HEALTH CARE ACCESSIBILITY MODELING: EFFECTS OF CHANGE IN SPATIAL REPRESENTATION OF DEMAND FOR PRIMARY HEALTH CARE SERVICES

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Abstract. Health care accessibility can be measured by the number of prospective patients who could reach a medical facility within a prescribed time limit. The representation of health care demand in estimating accessibility is an important consideration since different spatial aggregations of demand have different consequences with regard to accessibility estimates. This article examines the effects of aggregating population demand for primary health care, ranging from census tract to aggregated census block, on estimates of primary health care accessibility. Spatial representations of aggregated demand were incorporated into a location-allocation model in order to determine a measure of accessibility represented by the unmet demand for primary health care services. The model was implemented for the U.S. State of Idaho, based on the allocation of Idaho residents' demand for primary health care to the state's existing primary health care facilities. The results confirm a relationship between the level of demand aggregation and the level of potential accessibility. In case of a rural state such as Idaho the relationship is positive; higher levels of aggregation result in higher measures of accessibility.

Key words: health care accessibility, GIS, location-allocation, scale, spatial aggregation

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Introduction

This article examines the effect of scale in representing the demand for primary health care services in modeling health care accessibility. The concept of spatial accessibility in health care services refers to the ability of an individual to: 1) reach a location of health care service from a location of his/her residency within some prescribed maximum time interval, and 2) receive a medical service. In geographical health research, the concept of accessibility has been investigated through the lens of spatial analysis (Wang 2011, Kwan, Weber 2008, Laditka, 2004, Martin, Wiliams 1992) and Geographic Information Systems (GIS) (Burkey et al. 2012, Cromley, McLafferty 2002, Lin et al. 2002, Lovett et al. 2002, Parker, Cambell 1998). Among the modeling approaches to health care accessibility, gravity models (Wang, Roisman 2011) and location-allocation models (Oppong, Hodgson 1994, Langford, Higgs 2006) have been frequently used to account for the effects of distance, availability of health care, and demand for service.

Health care accessibility can be investigated from two different perspectives. First, potential accessibility measures can be derived based on the estimated number of people who could reach a medical facility within a prescribed time limit. Second, realized accessibility measures can be computed showing how many people actually did receive medical services. With regard to the second perspective, detailed patient-level information is typically unavailable. As a result, most accessibility studies have developed potential measures of accessibility based on straight-line distances or travel-time distances between locations of health services and aggregate locations of the population. These measures can then be used to identify areas where accessibility is poor and where additional health facilities are needed to improve accessibility (Langford, Higgs 2006).

One of the requirements, and challenges at the same time, of assessing potential accessibility to health care services with location-allocation models has been the choice of scale, at which population's demand for health care services is represented. Typically, demand for goods or services, health care including, is represented in location-allocation models at a point (Rushton 1989). Because the population data are almost always available at statistical enumeration units (e.g. zip codes or census tracts), most accessibility studies have used the centroid of the enumeration unit to represent that enumeration unit's population. Verter and Lapierre (2002) used the centroids of 638 populated regions as the demand locations for a location-allocation model in order to locate preventative health care facilities that maximized participation in prevention programs with the rationale that distance is a major determinant of participation in such programs. In a study by Mitropoulos et al. (2006), patient level data about the annual number of visits to existing health care facilities was obtained for all inhabitants of 228 population regions in semi-rural Achaia, Greece. The centroids of these regions were used as the locations of demand for health care facilities. Brabyn and Skelly (2002) used the centroids of meshblocks in New Zealand (meshblocks are the most detailed census enumeration units available) as the locations of demand in an accessibility model. In a study by Wang and Luo (2005), population-weighted centroids of census tracts (based on block-level population data) were used instead of simple geographic centroids, to represent population locations more accurately. This process resulted in a computationally manageable number of demand points (2952) and was particularly successful in refining the locations of population in rural areas where notable areas of land are unpopulated.

Since the demand for health care services is a function of population distribution across a geographical space, any area-to-point transformation is inherently burdened with an error resulting from continuous demand distribution (statistical enumeration zones) aggregated into discrete (point) representations of demand (Daskin et al. 1989). It is also possible to distribute the population evenly across an enumeration unit (so called *pro rata* method) as a series of evenly spaced points dispersed throughout the entire enumeration unit (Langford, Higgs 2006). If uniform distribution is a valid assumption, the *pro rata* method may offer more accurate estimates of population location than the centroid method. This assumption may be valid in small, dense urban environments but is less likely to be valid in rural areas where population tends to concentrate in small settlements separated by areas of unoccupied/unpopulated land. In addition, this pro-rata technique for representing population locations typically results in a vast number of demand points, which presents a computational challenge for assessing accessibility with a location–allocation model. The use of large-scale/small-area statistical enumeration units (e.g. census blocks in the U.S.), in order to reduce the area-to-point transformation error, results in a similar computational challenge and is only practical for small study areas.

This article examines the effects of area-to-point demand aggregation in location-allocation model on accessibility to primary health care service centers. The level of accessibility is measured by unmet demand for primary health care services due to distance and/or lack of service capacity. This approach results in identifying areas without adequate accessibility (given the driving distance and service capacity constraints). The article explores the consequences of different demand representations from the coarsest (small scale) to the finest (large scale) including tract centroid, block group centroid, and block centroid on the amount of unmet demand.

These progressively larger-scale representations and the resulting accessibilities are examined at different driving times, beginning with 30 minutes driving time, through 45 and 60 minutes travel times. In the remainder of the paper a location-allocation model adopted for calculating the unmet demand for primary health care services is presented in section two along with data requirements and study area description. Results of modeling accessibility to primary health care services under different spatial representations of demand are presented in section three. The discussion and conclusion are offered in section four.

Modeling approach, data requirements, and study area

Accessibility is one of the most widely used metrics in measuring the value of location in service delivery (Church, Murray 2009). Accessibility can also be conceptualized as a function of allocating demand for services distributed among multiple locations to service centers. This conceptualization has motivated the use of location-allocation models in studies of accessibility to health services and in planning of health services with explicit consideration given to the locations of service providers, service capacities, geographical distribution of patients, and ease of access to health services (Mitropoulos et al. 2012, Harper et al. 2005). In this study a location-allocation model maximizing the coverage of service, called Maximal Covering Location Problem (MCLP) has been used to account for accessibility to primary health care services. The MCLP model introduced by Church and ReVelle (1974) is designed to maximize the demand for service assigned to a selected number of service sites within a specified distance. Traditionally, the model has been used to find an optimal subset of service sites from the set of all possible service sites (Gerrard et al. 1997, Oppong, Hodgson 1994). In this study, the model was used in a non-traditional way by employing all existing service sites into the allocation of demand, thus effectively forcing the model algorithm to select all existing service sites and then assign the demand to the sites in a manner that would maximize the total assigned demand, and hence the coverage of service demand.

