

# Effect of Database Errors on Intervisibility Estimation\*

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## Abstract

*One of the most common uses of digital terrain databases is in the evaluation of intervisibility, or clear line of sight, between points in space. These evaluations are often used to make decisions regarding deployment of equipment or personnel. However, there will be errors or discrepancies between the database and the true terrain, and, because of these discrepancies, the visibility in the field will differ from that predicted using the database. This paper describes a method for calculating the probability of visibility over an area for a given error specification. Results are described showing the sensitivity of visibility uncertainty to database error and terrain roughness. Sensitivity to other parameters is discussed. The results show that databases are very good for predicting masking but are less reliable for predicting visibility. Also, the reliability of the visibility predictions increases with increasing terrain roughness.*

## Introduction

The past two decades have seen enormous strides in the application of computer technology to cartography and geodesy. Unlike paper maps, a digital map may be updated rapidly as new information is received, and map data may be easily displayed in a variety of formats and scales. But the feature of digital maps that provides the greatest improvement over paper maps may be the ability to deal conveniently with height data, in particular, the ability to evaluate line-of-sight opportunities; that is, to determine whether a clear line of sight (CLOS) exists between two points in space. Numerous applications have been cited (see, e.g., Lee (1994), Miller and Xiang (1992), and Fels (1992)).

For these applications, the analyst uses the digital elevation model (DEM) to make predictions of line-of-sight opportunities, or intervisibility, between points in space. These predictions then form the basis for decisions. For example, the analyst may use the map to find a point that offers maximum surveillance coverage of an area, and then to dispatch an observer to the site.

Intervisibility algorithms currently use elevation data as stored in the database. However, the digital map will contain errors of various sorts relative to the true terrain: i.e., height measurement errors, presence or absence of features, interpolation errors, misalignment, etc. Each of these errors can have an effect on line of sight, such that the intervisibility from the field site may differ considerably from that predicted using the database. In some cases, it is possible that

these differences can have serious consequences for the system. It would thus seem that methods should be found to assess the reliability of intervisibility calculations. The user needs a way to evaluate the confidence in the CLOS assessments from different points: it would be preferable to send an observer to a point where there is a 95 percent chance of CLOS rather than to one having only a 10 percent chance; such options are not readily available in the current processes involving binary representation of the viewshed.

Some work in assessing the uncertainty in viewshed prediction has recently been reported (Fisher, 1991; Fisher, 1992; Mills *et al.*, 1992). In these, the variation in the viewshed was evaluated by generating a number of realizations of height errors, adding the generated height values to the DEM heights, and then calculating the viewshed. The fraction of realizations where a given point was visible is then used as a measure of the reliability of the DEM's calculated viewshed. One common conclusion that emerged from all of these studies is that the viewshed as calculated using the DEM is likely to be overestimated relative to the actual viewshed.

Two other studies (Marlin, 1992; O'Rourke, 1992) compared intervisibility results using databases of different resolutions. The conclusions of the two studies were similar; both showed that intervisibility results are sensitive to database resolution, and both implied that the higher the resolution of the database, the more accurate would be the masking predictions. Typical measures used to compare results across resolutions were fraction of points visible and range at initial unmask.

The following sections describe a numerical technique for estimating the probability of CLOS at each point within the coverage area. The purpose is twofold: first, to develop a method for quantifying the effects of database errors on the estimation of CLOS, and second, to determine how various characteristics of the system and environment influence the sensitivity of intervisibility to database errors.

## Intervisibility Calculations

Intervisibility refers to clear line of sight (CLOS) between two points in space. The procedure for evaluating CLOS using a digital terrain database involves stepping through the database along a line between the points, and evaluating the terrain height at each step, as shown in Figure 1. If the terrain height extends above the line joining the points, then the points are considered mutually masked. An intervisibility map of an area (viewshed) is typically prepared by sending out rays in all directions, and evaluating the LOS for each grid point in the selected area.

