Effects of the modifiable areal unit problem on the delineation of traffic analysis zones

José Manuel Viegas, I. Miguel Martínez,
CESUR, Department of Civil Engineering, Instituto Superior Técnico, Lisbon Technical University, Avenida Rovisco Pais, 1049-001 Lisboa, Portugal; e-mail: viegas@civil.ist.utl.pt, martinez@civil.ist.utl.pt

Elisabete A Silva
Department of Land Economy, University of Cambridge, 19 Silver Street, Cambridge CB3 9EP, England; e-mail: es424@cam.ac.uk

Received 24 March 2007; in revised form 17 October 2007; published online 29 August 2008

Abstract. Transportation analysis is typically thought of as one kind of spatial analysis. A major point of departure in understanding problems in transportation analysis is the recognition that spatial analysis has some limitations associated with the discretization of space. Among them, modifiable areal units and boundary problems are directly or indirectly related to transportation planning and analysis through the design of traffic analysis zones (TAZs). The modifiable boundary and the scale issues should all be given specific attention during the specification of a TAZ because of the effects these factors exert on statistical and mathematical properties of spatial patterns (ie the modifiable areal unit problem—MAUP). The results obtained from the study of spatial data are not independent of the scale, and the aggregation effects are implicit in the choice of zonal boundaries. The delineation of zonal boundaries of TAZs has a direct impact on the reality and accuracy of the results obtained from transportation forecasting models. In this paper the MAUP effects on the TAZ definition and the transportation demand models are measured and analyzed using different grids (in size and in origin location). This analysis was developed by building an application integrated in commercial GIS software and by using a case study (Lisbon Metropolitan Area) to test its implementability and performance. The results reveal the conflict between statistical and geographic precision, and their relationship with the loss of information in the traffic assignment step of the transportation planning models.

1 Introduction
The modified area unit problem (MAUP) emerges from the common practice in transportation analysis of collecting data and organizing them by geographic zones, such as census blocks or census tracts. These datasets may also be aggregated further to a spatial zoning system that is chosen for a particular application. Such spatial units are often arbitrary and reflect the needs and experience of the analyst.

One transportation application in which spatial aggregation is common practice is travel-demand modeling. Though many transportation textbooks provide good guidelines for designing these zoning systems (eg Ortúzar and Willusen, 2001), the transportation analyst usually defines these systems on the basis of intuition and other rules which are difficult to codify. This can affect the results of the travel-demand analysis, since each boundary change affects the proportion and pattern of interzonal trips versus intrazonal trips, the latter not being captured in the modeling process (Ding, 1994).

The MAUP occurs when the spatial zoning system used to collect and/or analyze geographic data is ‘modifiable’ or arbitrary. Since the spatial units are arbitrary, the results of the analysis based on these units may be arbitrary—that is, they may be an artifact of the spatial units rather than reflecting the true underlying geographic process.
MAUP effects can be divided into two components. Scale effects result from spatial aggregation of the data. Zoning effects relate to the changes in the spatial partitioning at a given level of spatial aggregation (Openshaw and Taylor, 1979; Wong and Amrhein, 1996). Openshaw and Taylor (1979; 1981) explain that it is possible for data users to exert some influence over, or to minimize the impact of, the MAUP. To achieve this it is recommended that analysts:

- start from the smallest division available, or the smallest they can process;
- aggregate these divisions in a fashion relevant to their investigation; and
- assess the repetitiveness of their results for several aggregations.

Although this does not completely solve the MAUP, it does allow analysts to exert corrective influence over the problem rather than ignoring it. In the past most analysts ignored MAUP effects because the data and tools to deal with these effects were not available. However, digital cartographic data and GIS tools are now available with which to assess the effects of zoning systems and to develop optimal zoning systems for particular applications such as areal interpolation and boundary delineation (Duckham et al, 2001; Eagleson et al, 2002; Hall and Arnberg, 2002; Xie, 1995), or more specific studies like road accidents (Thomas, 1996) and residential location (Guo and Bhat, 2004). These methods can be used for traffic analysis zones (TAZs) design in transportation planning.

Some developments have been made in this field—for example, Openshaw (1977) devised the automated zone design program (AZP) for investigating the MAUP. During the mid-1990s, through the use of new technology, digital data, and improved algorithms, AZP was further refined and extended, forming the zone design system (Openshaw and Alvanides, 1999; Openshaw and Rao, 1995). These zone design systems have been developed to allow the data analyst the freedom to start with data at one scale and then reaggregate them to create a new set of regions designed to be suitable for a specific purpose, independent of the collection boundaries used (Openshaw and Rao, 1995).