2.1. Model formulation

A mathematical formulation of the MCLP is as follows:

Maximize $z = \sum_{i \in I} a_i \cdot y_i$

Subject to:

1) $\sum_{j \in N_i} x_j \geq y_i$ for all $i \in I$

2) $\sum_{j \in J} x_j = P$

3) $x_j = (0,1)$ for all $j \in J$

4) $y_i = (0,1)$ for all $i \in I$

where:

I = the set of demand locations,

J = the set of service sites,

$N_i = \{j \in J \mid d_{ij} \leq S\}$; the set of service sites j that can reach demand location i within the maximal service distance S,

S = the distance beyond which a demand location is considered "uncovered" (the value of S can be chosen differently for each demand location if desired),

d_{ij} = the shortest distance from location i to location j;

x_j = {1 if a service is allocated to site j, 0 otherwise};

y_i = {1 if a service is allocated to site i, 0 otherwise},

a_i = service demand in location i,

p = the number of service facilities to be located.

The model's objective is to maximize the amount of covered demand. Constraint (1) ensures that demand is covered (allocated to point of service) if there is at least one service location available within the admissible service distance S. Constraint (2) requires that p service locations be selected (the p number is set by a modeler). Constraints (3) and (4) serve as binary integer restrictions on model location (x_j) and allocation (y_i) variables. The MCLP model can be solved on a transportation network, where the network nodes represent locations of demand and service centers, and the network links represent linkages between the nodes. Each of the network links has some defined impedance (e.g. travel time or distance) that represents the separation between nodes. The total impedance between each demand node and each service node is defined as the total impedance encountered between the two nodes while traveling the shortest distance over the network. A demand node (location) is considered covered if it is within some user specified S distance to a service node.

MCLP model data requirements

The MCLP model that relies on transportation network representation of demand and service locations can be conveniently implemented and solved with GIS software supporting network data model. To solve the MLCP model in a GIS environment, three different data sets/GIS layers are required:

- a road network as a line layer,
- locations of service centers in a point layer, and
- locations of demand, also in a point layer.

The network representation in GIS requires that all demand and service locations be connected to the road network in order to correctly model the network flows. This requirement has practical implication on data pre-processing as demand locations, which are customarily represented by centroids of geographical statistical units (e.g. census tracts or postal codes), are frequently found off the road network and must be connected to the network in order to facilitate the model solution.

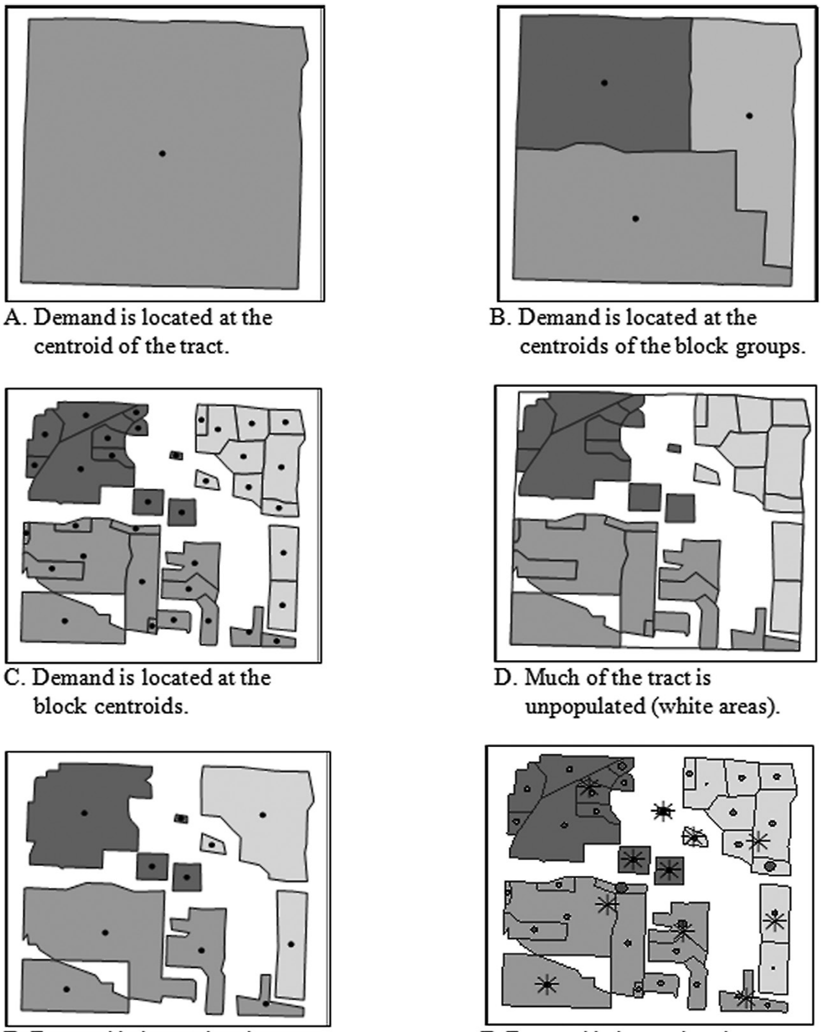
Four different representations of demand were used in this study. They included, in the progression from small to large scale; census tract, census block group, aggregated block region – comprised of contiguous populated blocks within each census block, and aggregated block region weighted by the block population. In each four representations, the demand for health care services was assigned to a corresponding centroid. Figure 1 illustrates various representations of demand used in the study (cases A, B, E, and F). Cases C and D, not used in the study, represent populated census blocks with their centroids (C) and populated blocks aggregated into regions (D). These two cases are included in Figure 1 for illustrative purpose to: (1) demonstrate a situation common in rural areas where some census blocks do not have any resident population, and (2) explain how block regions (cases E and F) were derived from aggregating the contiguous, populated blocks.