\*A copy of the complete results, including color figures, is available from the author. Also available is a demonstration disk for PC.

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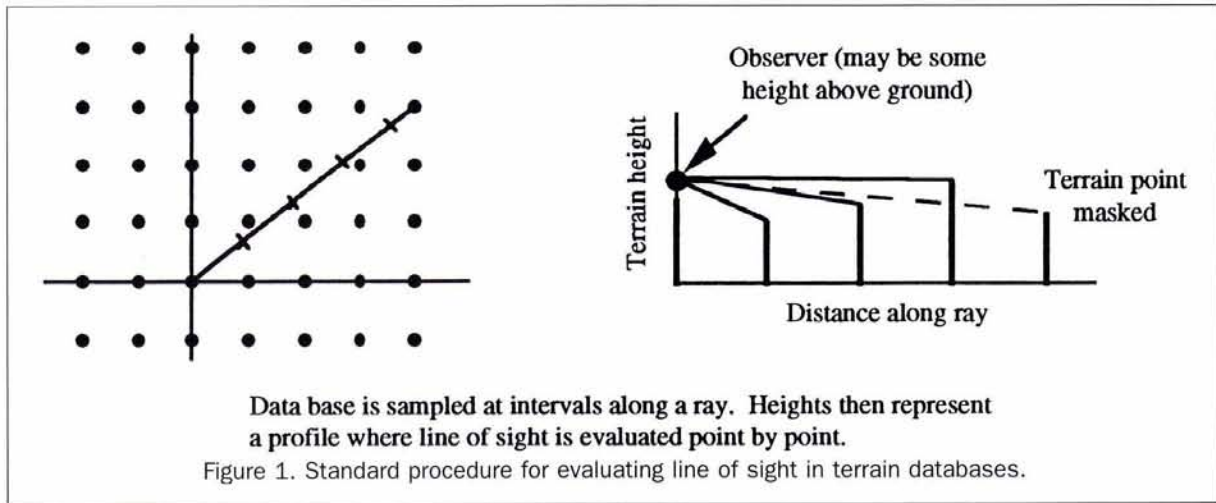
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Visibility depends on both the height of the target and the height of the observer. But just as elevating the observer to see over a point of terrain will increase the visible regions, in a similar manner any error that increases (decreases) terrain height will decrease (increase) visibility. The user should thus be aware of the potential effects of database errors on coverage. The next section describes some major sources of errors in the database.

## Sources of Errors

### Elevation Errors

Databases containing terrain elevation values are normally prepared and issued as heights at nodes of a uniform grid spacing over a specified geographical area. For example, the area may be one square degree, and the grid spacing one arc second (about 30 metres at the equator). Heights at the nodes (or "posts") are obtained from stereophotographs of the area ("photo-source"), by digitizing paper maps ("carto-source"), or, more recently, from satellite data. With any process, the reported post height may differ from the true height at the specified grid point on the Earth. The magnitude of this error is often defined as a height range within which 90 percent of the errors lie.

Truncation error can also be significant. If the units are metres, then the reported elevation can be in error by 0.5 metres. In a line-of-sight calculation, an error of 0.5 metres at a range of 100 metres will project to 50 metres at 10 kilometres, which may be highly significant in some applications.

Another potential error is elevation bias. The values are normally presented as elevation above the height of the local geoid. If neighboring sectors do not use the same reference geoid, substantial discontinuities can exist across sector boundaries.

### Registration Errors

In addition to height errors, the database may be misaligned with the Earth reference, or misalignment may occur during the process of recording heights. This error is usually characterized as a circular error, this being the radius of the circle within which there is a 90 percent probability that the point lies. For purposes of the analysis to be presented below, this error will not be treated explicitly; instead, it will be assumed that alignment errors may be treated as contributions to the elevation errors.