Alvanides et al (2000) also developed a zoning system methodology that analyses the impact of the zoning system on the data-flow results. In the data-flow context it is considered that the zoning design problem might have four different objectives that need to be met:

- to use zoning as a data reduction and descriptive device in order to reduce discrete-event or data-flow volumes to a convenient level for spatial management and data reporting purposes;
- to optimize the spatial representation performance of a zoning system so that the partitioning minimizes distortion and bias;
- to use zoning as an analysis and visualization tool designed to make the flows visible in an understandable map form, as a useful description of spatial organization and flow structure;
- to ease modeling problems or to enhance model performance by tuning the spatial aggregation to generate more model-friendly data.

Recently, other authors (Chang et al, 2002; Ding, 1998; Khatib et al, 2001; Zhang and Kukadia, 2005) have tried to assess the impacts of MAUP on the results of transportation planning models. Ding (1998) concludes that TAZs affect the data-flow results, particularly when the number of TAZs is small, and therefore scale effects play an important role in the quality, validity, and reliability of some of the results.

From a somewhat different perspective, Khatib et al (2001) have analyzed the match between the traffic analysis zoning structure and the detail level of the transportation network used in the model. The study suggests that the literature assumption that the zoning structure should match the detail level of the transportation network
used in the model might only be partially correct. It concluded that using a less
detailed network resulted in a higher percentage root-mean-square error (PRMSE)
for all zoning structures.

In a later study, Chang et al (2002) concluded that the level of network detail had a
negligible effect on trip length or the proportion of interzonal trips, but impacted
the value of PRMSE in two ways: on the one hand, larger TAZs resulted in lower
PRMSE values on the less detailed network; on the other hand, the more detailed
network resulted in lower PRMSE values than did the less detailed network for all link
groups, regardless of the geographic level of the TAZs.

Zhang and Kukadia (2005) also measured the effect of the level of spatial data
aggregation (urban form indicators) on predicting model choice decisions in transpor-
tation-planning models. They confirm the presence of the MAUP and discuss some
approaches to deal with it, based on a careful choice of scale and area unit definition.

Another approach to assess MAUP effects is to perform a sensitivity analysis by
changing the zoning system and rerunning the analysis. For example, Chou (1991)
recomputed a spatial autocorrelation at different levels of map resolution to assess
the aggregation effects. Moellering and Tobler (1972) developed a scale-dependent
analysis of variance technique. Batty (1976) developed a general information statistic
to measure aggregation effects in spatial analysis. Batty and Sikdar (1982a; 1982b;
1982c; 1982d) used these statistics to assess aggregation effects in spatial interaction
models.

In this paper the MAUP effects on traffic zoning methods are analyzed using
elemental grids of different dimensions. A methodology of analysis of the MAUP scale
effects is developed and its consequences for traffic demand modeling are discussed—
especially the conflict underlying the geographic and statistical error dimensions when
dealing with this kind of data, and the impact on policy-making decision uncertainty.
For this analysis the Lisbon Metropolitan Area (AML) was used as a case study, with
an area of approximately 320 000 ha, using as the dataset a 1994 mobility survey of this
metropolitan area.

The mobility survey used for this paper has a sample of 30 681 individual surveys
that describe all trips of each individual during one day, resulting in a total of 58 818
trips, all of which have their origin and destination geocoded. Each survey has a
sample-to-universe expansion coefficient, on the basis of which an estimation can be
given of the total average daily trips (made in the AML, resulting in a total of
11 124 776 trips per day (22.81% of those are walking or bike trips).

2 Methodology of analysis
The analysis of the MAUP effects described in this paper is performed according to
the objectives of the TAZ delineation. For this purpose a GIS-based application was
developed in Geomedia Professional (Intergraph, Huntsville, AL), thereby allowing
analysis over a grid of variable dimension and form.

The option for a grid can be justified with several arguments.
(1) The main goal of this methodology is to define valid and reliable zones, which
implies that, if we started with aggregated information in 'polygons', we could be
introducing zonal effects, creating zones from a priori defined 'zones and polygons',
and therefore distorting the results by introducing aggregation effects of data into our
analysis and, therefore, into our results.
(2) 'Cell'-based analysis is the basis of several approaches, such as genetic algorithms
and cellular automata, which can pick up these zones and further use them for specific
goals.
Starting with ‘object-based data’, instead of starting with disaggregate data and ‘cleaning’ or refining it in order to obtain sensible aggregate data, would be methodologically wrong, as it would be very dependent upon the perspective of the analyst, and would introduce more errors in early stages of the process.

Using the matrix methodology also provides high flexibility with which to move the origin of the matrix in geographic terms—it is a ‘mechanical’ kind of approach that can be clearly explained, and implemented, and the results can be clearly evaluated in terms of causality.