Study area

The MCLP model was applied to assess the accessibility to primary health care services in the U.S. State of Idaho. In the U.S., access to medical facilities is considered vital not only to individuals needing medical care, but also to the communities in which these individuals participate. The federal guideline for adequate access to primary care services states that all individuals should reside within a 30-minute driving distance (roughly 20 miles under normal conditions with primary roads available or 15 miles in mountainous terrain with only secondary roads available) from a primary health care facility (PHCF) (U.S. Department of Health and Human Services 1993). While this is a laudable goal, it is often difficult to achieve.

The low population density of most rural areas, along with a low patient to doctor ratio, results in a large percentage of the rural population residing further than 30 minutes from a health care facility. The resulting inequality in health care services between urban and rural residents has been a matter of concern to federal and state health officials.

The state of Idaho is a good example of the difficulties of providing access to health care equally to all residents. In 2010, Idaho had the second lowest active physician to population ratio of all (50) U.S. states and the third lowest active primary care physician to population ratio, with 184.2 active physicians per 100,000 people, and 67.2 active primary care physicians per 100,000 people. These ratios were far below the national rates of 258.7 active physicians per 100,000 people and 90.5 active primary care physicians per 100,000 people (Association of American Medical Colleges 2011). The low physician to population ratios might be explained partially by the low population density within the state. In 2010, Idaho was estimated to have a population density of 19 persons per square mile (7.34 persons per square km), compared to the estimated national average



A. Demand is located at the centroid of the tract.

B. Demand is located at the centroids of the block groups.

C. Demand is located at the block centroids.

D. Much of the tract is unpopulated (white areas).

E. Demand is located at the centroids of contiguous block regions within a tract.

F. Demand is located at the weighted centroids (asterisk) of contiguous block regions. The point symbol size is proportional to the amount of demand in each block

Fig. 1. Demand representations used in the study

of 87.4 persons per square mile (33.75 persons per square km) (U.S. Census Bureau 2010). In order to improve health care accessibility in rural areas like Idaho, it is necessary to know where under-serviced areas exist, or in other words, where demand for healthcare is unmet.

Location-allocation accessibility modeling can be used to determine where demand for primary health care services (PHCS) is unmet. This modeling approach can also be used to determine optimal locations for potential new health care facilities that would reduce unmet demand in rural areas. In this paper the former use of location-allocation accessibility modeling is presented.

Data preparation

The implementation of MCLP model in order to calculate the amount of unmet demand for PHCS (representing the accessibility to PHCS) required population data by sex and age groups at the block, block group, and census tract levels. The population data was obtained from the publically available U.S. Census 2010 Summary File 1. The estimated annual rates of primary health care visits based on age and sex were obtained from the Center for Disease Control (2008). The rates were then multiplied by the population figures for each census enumeration unit (block,

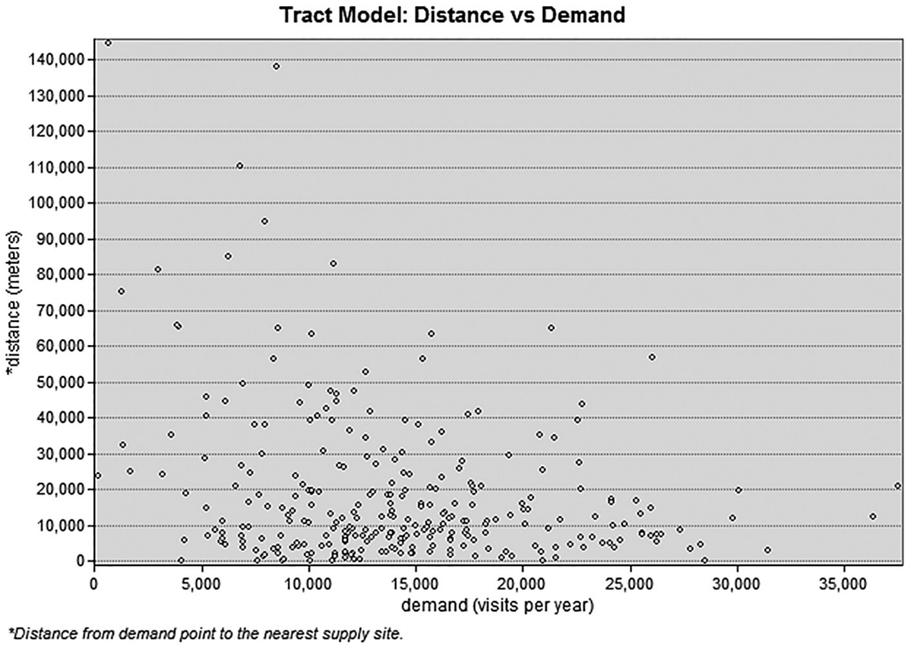


Fig. 2. Tract model: distance vs. demand

block group, or tract) to arrive at the estimate of demand for primary health care services. Detailed road network coverage in a GIS file format (ESRI's line feature layer) was secured from Idaho Department of Transportation. Finally, point-based GIS data layer (ESRI's shape file format) containing information regarding the locations of all primary health care facilities in Idaho and the number of primary care hours they can provide was obtained from Idaho Department of Health and Welfare. The estimated number of visits per year was then calculated for all primary health care facilities using the U.S. Public Health Service standard of 4,200 visits per year for primary care physicians and 2,100 visits per year for midlevel providers. This calculation yielded the estimate of service supply for each primary health care facility in Idaho.

The MCLP model was implemented in GIS software (ArcGIS 9.3). Running the model required creating a network data layer in GIS with point-based demand locations (populated area centroids) and primary health care service facilities represented by the network nodes. A few of the block group and aggregated block region centroids located off the network had to be connected to the network, in order to maintain the network's topology. This was accomplished by digitizing linear segments ranging in length from 160 m to 805 m (0.1 mile to 0.5 mile). The overall effect of these artifacts on the modeling results was deemed negligible.