### Feature Effects

Surface features can have a significant effect on line of sight. Treatment of features is a vexing problem in masking analysis,

in particular, the effects of forests. The process of analyzing stereophotographs of wooded areas may yield the height of the ground (if the trees are sparse or the trees are deciduous and the photographs are taken in winter), the height of the tops of the trees (dense forest where penetration is limited), or somewhere in between (Slocum, 1991). If the analyst does not know how the tree heights have been treated, it will not even help to know where the trees are, because the analyst will not know for certain whether to add the tree heights to the reported terrain height, or to assume that the reported height is the top of the trees. For the results described in this study, however, the heights in the DEM are assumed to represent the envelope of obstacles to CLOS, including both terrain and features.

### Interpolation Errors

Line of sight should be based on the tangent line from the observer over all intervening terrain. However, terrain heights are recorded at posts on a grid, and some error can accrue because the terrain between posts is not accounted for. In most applications, the terrain is assumed to be linear between posts (or bilinear within patches). As the grid size increases, this assumption becomes worse, because there is a greater deviation from linearity. Thus, the treatment of errors should include the effects of intermediate terrain extending up to block line of sight, and these effects are dependent on grid size. In this study, no special provision is made for interpolation error; however, if databases of larger grid size are used, this could become a major effect.

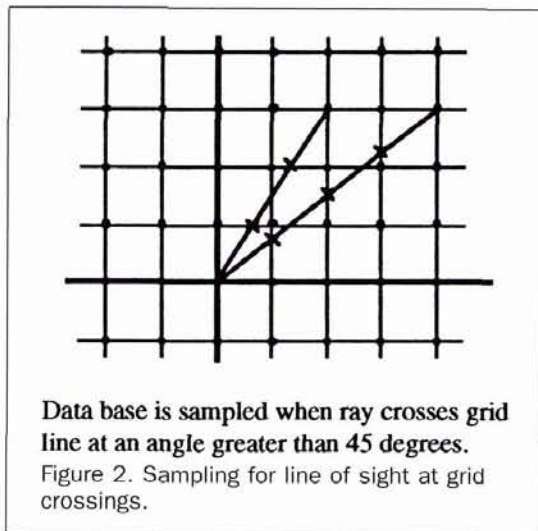
Limited use has been made of higher order approximations (biquadratic, bicubic splines, etc.) to the terrain shape (Marlin, 1992), but it was concluded that the alleged improvement in accuracy did not justify the computational complexity.

### Database Sampling

Line of sight between two points in space is evaluated by finding the azimuthal line between the points on the terrain database, and then sampling the heights along this line to determine whether any terrain point extends above the direct line in space between the points. It is obvious that the evaluation of masking will be dependent on sample spacing, in much the same way that it is dependent on grid size, as well as on the method of interpolation. In this study, the database is sampled when the azimuthal ray crosses a grid line; no examination was made of using finer or coarser sample spacing.

Fisher (1993) compared viewsheds produced using a number of different algorithms, and concluded that there is





considerable variation in predicted viewshed among algorithms. The method described herein for estimating probability of visibility might be applied to other algorithms, and thus perhaps provide insight into the relative reliability of different algorithms. This is left for future studies.

### Computational Techniques

The computational scheme to be described in this section is an efficient method for estimating the potential effects of the various types of errors on the evaluation of terrain masking. The purpose is more to gain an appreciation of these effects and their magnitudes than to compute precise statistical values; hence, approximations are used where necessary to avoid the enormous computational cost of a rigorous statistical analysis. It is hoped that this initial work will be expanded to establish a more rigorous framework for this analysis. However, the results to be presented below offer some significant insights into the potential effects of errors on viewshed estimation.

