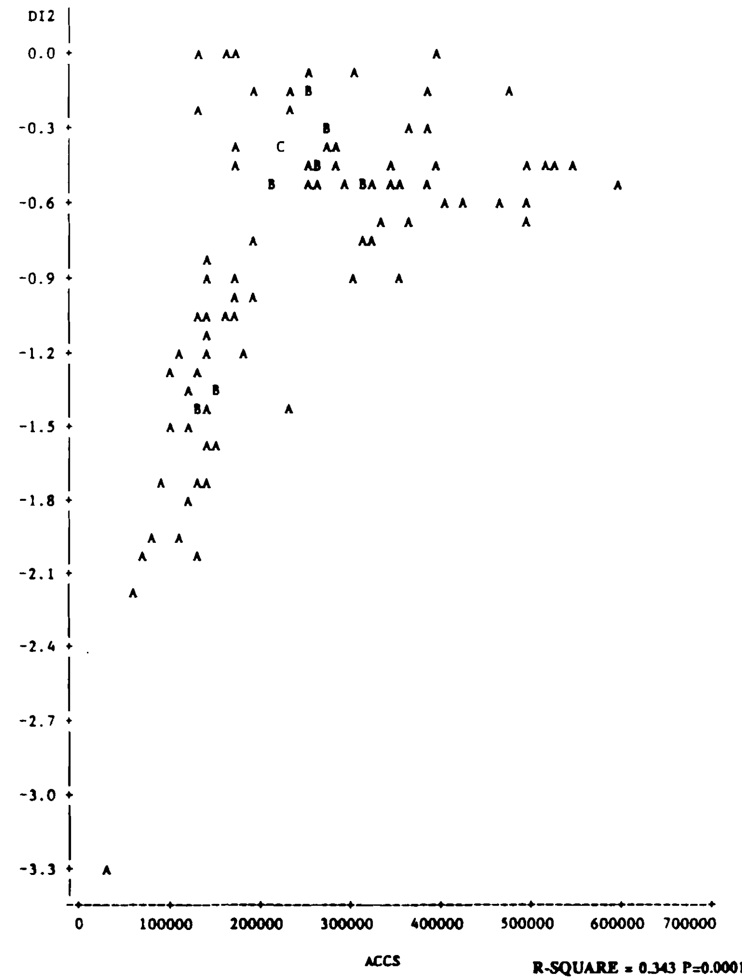
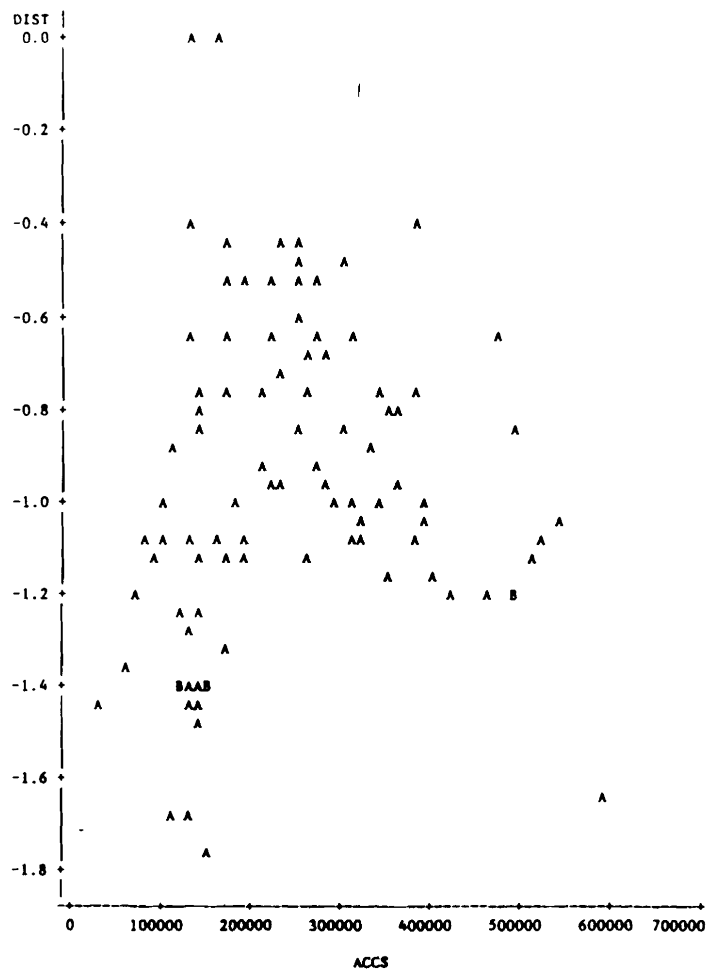


FIG 4: A PLOT OF THE DISTANCE PARAMETER FROM THE MODEL INCLUDING ACCESSIBILITY AGAINST CENTRALITY
(With Paterson, Newark, New Brunswick & Camden removed)



R-SQUARE = 0.009 P=0.367