In order to analyze and try to solve MAUP effects in TAZs, and hence to contribute to the development of more valid and reliable traffic zones, the reader of this paper should be familiar with specific transportation and geographic concepts. The analysis of this problem requires the following background information in traffic modeling basic concepts important for TAZ delineation:

- The discretization (zoning) process adopted for the description of trips implies that information about the start and end points of trips will no longer be available at a level of resolution finer than the zone.
- All trips starting (ending) in a zone will be coded as starting at the same virtual point, its centroid.
- Intrazonal trips cannot be assigned to the network, as they now have the same origin and destination ‘point’. Therefore, these trips constitute lost information for the traffic demand modeling, and their number should be minimized.
- Geographic precision in the localization of origins and destinations of trips decreases as zones get larger.
- On the other hand, for a constant survey sample size, statistical precision of the estimate of the number of trips starting or ending in a zone decreases when zones get smaller (estimation intervals of confidence get larger).
- Similarly, for the cells of an O–D (origin–destination) matrix, low values have high statistical errors.

The first step of this methodology is the insertion, using GIS software (in this case Geomedia Professional), of the origin and destination of trips of the mobility survey, of the geographic shapes and data available for the AML, and of the analysis grids.

Different dimensions and forms of the analysis grid were tested. The initial cell form chosen was the square, because of the universal use of this form and its ease of manipulation. This paper reports the analysis performed using square cells, although similar analysis were also carried out for other geometric shapes, such as the hexagon, with identical results. Regarding grid dimensions, an upper and a lower limit of the square side and a step size of variation were defined. The lower bound of the square dimension used was 200 m, because this is just a bit larger than the average distance between urban street intersections, and for computational reasons, because a smaller cell size would make the GIS-based application developed for this study very slow (a square of 200 m represents a total of 250 000 elements to analyze for the whole AML region). The upper bound chosen for the grid square was 2000 m, which could represent the average distance between urban motorway intersections, and is a multiple of the lower bound, resulting in a 200 m variation step and ten different grids of analysis.

With all the inputs available, the GIS application looks at two kinds of factors: the dimension of the grid and the location of the grid origin. The same indicators were used to measure the effects of both factors. The selected indicators were:

- maximum cell value of the O–D matrix;
- average cell value of the O–D matrix;
- percentage of cells without any trips in the O–D matrix;
- percentage of intrazonal trips in the O–D matrix;
- maximum number of origins or destinations per cell;
- average number of origins or destinations per cell;
- percentage of cells with no trip origins or destinations (ie no trips);
- percentage of trips in non-statistically-significant O–D matrix cells (that is, O–D matrix cells with an estimated flow value lower than half of the confidence interval for the probability of a cell using a binomial distribution).

The effect of the location of the origin of the grid was tested by considering variations in each quarter of both grid axes for each grid dimension defined, resulting in sixteen different values of all indicators for the same grid dimension.

The definition of the optimal grid dimension and origin location could be obtained by defining a goal function, using the indicator values developed, but as the main objective of this paper was to estimate and measure the MAUP effects prior to the TAZ delineation, this is not presented here.

3 Analysis of MAUP scale effects

After the GIS-based application had been run for all grid dimensions and all the outputs were obtained, an analysis of the MAUP scale effects was undertaken, or, in other words, the impact of cell size variation on the data aggregation results was analyzed. This analysis started by looking at the impact of grid dimension on the spatial distribution of trips. The spatial distribution of trips consists of adding, for each cell, all the origins and destinations within its boundaries.

Figure 1(a) presents the spatial distribution of trips within the study area for the 2000 m grid cells. As expected, the greater concentration of trips occurs within the Lisbon city center borders and in their surroundings. The Cascais and Sintra corridors (nearby municipalities of Lisbon which are included within the AML and Almada (a municipality on the left bank of the Tagus River) also have a high quantity of trips, as does the corridor along the A1 motorway up to Vila Franca de Xira, a town that works as a regional interchange.

If this analysis is made for other grid dimensions, the number of zones with no trips increases significantly. The cells that maintain a higher number of origins or trip destinations are always within the Lisbon city boundaries, as can be seen in figures 1(b), and 1(d) (spatial trip distributions for cells with size 1200 m, 800 m, and 200 m, respectively).

To evaluate the conflict between statistical and geographical error for the different grid dimensions used in this paper, the indicators previously described were used. The most significant indicators were the percentage of intrazonal trips in the O–D matrix, the percentage of noise (trips in non-statistically-significant O–D matrix cells), and the percentage of zones with no trips.

To measure the variation of the first indicator with the grid dimension, the average of the values obtained for sixteen different locations of the grid origin had to be computed for each grid dimension. The values obtained are presented in table 1.

Elasticity here means that the relative variation of the average percentage of intrazonal trips for a given grid dimension, with respect to that obtained for the next-smallest grid dimension, divided by the relative variation between those two grid dimensions (in the same order).

The variation of this indicator (percentage of intrazonal trips) is not very significant for the range of cell sizes analyzed, with a range of approximately 8.5% between the maximum and minimum value, and it increases in the same direction as the grid dimension, as expected. This fact reflects some scale effect over the data. Within the range used, the elasticity of this indicator with respect to the grid dimension shows a slight increase with the grid dimension.
To measure the variation of the second indicator with respect to the grid dimension, the same methodology was applied. The values obtained are presented in table 2. The variation of this indicator is much more significant (approximately 36% between the maximum and minimum values) and decreases with the grid dimension. This fact reflects a strong scale effect over the statistical precision, but the elasticity of this value tends to stabilize near the 1000 m cell size.