### Line-of-Sight Calculations

There are a number of techniques in use for estimating intervisibility over a terrain database, several of which are described by Fisher (1993). One common method is to select an origin (the "observer"), and to send out from this origin a series of rays, uniformly spaced in azimuth. The terrain is sampled along each ray, usually at fixed intervals, and the terrain height at the sample point is estimated by an appropriate interpolation scheme. The elevation angle from the observer at the origin to this terrain point is then computed. If this angle is greater than the angle to any previous point along the ray, the terrain is considered visible; if it is less than the maximum elevation angle over all previous points, the terrain is masked. The elevation difference between the projected height of the maximum angle and the terrain height at the sample point is sometimes called the "masking depth." If the masking depth is less than the designated target height, the target is considered visible to the observer.

It is sometimes desired to calculate masking depth at each grid point in the prescribed coverage space; for example, if a user is attempting to find low-altitude penetration paths through a defended area where the locations of the defenses are known, it is useful to know how many defenders have clear line of sight to each point, because risk increases with redundant coverage. If the above described procedure is used for the intervisibility calculations, computing the masking depth at each point involves interpolation between adja-

cent rays. In the analyses used for this paper, this interpolation is avoided by evaluating the line of sight from the origin to each point in the coverage area. The terrain height is evaluated each time the ray crosses a grid line at an angle greater than 45 degrees; the terrain height at the crossing point is evaluated by linear interpolation and the elevation angle from the observer is calculated and processed as described above. Figure 2 shows this computational procedure.

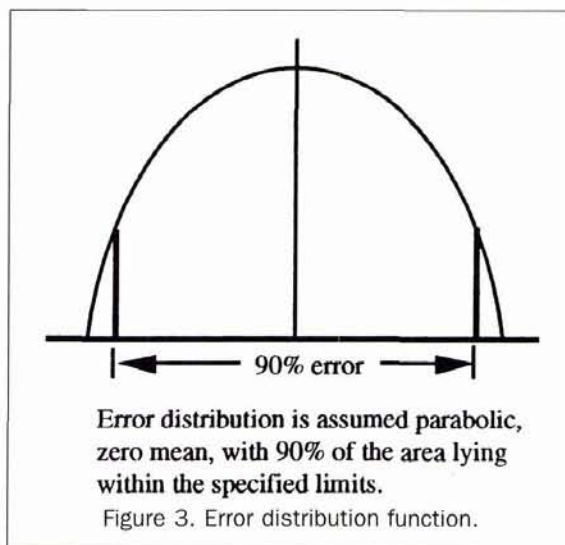
### Treatment of Errors

As stated above, the statistical analysis used here is more heuristic than rigorous. This is done for two reasons. First, there is insufficient knowledge of the nature of the errors, and any analysis based on a specific distribution of the errors (e.g., Gaussian) may not be applicable to the actual distribution (which may very well be non-parametric). Second, computational limitations, both in memory requirements and execution time, preclude the use of highly complex multi-dimensional techniques. For this study, then, all errors (see the previous section) are lumped together at each sample point, and this distribution is assumed to be parabolic, characterized by a single parameter: the interval within which 90 percent of the points are assumed to lie. Figure 3 illustrates this distribution.

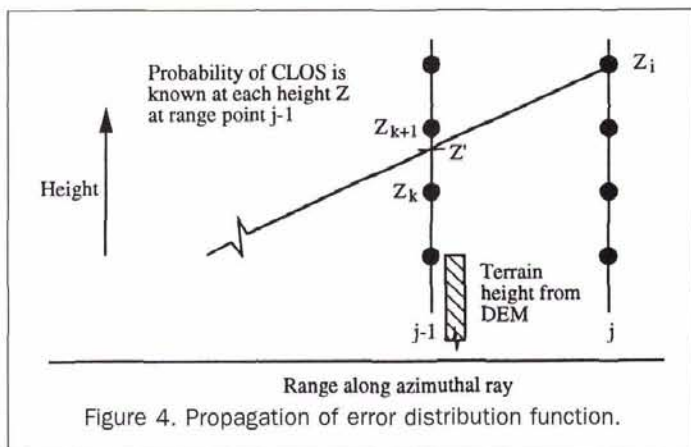
Admittedly, this distribution cannot be supported by data available in the open literature. However, the purpose of this initial analysis is not to provide precise numbers, but rather to provide insight into the sensitivity of results to database errors. We assume that differences attributable to the shape of the error function will be negligible compared to differences due to the magnitude of the error. It is left for future studies to investigate this more fully.