Results

The MCLP model was run with four different representations of demand ranging from census tract, through census block group, aggregated block region, to aggregated block region weighted by the block population, and with three driving time constraints; 30 minutes (corresponding to the federal guideline), 45, and 60 minutes. The latter two driving time constraints were introduced in order to gain a better understanding of the amount of unmet demand under the relaxa-

Table 1. Tract model results

Driving time (min)	Meters	Miles	Met demand: patient visits	% Met	Unmet demand: patient visits	% Unmet
30	24,140	15.0	3,179,030	80.1	787,706	19.9
45	36,210	22.5	3,513,030	88.6	453,702	11.4
60	48,280	30.0	3,778,126	95.2	188,608	4.8

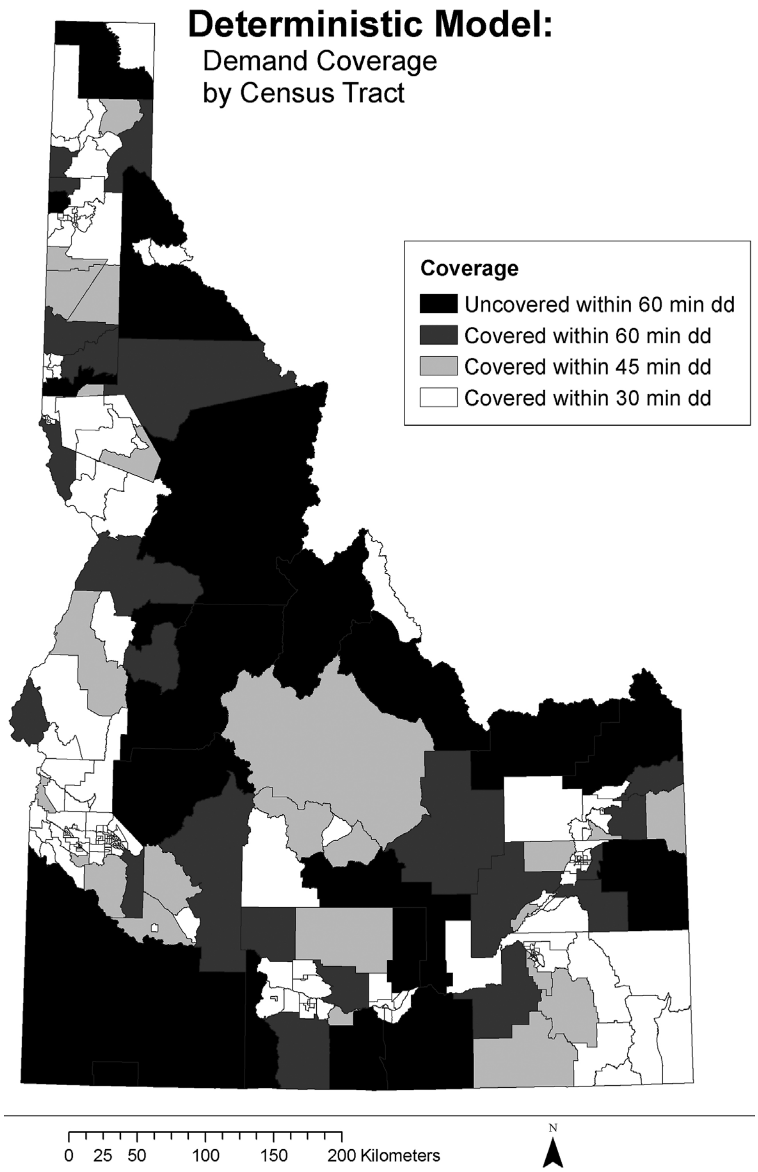


Fig. 3. Tract model coverage (dd = driving distance)

tion of the federal guideline. Overall, there were 12 specific instances of the MCLP model representing the combinations of scale of demand representation and travel time constraint. These models are referred to in this paper as *deterministic* models (as opposed to predictive models) since they were run in order to determine an optimal allocation scheme of demand to all existing service centers rather than to find out, which of the candidate locations would be selected for sitting new service centers.

As representation of demand used in the model moved from a low number of enumeration units (tract models) to a higher number of enumeration units (weighted and non-weighted aggregated block models), the amount of unmet demand for PHCS, representing accessibility, decreased. Results of the weighted aggregated block model, which is assumed to be the most accurate model because of its potential to more accurately locate population/demand, indicate that 11.6% of Idaho's population is farther than the federal guideline of 30 minutes driving distance to the nearest primary health care provider. A more detailed presentation of the results follows below.

Tract-based model

Idaho contains 280 census tracts, with an average census tract size of 772.0 km^2 and a standard

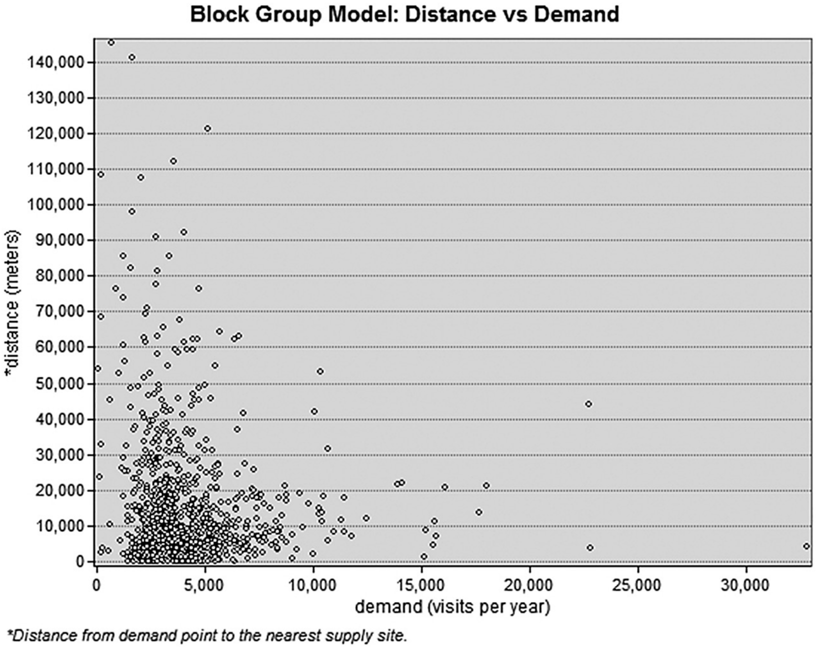


Fig. 4. Block group model: distance vs. demand

deviation of 1,994.9 km^2. Each of the three deterministic tract models (30, 45, and 60 minutes driving time constraint) was run using a representation of demand at the centroid of the tract resulting in 280 demand points. In the tract models, the average distance from a tract demand point to the nearest primary health care facility is 18,415.8 meters (11.44 miles), and the average demand for primary health care services for a tract is 14,166.9 visits per year.