![Figure 1. Spatial trip distributions of the AML (Lisbon metropolitan area): (a) for a 2000 m cell size, (b) for a 1200 m cell size, (c) for an 800 m cell size, and (d) for a 200 m cell size. Conceiços are spatial subdivisions of Portugal, one level below distritos and one level above freguesias.](image-url)
Another important indicator is the percentage of cells with no trips (no origins or destinations). As with the other indicators, it was important to calculate for each grid dimension the average value for all the origins of the grid. The values obtained are presented in table 3.

In order to measure the relationship between the statistical precision (level of noise) and loss of information generated by the intrazonal trips of the O–D matrix, a chart presenting the joint evolution of these values was created. The results are presented in figure 2, in which the variation of the grid dimension and grid origin positioning are incorporated.

By observing this figure it can be seen that it is difficult to establish an optimal grid dimension, owing to the existing trade-off between both indicators with the variation in grid size. The choice of grid dimension should be based on the definition of maximum and minimum values allowed for each indicator, and should depend on the case study, study scale and goal, and the mobility data available. It should always therefore be a sensible choice which takes account of the existing trade-off and its impacts for traffic assignment and transportation planning.

It is also important to note that the grid origin location has a greater impact on the O–D matrix statistical error than on the percentage of information loss in the O–D

### Table 1. Variation of the intrazonal trip percentage with grid dimension.

<table>
<thead>
<tr>
<th>Grid dimension (m)</th>
<th>Average intrazonal trips (%)</th>
<th>Difference from minimum value (%)</th>
<th>Difference from maximum value (%)</th>
<th>Elasticity relative to grid dimension (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>200</td>
<td>17.87</td>
<td>0.09</td>
<td>0.29</td>
<td></td>
</tr>
<tr>
<td>400</td>
<td>18.70</td>
<td>0.21</td>
<td>0.34</td>
<td>0.0042</td>
</tr>
<tr>
<td>600</td>
<td>19.50</td>
<td>0.33</td>
<td>0.26</td>
<td>0.0040</td>
</tr>
<tr>
<td>800</td>
<td>20.35</td>
<td>0.30</td>
<td>0.28</td>
<td>0.0043</td>
</tr>
<tr>
<td>1000</td>
<td>21.34</td>
<td>0.46</td>
<td>0.29</td>
<td>0.0049</td>
</tr>
<tr>
<td>1200</td>
<td>22.38</td>
<td>0.45</td>
<td>0.47</td>
<td>0.0052</td>
</tr>
<tr>
<td>1400</td>
<td>23.25</td>
<td>0.35</td>
<td>0.44</td>
<td>0.0043</td>
</tr>
<tr>
<td>1600</td>
<td>24.17</td>
<td>0.60</td>
<td>0.52</td>
<td>0.0046</td>
</tr>
<tr>
<td>1800</td>
<td>25.28</td>
<td>0.34</td>
<td>0.37</td>
<td>0.0056</td>
</tr>
<tr>
<td>2000</td>
<td>26.39</td>
<td>0.83</td>
<td>0.78</td>
<td>0.0056</td>
</tr>
</tbody>
</table>

### Table 2. Variation of the percentage of trips in non-statistically-significant O–D (origin–destination) matrix cells.

<table>
<thead>
<tr>
<th>Grid dimension (m)</th>
<th>Average trips in non-statistically-significant O–D matrix cells (%)</th>
<th>Difference from minimum value (%)</th>
<th>Difference from maximum value (%)</th>
<th>Elasticity relative to grid dimension (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>200</td>
<td>73.05</td>
<td>0.32</td>
<td>0.11</td>
<td></td>
</tr>
<tr>
<td>400</td>
<td>72.34</td>
<td>0.32</td>
<td>0.24</td>
<td>−0.0035</td>
</tr>
<tr>
<td>600</td>
<td>70.78</td>
<td>0.58</td>
<td>0.30</td>
<td>−0.0078</td>
</tr>
<tr>
<td>800</td>
<td>67.29</td>
<td>0.59</td>
<td>0.61</td>
<td>−0.0175</td>
</tr>
<tr>
<td>1000</td>
<td>62.34</td>
<td>0.65</td>
<td>0.83</td>
<td>−0.0247</td>
</tr>
<tr>
<td>1200</td>
<td>57.08</td>
<td>0.97</td>
<td>1.14</td>
<td>−0.0263</td>
</tr>
<tr>
<td>1400</td>
<td>52.03</td>
<td>0.81</td>
<td>1.02</td>
<td>−0.0253</td>
</tr>
<tr>
<td>1600</td>
<td>46.88</td>
<td>1.39</td>
<td>0.88</td>
<td>−0.0258</td>
</tr>
<tr>
<td>1800</td>
<td>41.75</td>
<td>1.23</td>
<td>1.27</td>
<td>−0.0257</td>
</tr>
<tr>
<td>2000</td>
<td>37.77</td>
<td>1.11</td>
<td>1.49</td>
<td>−0.0199</td>
</tr>
</tbody>
</table>