### Computational Procedure

The probability distribution of the line of sight is propagated in much the same way as the straight line-of-sight calculation described above. At each point  $j$  along the ray, let  $F_j(Z_i)$  represent the probability that a clear line of sight (CLOS) exists at a height  $Z_i$  over all previous terrain points along the ray. The process is illustrated in Figure 4. Assume that the probability of a CLOS over all previous terrain is known at each height  $Z_k$  at point  $j - 1$ ; call this  $F_{j-1}(Z_k)$ . In order to have a CLOS at height  $Z_i$  at point  $j$ , there must be a CLOS over all terrain up to point  $j - 1$ , and there must be a CLOS over the terrain at point  $j - 1$ . Let  $Z'$  be the height of the direct ray from the origin to height  $Z_i$  at point  $j$  when it reaches







point  $j - 1$ . The probability of a CLOS to height  $Z_i$  at point  $j$  over all terrain up to point  $j - 1$  is estimated by linear interpolation of the function  $F_{j-1}(Z)$  between the heights above and below  $Z'$ . The probability of a CLOS over point  $j - 1$  is the probability that the height of the terrain at the point is less than  $Z'$ , which is the integral of the error function up to  $Z'$ . The probability of a CLOS at height  $Z_i$  at point  $j$  is the product of these two values. This process is carried out for each height  $Z_i$  at point  $j$ . The height spacing is variable according to the variation in the values of  $F(Z_i)$ , but it is never less than one metre.

This is the procedure for calculating the function  $F(Z_i)$ . Let  $p_j(Z_i)$  represent the probability density function of the terrain height at point  $j$  (in this analysis, this distribution is assumed to be parabolic with mean value equal to the height indicated in the database). Now the probability that a target at height  $H$  above the ground at point  $j$  along the ray is visible to the observer at the origin is given by

$$P(\text{vis}) = \int_{-\infty}^{+\infty} F(Z + H)p(Z)dZ.$$

This is evaluated at each grid point within the radius of coverage.

The algorithm was coded in C and implemented on a Macintosh IIci computer. In some cases, linear approximations to functions were used in order to reduce computation time. The algorithm also took advantage of certain geometric similarities. The time required to assess probability of visibility and display the results for an area of radius 100 grid points (e.g., 10 kilometres at a 100-metre grid), covering approximately 31,400 points, was approximately 22 seconds. The process is linear in the number of points in the area; thus, the time required to evaluate the function for an area of radius 200 grid points is 88 seconds.

## Results

Intervisibility evaluations are undertaken to answer the question, "Will an observer at point A have a clear line of sight (CLOS) to a target at point B?" In the current study, this is rephrased as, "What is the probability that an observer at point A has a CLOS to a target at point B?" That is, how reliable is the database in assessing intervisibility? The results are presented in several forms. First, coverage maps are shown indicating, by shade, the probability of a CLOS from the observer to all points within the designated coverage area. Second, the data are summarized as an uncertainty matrix (also called the confusion matrix), which indicates the probabilities that areas are masked or visible, given that they are predicted masked (or visible) by the database. Third, results are summarized as histograms showing the fraction of points having certain probabilities of visibility.

## Terrain Database

The database used in these analyses is an area of central California, including portions of the Owens Valley and also parts of the Sierra Nevada. The terrain ranges from mild to very rough. The data are stored on a planar grid with uniform grid spacing throughout. The total coverage area is 120 by 120 km at low resolution (300-metre grid); when higher resolution sectors are used, the area is reduced to maintain the same array dimensions. Thus, the 100-metre database is a 40- by 40-km sector within the larger area. Figure 5 shows the area, with the (approximate) latitude and longitude of the southwest corner indicated for reference.