In Figure 2, all of the 280 tract demand points are plotted based on their respective distances to the nearest PHCF and their demand for PHCS.

The tract model at the 30 minute driving distance constraint resulted in 19.9% of the state's demand for PHCS unmet (80.1 of the demand was met). Using the 45 and 60 minute driving distance constraints resulted in 11.4% and 4.8% respectively of the demand for PHCS unmet (see Table 1).

Figure 3 shows the results of the deterministic tract models. Census tracts that are farther than 60 minutes driving time from the nearest primary health care service center are shown in black. Tracts that are between 45 and 60 minutes driving distance from the nearest service center are shown in dark grey. Tracts that are between 30 and 45 minutes driving distance from the nearest service center are shown in light grey and tracts that are within 30 minutes driving distance from the nearest hospital (tracts that are covered within the federal guideline) are shown in white. The resulting pattern of accessibility to primary health care services, expressed by the coverage under the specific driving time constraints, corresponds to the distribution of Idaho's population with the bulk of the population located in northern Idaho (the region called Idaho Panhandle) and in southern Idaho along the Snake River plane.

Block group model

Idaho contains 952 block groups, with an average block group size of 226.7 km^2, with a standard deviation of 739.4 km^2. The block group models were run using a representation of demand

Table 2. Block group model results

Driving time (min)	Meters	Miles	Met demand	% Met	Unmet Demand	% Unmet
30	24,140	15.0	3,401,997.8	85.8	564,736.3	14.2
45	36,210	22.5	3,664,521.3	92.4	302,212.8	7.6
60	48,280	30.0	3,812,745.3	96.1	153,988.8	3.9

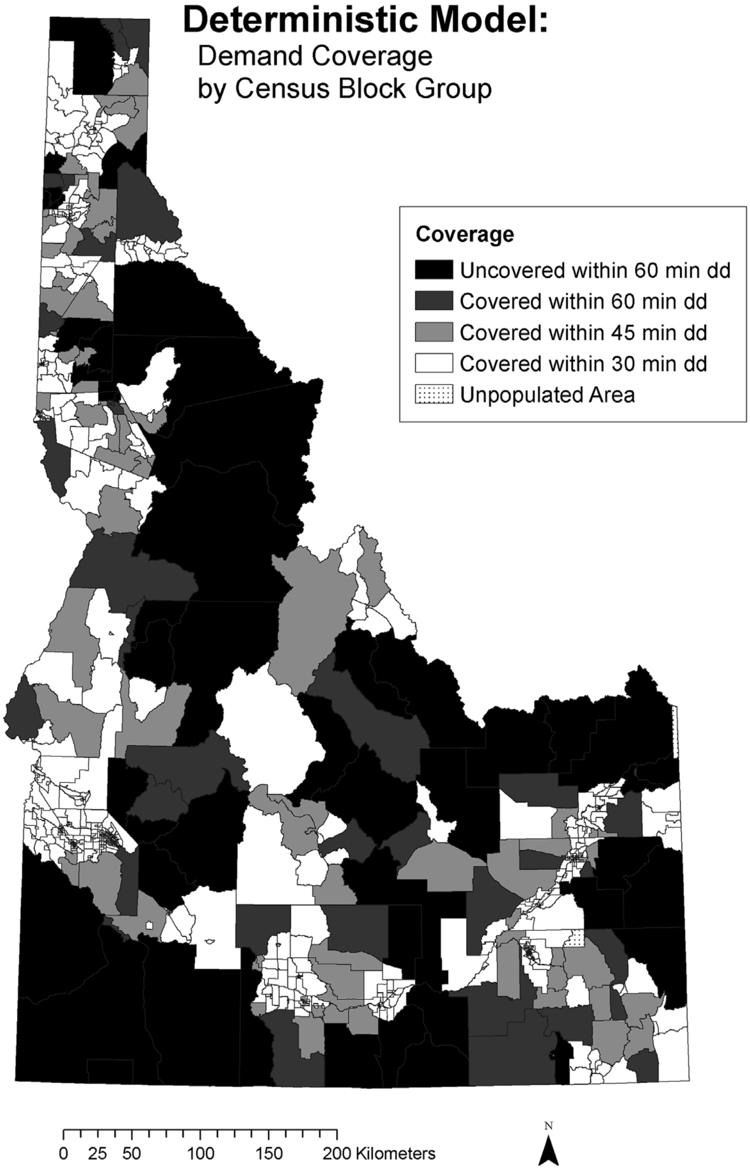


Fig. 5. Block group model coverage

at the centroid of each of the 952 block groups; this resulted in 3.4 times the number of demand points as in the tract models. Manual editing in GIS was required to properly connect four of the block group centroid points to the road network.

The average distance from a block group demand location to the nearest primary health care facility is 14,592.4 meters (9.07 miles), and the average demand for primary health care services for a block group is 4,166.7 visits per year. In Figure 4 all of the 952 block group demand points are plotted based on their respective distances to the nearest PHCF and their demand for PHCS.

The percentage of unmet demand for PHCS yielded by the block group models at a 30 minute driving constraint is 14.2% (met demand is

Table 3. Aggregated block model results

Driving time (min)	Meters	Miles	Met demand	% Met	Unmet Demand	% Unmet
30	24,140	15.0	3,527,236.0	88.9	439,497.8	11.1
45	36,210	22.5	3,734,338.3	94.1	232,395.8	5.9
60	48,280	30.0	3,836,851.8	96.7	129,882.2	3.3