Another important indicator is the percentage of cells with no trips (no origins or destinations). As with the other indicators, it was important to calculate for each grid dimension the average value for all the origins of the grid. The values obtained are presented in table 3.
matrix (approximately twice the impact), although in the chart it looks the other way around because of the different scales of the two axes.

In order to obtain good traffic zoning it is important to have simultaneously a good statistical precision, a good geographic precision, and the minimum information loss possible (percentage of intrazonal trips in the O–D matrix). These three requisites can be estimated through the percentage of intrazonal trips; the size of zones (in this case cells), measured as the equivalent radius of the zone [radius of an equivalent circular zone, \( R_{E} = (T_{\text{AREA}}/\pi)^{1/2} \), where \( T_{\text{AREA}} \) is the area of the TAZ]; and the percentage of trips in nonsignificant O–D matrix cells.

It is not possible to reach a global optimum for these requests (independent of the weighted contribution of each indicator), but the existence of an optimum for a set of weights of each indicator in this relationship can be found.

The analysis of the relationship between the three indicators is presented in figure 3. It can be seen from the figure that it is difficult to establish an optimal grid size in order to minimize the three variables, owing to the existing trade-off between them.

The goal function for this analysis must be the minimization of distance (of the points along the plotted line) to the origin. But that distance should be corrected by the weight (or importance) that is given to each variable.

### Table 3. Variation of the percentage of zones with no trips against grid dimension.

<table>
<thead>
<tr>
<th>Grid dimension (m)</th>
<th>Average number of zones with no trips (%)</th>
<th>Difference from minimum value (%)</th>
<th>Difference from maximum value (%)</th>
<th>Elasticity relative to grid dimension (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>200</td>
<td>96.79</td>
<td>0.38</td>
<td>0.74</td>
<td>-0.0215</td>
</tr>
<tr>
<td>400</td>
<td>92.49</td>
<td>1.10</td>
<td>2.06</td>
<td>-0.0297</td>
</tr>
<tr>
<td>600</td>
<td>86.55</td>
<td>1.85</td>
<td>4.00</td>
<td>-0.0335</td>
</tr>
<tr>
<td>800</td>
<td>79.85</td>
<td>3.09</td>
<td>5.94</td>
<td>-0.0348</td>
</tr>
<tr>
<td>1000</td>
<td>72.89</td>
<td>3.87</td>
<td>7.60</td>
<td>-0.0348</td>
</tr>
<tr>
<td>1200</td>
<td>66.83</td>
<td>4.39</td>
<td>8.73</td>
<td>-0.0303</td>
</tr>
<tr>
<td>1400</td>
<td>60.46</td>
<td>3.80</td>
<td>9.66</td>
<td>-0.0318</td>
</tr>
<tr>
<td>1600</td>
<td>55.76</td>
<td>3.72</td>
<td>9.56</td>
<td>-0.0235</td>
</tr>
<tr>
<td>1800</td>
<td>51.66</td>
<td>4.63</td>
<td>9.84</td>
<td>-0.0205</td>
</tr>
<tr>
<td>2000</td>
<td>48.71</td>
<td>4.32</td>
<td>10.45</td>
<td>-0.0148</td>
</tr>
</tbody>
</table>

**Figure 2.** Variation of the percentage of intrazonal trips in the O–D matrix with the percentage of trips in non-statistically-significant O–D matrix cells.
A sensitivity analysis of the variation of the weights given to each variable was carried out. The results are presented in figure 4 and show that only the smallest and largest grids present the highest value for the goal function with the variation of the weights of the three indicators. The 200 m grid has the widest range of weight values for which this grid is optimal, owing to the existence of two indicators that are optimized with the cell size minimization (intrazonal trips percentage and equivalent radius of zones).

However, it is important to be aware that the distance goal function uses a compensatory model in which low values in one attribute can be compensated by the high values in another attribute. This analysis was then corrected by the introduction of thresholds (minimum and maximum acceptable values) for each indicator (see table 4). Grid sizes that did not fall within these values were discarded.

The results obtained for this analysis, after the application of the thresholds, are presented in figure 5, which shows three different optimal grid sizes depending on the weights of the various indicators. The 1200 m grid has the widest range of weights for which it is optimal.

---

**Figure 3.** Relationship between the percentage of intrazonal trips of the O–D matrix (\(x\)), the percentage of trips in nonsignificant O–D matrix cells (\(y\)), and the equivalent radius of the zones (\(z\)).