## Observer Parameters

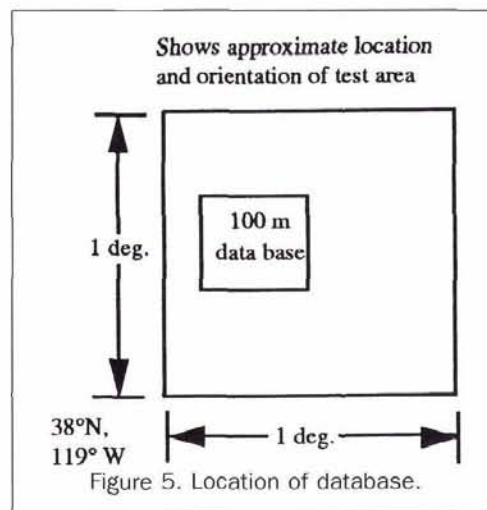
Two reference locations were selected for the observer positions: one on a hummock with nominal visibility of the surrounding rolling terrain area, and one in the more mountainous portion having nominal coverage of several valleys (potential attack routes). Figures 6a and 6b show the visibility coverage from each of these positions as predicted by the 100-m database. The observer is placed 3 metres above ground level (AGL) at the origin; the target height is 60 metres AGL. The coverage radius is 25 km (250 grid points). The visible portion is 34 percent in the first case and 41 percent in the second case.

## Reference Cases

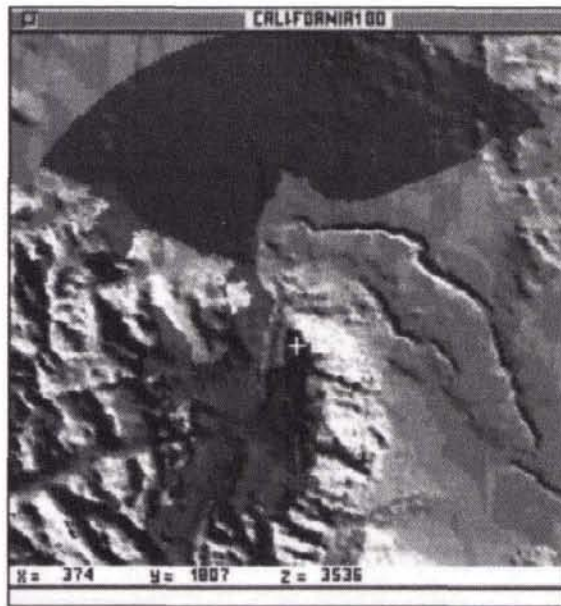
The parameter values listed above are used as the reference values. Sensitivity studies around the reference values show how the expected visibility compares with the predicted visibility as a parameter is changed.

The nominal elevation error was taken as 15 metres (90 percent). This means that at 90 percent of the points the difference between reported height and "true" height is less than 15 metres. For this study, to facilitate computation, it is assumed that the error distribution is parabolic, with zero mean and having 90 percent of its area lying within the specified limits (see Figure 3). Although this may not reflect the true nature of the distribution, intuition (supported by numerical experiments using different distributions) indicates that altering the shape of the distribution (while keeping the 90 percent limits the same) will have a negligible effect on the results. Further examination of this issue is left to later studies.