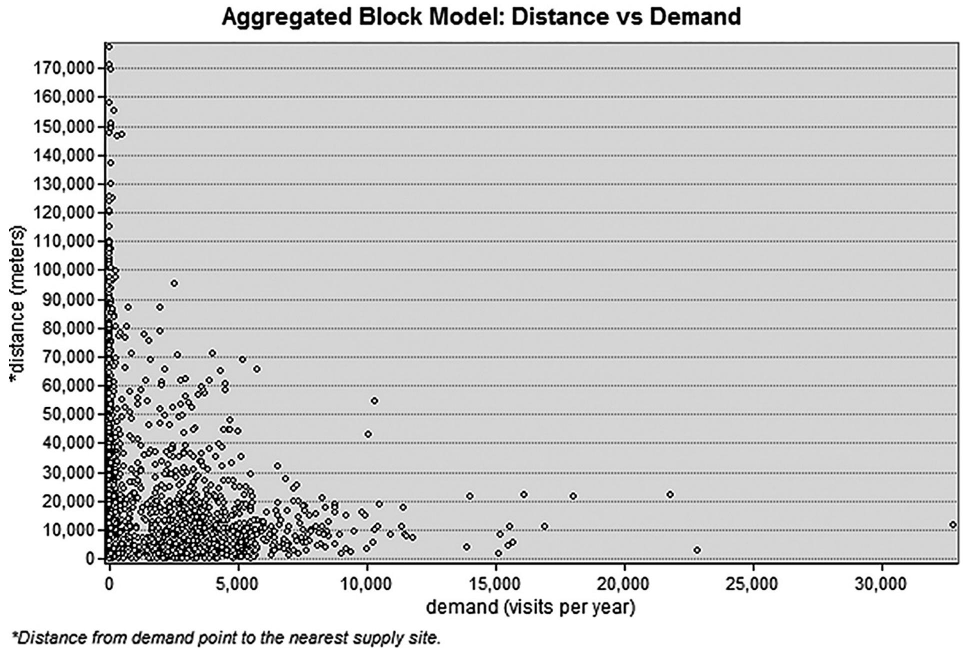


Fig. 6. Aggregated block model: distance vs. demand

85.8%). At the 45 and 60 minute driving times, 7.6% and 3.9% respectively of the state's demand for PHCS is unmet (see Table 2).

Figure 5 shows the results of the deterministic block group model. The pattern of accessibility to primary health care at the scale of block group is similar to the pattern at the tract scale (Fig. 3) but not identical. In the allocation pattern obtained with the block group models there is a visible expansion of areas meeting the 30 and 45 minute driving time constraints as compared to the allocation pattern produced by the tract models.

Aggregated block model

Idaho contains 1926 aggregated block clusters (groups of contiguous census blocks within the existing census block groups). Using the centroids of these aggregated block clusters results in roughly twice the number of demand points present in the block group model. The average size of these block clusters is 52.8 km^2, with a standard deviation of 188.4 km^2. The average distance from an aggregated block cluster demand point to the nearest PHCF is 21,242.5 meters (13.2 miles), and the average demand for primary health care services for an aggregate block group is 2,059.6 visits per year. Manual editing in GIS was required to properly connect 68 of the aggregated block cluster centroids to the road network. In Figure 6, all of the 1926 aggregated block group demand points are plotted based on their respective distances to the nearest PHCF and their demand for PHCS.

The percentage of unmet demand for PHCS yielded by the aggregated block group models at a 30 minute driving constraint is 11.1%. At the 45 and 60 minute driving time constraints, 5.9% and 3.3% respectively of the state's demand for PHCS is unmet (see Table 3).

Figure 7 shows the results of the aggregated block model. The allocation pattern at the block scale reveals large unpopulated areas in the north-eastern, central, south-western, and south-eastern parts of Idaho, confirming the low population density of the state (7.34 people per

Table 4. Weighted aggregated block model results

Driving time (min)	Meters	Miles	Met demand	% Met	Unmet Demand	% Unmet
30	24,140	15.0	3,508,209.8	88.4	458,524.3	11.6
45	36,210	22.5	3,724,111.5	93.9	242,622.4	6.1
60	48,280	30.0	3,887,181.3	98.0	79,552.9	2.0

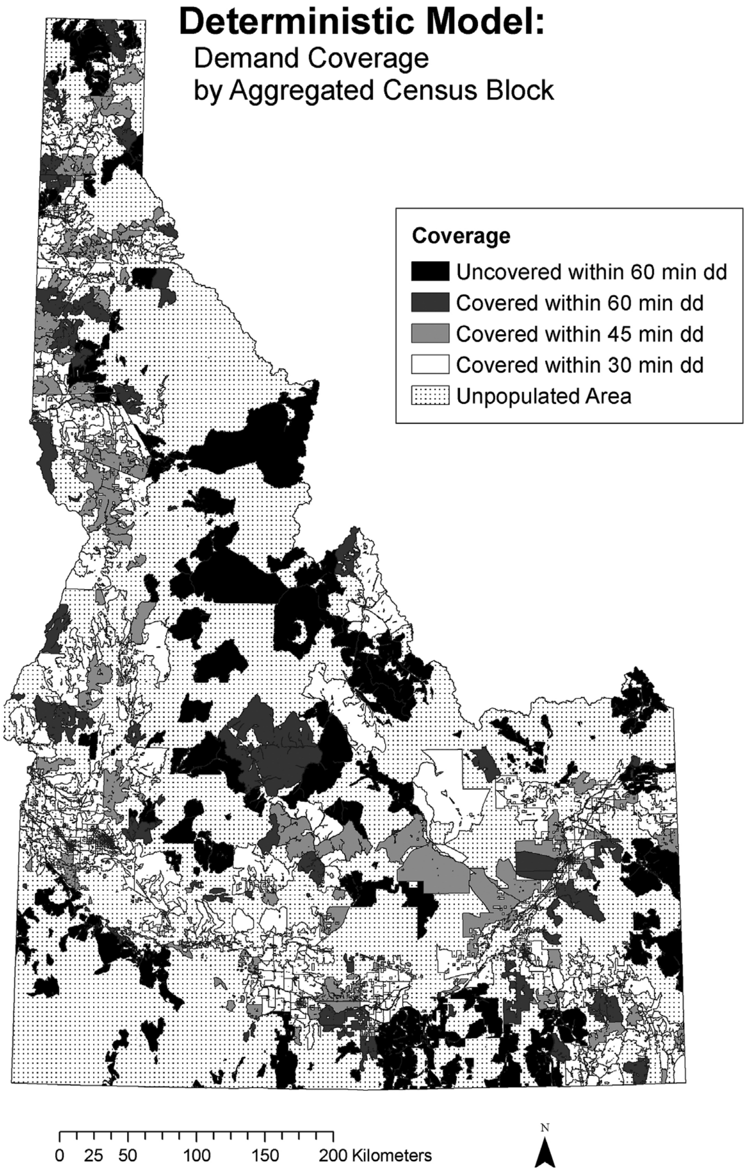


Fig. 7. Aggregated block model coverage

square km). The general pattern of the spatial distribution of demand for primary health services, covered by the 30 and 45 minute driving time constraints, is similar to the allocation patterns produced by the tract and block group models. The difference between the former and the latter can be easily observed as the pattern produced by the aggregated block model is much more fragmented than the patterns produced by the tract and block group models due to small area size of census block – the fundamental areal unit used in the aggregate block model.