**Figure 4.** Sensitivity analysis of the variation of the weight of each indicator for the distance goal function.

A sensitivity analysis of the variation of the weights given to each variable was carried out. The results are presented in figure 4 and show that only the smallest and largest grids present the highest value for the goal function with the variation of the weights of the three indicators. The 200 m grid has the widest range of weight values for which this grid is optimal, owing to the existence of two indicators that are optimized with the cell size minimization (intrazonal trips percentage and equivalent radius of zones).

However, it is important to be aware that the distance goal function uses a compensatory model in which low values in one attribute can be compensated by the high values in another attribute. This analysis was then corrected by the introduction of thresholds (minimum and maximum acceptable values) for each indicator (see table 4). Grid sizes that did not fall within these values were discarded.

The results obtained for this analysis, after the application of the thresholds, are presented in figure 5, which shows three different optimal grid sizes depending on the weights of the various indicators. The 1200 m grid has the widest range of weights for which it is optimal.
Another analysis was developed in order to find out the most favorable cell size, considering the same variables as before (intrazonal trip percentage, equivalent radius of the zone, and percentage of trips in non-statistically-significant O–D matrix cells). This analysis considers a new indicator, identified as noise level—that is, the sum of the percentage of intrazonal trips and the percentage of trips in non-statistically-significant O–D matrix cells, with the intersection of both indicators (percentage of non-statistically-significant intrazonal trips) subtracted in order to avoid double counting.

The results of the variation of this new indicator with the cell size are presented in figure 6. Noise levels for grid dimensions smaller than 1400 m are very high (greater than 75%), indicating that more than 75% of the trips available from the mobility survey are lost as information for traffic modeling. The increase of the noise level with the decrease in cell dimension stabilizes near the 800 m cell. This fact indicates that the trade-off between noise level and geographic precision has a low elasticity in this zone of the chart.

### Table 4. Maximum and minimum threshold values for each indicator.

<table>
<thead>
<tr>
<th>Indicator</th>
<th>Maximum</th>
<th>Minimum</th>
</tr>
</thead>
<tbody>
<tr>
<td>Percentage of trips in non-statistically-significant O–D matrix cells</td>
<td>60</td>
<td>0</td>
</tr>
<tr>
<td>Equivalent radius of the zones (m)</td>
<td>1000</td>
<td>0</td>
</tr>
<tr>
<td>Percentage of intrazonal trips</td>
<td>25</td>
<td>0</td>
</tr>
</tbody>
</table>

![Figure 5. Sensitivity analysis of the variation of the weight of each indicator for the distance goal function (after correction for acceptable indicator ranges).](image)

![Figure 6. Relationship between noise level and cell size.](image)
A new sensitivity analysis was developed which uses a new goal function with these two indicators (noise level and equivalent radius of zones) and their respective weights (contributions) for the global outcome. The results of this analysis are presented in figure 7, where three different cell sizes are optimal for a range of the noise level weight—the 200 m grid and the 2000 m grid having the greatest ranges of dominance.

Repeating the correction already made for the previous analysis, in order to avoid the compensation of low values in one attribute by high values in another attribute, maximum and minimum threshold values were defined for each indicator (see table 5). Cell sizes that did not fall within these thresholds were discarded.

The results obtained for this analysis after the exclusion of the cell sizes that did not fall within the established indicator thresholds are presented in figure 8, which shows two different optimal cell sizes depending on the indicator weight values (1200 m and 1600 m square cell grids).

Other important indicators are the maximum number of origins or destinations per grid cell, and the average number of origins or destinations per grid cell. These values are estimated as the averages of the sixteen iterations made for each grid cell dimension. The values obtained for these indicators are presented in table 6 and in figure 9, from which it is possible to observe that an increase in the grid dimension does not always lead to an increase in the maximum number of origins or destinations per grid cell. The explanation for this fact resides in the high concentration of trips from some points, which can be contained sufficiently in smaller cells.

The average number of origins or destinations per grid cell, as expected, increases with the grid dimension—but as presented in figure 9, with a quadratic trend. This information is important, because a decrease in this value could mean less statistical...
precision for the traffic zoning; for this reason it should be seen as a constraint in the reduction of the grid dimension.

To characterize the flow degradation in the O-D matrix and the total number of origins or destinations per cell, ranking charts were used. As for all other indicators, different charts for all the positions of the origin grid and for all grid sizes were built. As an example of this kind of chart, figure 10 shows a ranking chart for the number of origins or destinations per grid cell, for a particular position of the origin of a 2000 m grid. Note that, in this figure, even for a grid of large dimension, cell values decrease very fast. This fact indicates that there are few cells with large numbers of origins or destinations of trips.