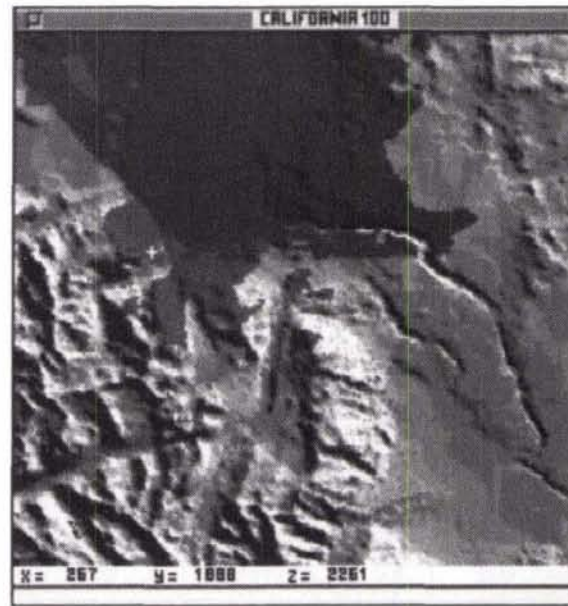
The correlation length of the errors is an important but often neglected parameter. The error distribution described above refers to any individual, randomly selected point. If a point is selected in the database and is found to be much







(a)



(b)

Observer Height 3m AGL. Target Height 60m AGL. Coverage Radius 25 Km. Grid Size 100m.

Observer Position Indicated By White Cross



Figure 6. Predicted visibility coverage. (a) From mountain site. (b) From plains site.

higher than the true terrain at those coordinates, then it would be expected that the indicated heights of the points immediately surrounding the selected point would also be higher than the true terrain. However, the farther away one samples, the less influence the selected point will have. The correlation length is the separation required for the correlation between the errors at two points to drop by a factor of  $1/e$ . If this correlation length (CL) is small (e.g., zero), the points are uncorrelated, and the error at each point is independent. If the CL is large (many kilometres), then the errors can be regarded as simply a bias, and will have little effect on calculations relating to height AGL. Thus, increasing CL has an effect similar to that of reducing the height error. We are not aware of any published data on the CL of existing databases. However, some informal studies indicate that a CL of between 1 and 2 km is realistic. For the reference case, the CL is taken to be 1.2 km. Sensitivity of results to CL are discussed in a later section.

Figures 7a and 7b show the expected coverage, with probability of visibility now indicated by shade. Much of the predicted area of coverage is indicated as high probability, implying that the database does predict visibility reasonably well. It is significant (although, upon reflection, not surprising) to note that the regions where the probabilities drop off are located along the edges of the regions predicted to be visible. This implies that the reliability of the visibility computations is not range-dependent *per se*, but dependent rather on the locations of the indicated transition regions near the edges of the visible areas.