Weighted aggregated block model

All the weighted aggregated block models used the same number of demand points as the aggregated block models: 1,926. However, unlike the aggregate block models that placed demand at the centroids of the contiguous block clusters, in the weighted aggregated block model, the placement of those 1,926 demand points was influenced (weighted) by the amount of demand in each of the individual blocks that comprise the block group clusters, causing shift in location of some of the centroids. Out of 1,926 demand centroids 544 had no change in their placement between the non-weighted and weighted ag-

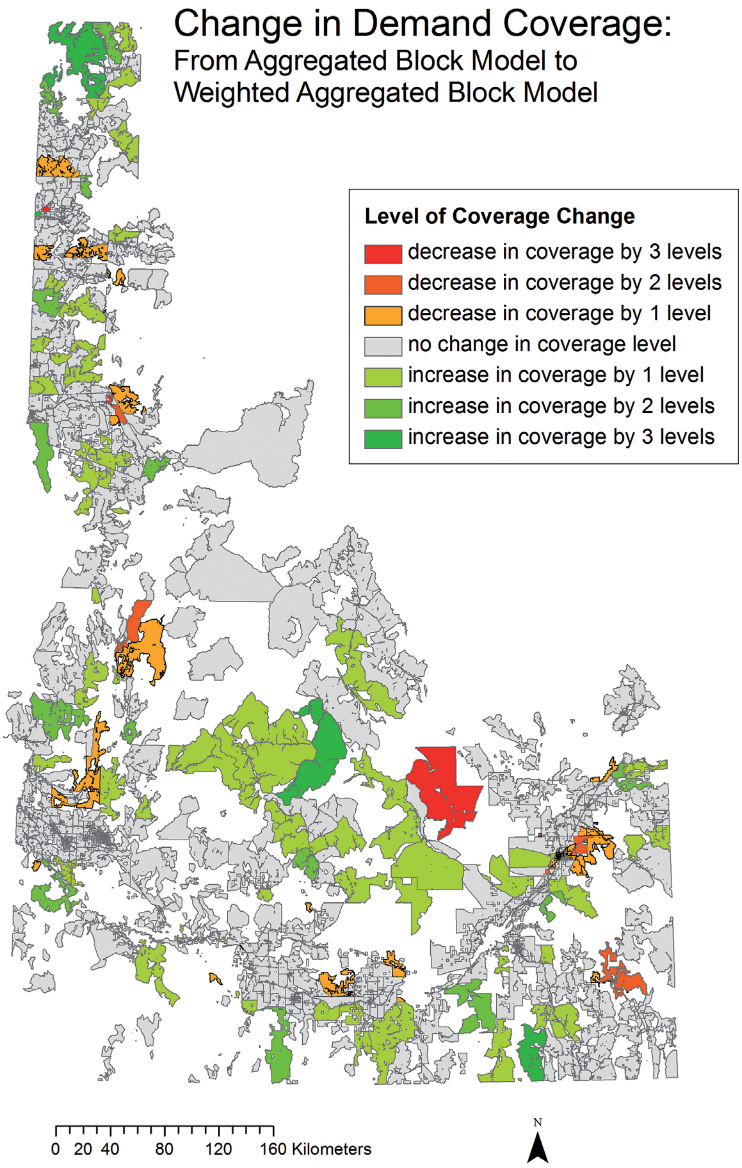


Fig. 8. Coverage change from non-weighted aggregated block model to weighted aggregated block model

gregated block models. Of the 1,382 demand centroid that did have a shift in placement, the average shift was 2,129.6 meters. Figure 8 shows the change in coverage from the non-weighted aggregated block model to the aggregated block model. Block clusters with negative values showed a decrease in their degree of coverage from the non-weighted to the weighted block model, block clusters with positive values showed an increase in their degree of coverage. A one degree coverage change in Figure 8 corresponds to an increase/decrease by one distance interval, e.g. from 30 to 45 minutes.

The average distance from a weighted aggregated block cluster demand point to the nearest primary health care facility is 21,301.6 meters, and the average demand for primary health care services is 2,059.6 visits per year. The percentage of unmet demand for PHCS yielded by the weighted aggregated block group models at a 30 minute driving constraint is 11.6% (88.4% of demand is met). At the 45 and 60 minute driving distances, 6.1% and 2.0% respectively of the state's demand for PHCS is unmet (see Table 4).

Figure 9 shows the results of the weighted aggregated block model. Upon a closer inspection, the differences in the coverage pattern between the weighted and unweighted models emerge. In the weighted model there are more aggregated block regions covered by the 30 minute