To describe the resulting curve of this chart two different trend lines were used: an exponential curve and a power function (\(AX^{a-1}\)). Both adjust well to the curve in its lower slope part, but the power function adjusts better at the higher values, as can be seen in figure 10. Although the exponential curve has a higher value of the \(R^2\) parameter (\(R^2 = 0.98\), versus \(R^2 = 0.90\) for the power function), because of its almost perfect adjustment at the lower values, it can not ‘explain’ the variation at higher values. For this reason the power function was selected as being representative of the ranking chart behavior. The calibrated coefficients for the chart presented in figure 10 were \(A = 321.474\) and \(X = -0.0194\).

### Table 6. Variation with grid dimension of the maximum and average numbers of origins or destinations per grid cell.

<table>
<thead>
<tr>
<th>Grid dimension (m)</th>
<th>Maximum origins or destinations per zone</th>
<th>Average origins or destinations per zone</th>
</tr>
</thead>
<tbody>
<tr>
<td>200</td>
<td>462,270.78</td>
<td>265.89</td>
</tr>
<tr>
<td>400</td>
<td>625,433.34</td>
<td>1,039.51</td>
</tr>
<tr>
<td>600</td>
<td>409,963.88</td>
<td>2,289.55</td>
</tr>
<tr>
<td>800</td>
<td>534,759.28</td>
<td>3,990.37</td>
</tr>
<tr>
<td>1000</td>
<td>618,473.19</td>
<td>6,122.74</td>
</tr>
<tr>
<td>1200</td>
<td>596,973.66</td>
<td>8,638.75</td>
</tr>
<tr>
<td>1400</td>
<td>612,476.44</td>
<td>11,571.47</td>
</tr>
<tr>
<td>1600</td>
<td>661,582.64</td>
<td>14,829.69</td>
</tr>
<tr>
<td>1800</td>
<td>980,089.69</td>
<td>18,500.10</td>
</tr>
<tr>
<td>2000</td>
<td>970,595.33</td>
<td>22,530.52</td>
</tr>
</tbody>
</table>

**Figure 9.** Maximum (left scale) and average (right scale) number of origins and destinations per grid cell, plotted against grid dimension.
To explain in an aggregated way the total number of origins or destinations per cell for each grid dimension, averages of the parameters of adjustment of the power function (\(A\) and \(X\)) were computed for each grid dimension, thus simplifying the interpretation of results. The calibrated coefficients (with \(R^2 = 0.99\)) were:

\[
A = 211.65x + 15486, \quad (1)
\]

\[
X = 1 \times 10^{-2}x + 0.9987, \quad (2)
\]

where \(x\) is the cell size.

In figure 11 it can be seen that the function, as the grid dimension grows, reveals a steeper slope and higher values of the parameter \(A\). The great concentration of origins or destinations of trips in a few cells when the grid dimension is bigger is no surprise and a reason why the statistical precision is higher.

Figure 10. Ranking chart for the total number of origins and destinations per grid cell, for a 2000 m grid. Exponential trend: \(y = 32144 \exp(-0.0194x)\), \(R^2 = 0.9837\).

Figure 11. [In color online, see http://dx.doi.org/10.1068/b34033] Power function adjustment of grid cell flows for varying grid dimensions.
Another analysis that reinforces the information obtained from the ranking curve of the total origins or destinations per cell is the definition of ranges of this indicator. Two thresholds were defined in order to distinguish cells with poor statistical precision (200 trips or less per cell) and cells with good statistical precision (30% of the maximum value per cell). The lower threshold was obtained from the average value of the expansion coefficient of the mobility survey sample, and is thus associated with the existence or not of trips in the O–D matrix cells of this zone. The upper threshold was obtained from the observation of ranking charts of this indicator, which present a very steep slope until approximately 30% of the maximum value per cell. These thresholds define three ranges of values, as presented in figure 12.

![Figure 12. Percentage of matrix cells in each range of flow values, according to the grid dimension.](image)

From the percentages presented in the figure it is possible to conclude that the high values of this indicator are a small percentage of the total number of cells and the increase with the grid dimension is not very significant. On the other hand, the low values of the indicator, which are an important constraint in aid of statistical precision, have a great variation with the grid dimension (−0.026% slope for the adjustment with a linear trend line). This information reinforces the importance of the grid dimension to the statistical precision (variation of 47% of low value cells between the 2000 m and 200 m square grid cells with the estimated slope).

4 Grid origin sensitivity analysis
A sensitivity analysis has been carried out to measure the influence of the grid origin location on the indicator. The results show that the indicators which presented a higher variation in their value were the percentage of intrazonal trips and the percentage of cells with no origin or destination (ie no trips).

The sensitivity analysis for the intrazonal trip percentage indicator was again made using the ranking charts. In figure 13 these ranking charts, of the values obtained for the sixteen different grid origins, are shown for two different grid dimensions. In these curves a negative slope can be seen, which decreases with the grid dimension (reducing the indicator variance). The intersects of the adjusted trend lines also increase with the grid dimension, as expected.