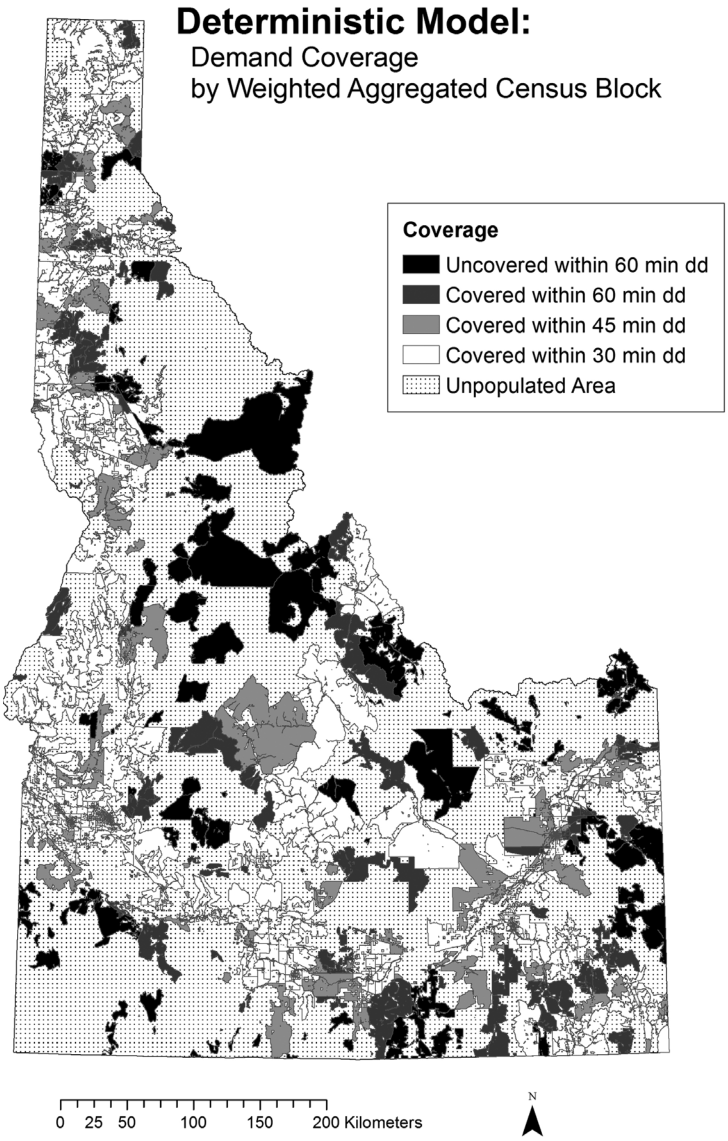


Fig. 9. Weighted aggregated block model coverage

driving time from the nearest service center in northern Idaho (near the border with Canada), north-western Idaho (bordering the state line separating Idaho from Oregon and Washington), and in the center of the state, than there are in the unweighted model. These finding, corroborated by Figure 8, can be explained by more accurate representation of demand distribution in the weighted model than in the unweighted model.

Discussion and conclusion

The modeling results show that as the representation of demand in the MCLP model moved from a smaller scale/lower number of enumeration units (tract models) to a larger scale/higher number of enumeration units (weighted and non-weighted aggregated block models), the amount of unmet demand for PHCS decreased and consequently the pattern of accessibility improved. The tract model yielded the greatest amount of unmet demand. The aggregated block model yielded the lowest amount (except at the furthest driving time constraint), and the weighted aggregated block model yielded slightly greater amounts of unmet demand than the non-weighted aggregated block model, and it yielded the least amount of unmet demand at the furthest driving time constraint. This can be ex-

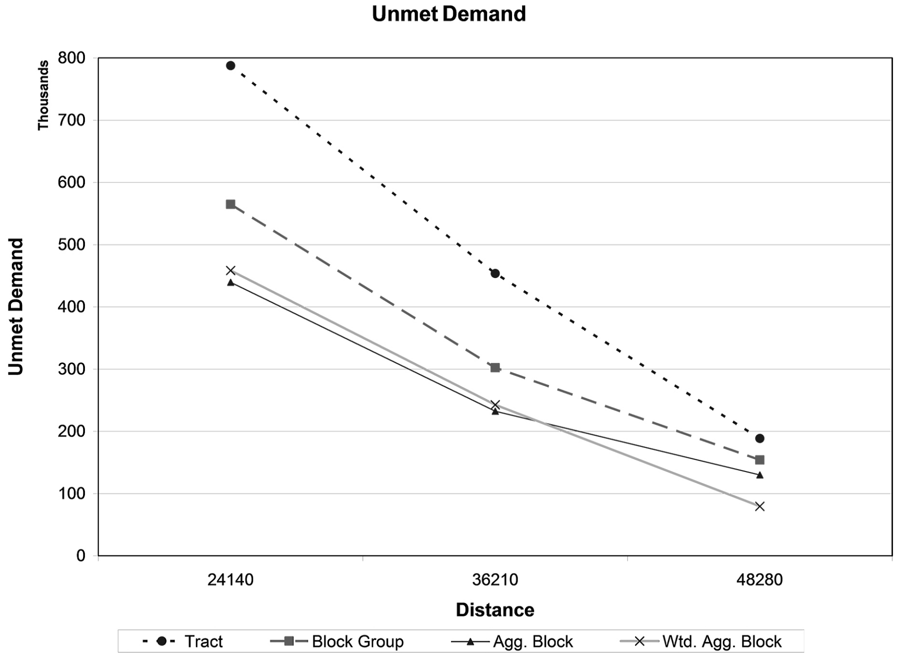


Fig. 10. Results of the models run with four representations of demand. The distances on the horizontal axis represent the equivalents (in meters) of 30, 45, and 60 minute driving time constraints

plained by the shift of centroids (in the weighted model) from non-populated to populated blocks. Figure 10 shows the amount of unmet demand found in the 12 deterministic models (four demand representations each at the three driving time constraints). All models in the study had the same total demand for PHCS: 3,966,732 visits per year. It can be seen that the tract model results in greater amounts of unmet demand at all driving distance constraints than the other three models.

The results of this study are subject to a number of assumptions beginning with the driving time; it is assumed that it takes 30 minutes to drive 15 miles. This assumes that in a rural, mountainous area, typical for much of Idaho, few freeways exist and roads are narrow, and often windy. This assumption does not account for traffic congestion, difficult intersections, weather conditions, etc. Another assumption was made that all residents would travel to their closest primary health care facility. This may be an acceptable assumption because in many rural areas a secondary PHCF would likely be quite far away. This study also assumes that demand exists at the centroids of enumeration units only and that that demand travels to service center from that single point. It is assumed that the Center for Disease Control's estimated visits per year for the different age and sex groups are accurate. It is also assumed that the conversion from PHCF visit hours per year into number of visits per year for each existing PHCF supply site is accurate.

The major finding of this study with potential relevance for future studies of accessibility, utilizing a location-allocation modeling approach, is that there is a relationship between the scale, at which the demand for service is represented and the level of service accessibility. In the case of Idaho, which is predominantly a rural state, this relationship is positive; increasing the scale, at which the demand is represented, results in an improved pattern of accessibility. The surprising finding is that the targeted representation of demand that was achieved by means of population weighting did not improve markedly the measure of accessibility, with the exception of the longest driving distance considered (60 minutes).

Future research could explore the capabilities of dasymetric mapping for improving the determination of population location in rural, sparsely populated areas for use in location-allocation coverage models. Dasymetric mapping is a technique used to refine information shown on choropleth maps by supplementing the data contained in choropleth maps with ancillary data. The ancillary data chosen should correspond to the information presented in the choropleth map. In this study, for example, the block demand map layer might be combined with an ancillary land-cover map that could distinguish developed from undeveloped locations. The use of dasymetric mapping techniques to determine locations of demand might allow for a more accurate placement of demand centroids within a populated region.

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