The same procedure was used for the next indicator (the percentage of cells with no origin or destination). In figure 14 two examples of the resulting ranking charts are shown; the curves have an approximately linear negative slope and decrease with the grid dimension (reducing the indicator variance). The intersects of adjusted trend lines
also decrease with the grid dimension as expected. It is also important to underline that these indicators do not have their maximum value at the same position, which makes a joint sensitivity analysis impossible.

The final step of the developed methodology was to determine the distance and angles relative to the starting grid location that could present the most favorable values of the intrazonal trip indicators (considered the most important for this analysis). The goal of this analysis is to find the translation of the grid which would give optimal values of the most important trip indicator. The resulting analysis should allow an evaluation of the average angle relative to the starting position location, and the exact point location.

The process used for this analysis was the determination, for each grid dimension, of the best neighbor location from all sixteen analyzed cases. The best neighbor location, for each grid cell dimension, is found using polar coordinates, which consist of a distance to an origin point (considered the indicial position of the grid for all the cell sizes) and the angle relative to the x-axis. After the determination of the best neighbor location for all sixteen analyzed cases, the average values of the obtained coordinate are calculated in order to determine a pattern for the best grid origin location.
The results of this analysis are presented in figure 15, in which it can be seen that the distance to the best neighbor (in terms of the percentage of the cell size) does not depend on the cell size (approximately constant at around 59%), and also that the angle, relative to the starting point, does not have regular behavior. From these results no stable behavior pattern can be established for the best angle with which to minimize the intrazonal trip percentage for the different grid dimensions (as a result of very low or inexistent correlations for these variables). The only information that can be obtained from this analysis is the average angle (all the values oscillate around it) for the minimization of the indicator, independent of the grid dimension (see figure 15). Therefore it is impossible to determine a best location for the grid origin, since one of the two polar coordinates is still undefined: the best-fit angle.

5 Conclusions
This study focused on the research of the MAUP scale effects in some important traffic demand modeling variables in order to develop a future TAZ delineation methodology with less MAUP interferences. A new analysis methodology and a GIS-based application were developed for this study in order to measure these effects on...
Some indicators considered relevant for the TAZ delineation, such as the percentage of intrazonal trips and the percentage of trips in non-statistically-significant O-D matrix cells. The model was applied over the AML and a mobility survey of this area made in 1994.

This paper reports these analyses, and it was possible to extract some important conclusions about some MAUP scale effects in the aggregated travel data that constitute important knowledge for the TAZ delineation.

Percentage of intrazonal trips in the O-D matrix:
- Cell size has a very significant impact on the percentage of intrazonal trips (variation range is 18%–27%—that is, a relative increase of 50%—as cell size grows from 200 m to 2000 m).
- Even for very small grid cells (200 m) the percentage of intrazonal trips is significant (18%)—a feature associated with the 22.81% of trips on the database used which are made by foot or by bicycle.
- Cell origin position has a small impact on the percentage of intrazonal trips (variation range is 20.80%–21.70% for a cell size of 1000 m).

Percentage of cells with no trips:
- Cell size has a very significant impact on the percentage of cells with no trips (variation range is 49%–97% as cell size decreases from 2000 m to 200 m).
- Cell origin position has a significant impact on the percentage of cells with no trips (variation range is 69%–80% for a cell size of 1000 m), which is a decisive factor for geographic precision.

Percentage of trips in non-statistically-significant O-D matrix cells:
- The position of the origin of the cell has a very significant impact on the percentage of trips in non-statistically-significant O-D matrix cells: the variation range is 38%–73% as cell size decreases from 2000 m to 200 m, which indicates the conflict between geographic and statistical precision.

These results show that zoning is not a trivial matter and give the significant consequences it may have for the generation of statistical and geographical errors. The variability of observed values of the main indicators for different grid sizes and origins, indicates the added value of careful zoning in the transport-planning decision-making processes.

This paper presents a robust approach to zoning for transportation studies that will not only look at scale effects (of aggregating or disaggregating data), but will
also be site sensitive to the variability of data throughout the territory at the same scale (through the fluctuation of the origin of the matrix). The transportation sector was selected to be a test base for this methodology, but it could also be of value in other sectors.

Acknowledgements. This research has been supported by the Portuguese National Science Foundation (FCT) since 2004. The private company TIS has also provided support by making available the AML Mobility Survey, and we are grateful to the software company INTERGRAPH for the Geomedia Professional 5.1 license.

References
Batty M, 1976, “Entropy in spatial aggregation” Geographical Analysis 8 1 – 21
Batty M, Sikdar P K, 1982b, “Spatial aggregation in gravity models. 2. One-dimensional population-density models” Environment and Planning A 14 525 – 553
Batty M, Sikdar P K, 1982d, “Generalization and large-scale applications” Environment and Planning A 14 795 – 822


Zhang M, Kukadia N, 2005, “Metrics of urban form and the modifiable areal unit problem” Transportation Research Record number 1902, 71 – 79