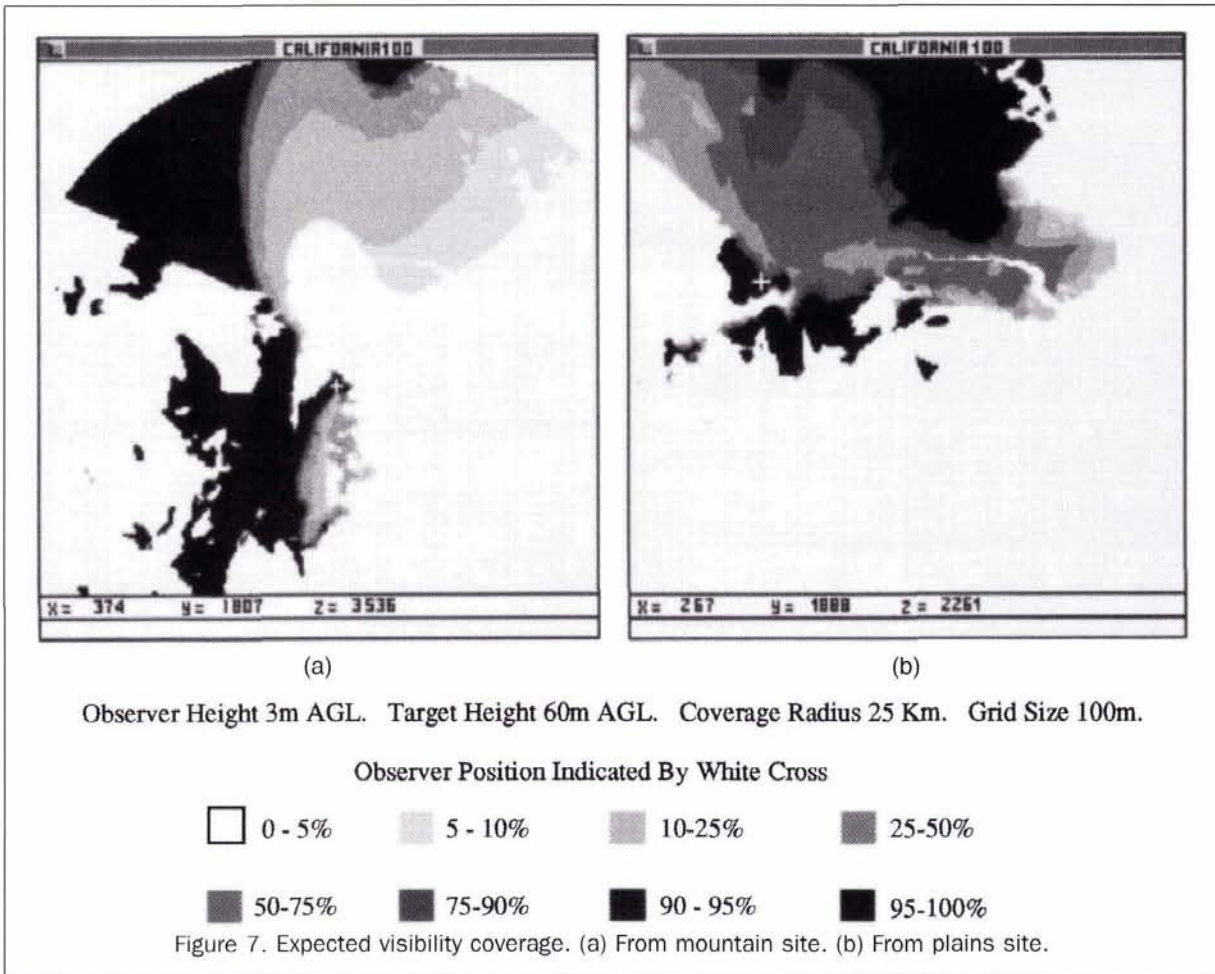
Table 1 shows the uncertainty matrices for the two sites.

In these tables, the predicted fraction is the fraction of points within the designated range indicated visible by the Boolean viewshed. The expected fraction visible is the sum of the calculated probability of visibility for all points within the coverage area, divided by the number of points. For the mountain site, the database predicts that 34 percent of the area will be visible; however, the expected visibility is only 25 percent. For the site on the plains, the predicted visibility is 41 percent, while the expected visibility is 32 percent. Thus, in both cases the observer in the field will likely see substantially less of the area than the database predicts.

It is important here to clarify the meaning of these expectations. They must not be interpreted as the probability that any given point will be visible, nor should they be interpreted to mean the probability that a point predicted visible will actually be visible (conditional probability). Rather, they are indications only of the fraction of total area visible, either predicted or expected. Further, because of the numerous assumptions made in the calculations, the values should be used only for comparison. Future studies will refine the analyses to make these expectations more reliable.

#### Database Error

Visibility calculations were made from the two reference sites using database errors (90 percent) of 2 m, 7 m, and 30 m, in addition to the reference value of 15 m. The uncertainty matrices are shown in Table 2. Figure 8 shows the expected visibility fractions for the two sites as functions of database error. The two graphs show differences worth noting. The plains site can tolerate small errors without effect,



but is far more sensitive when the errors become large. The mountain site results, however, suggest somewhat less sensitivity to increasing error. These differences may be explained by the following hypothesis: when the terrain is smooth, as around the plains site, the elevation angle to all of the target positions is small; thus, there is a high probability of interaction with terrain errors at many points. For the mountainous region, some of the points predicted visible are at higher elevation angles, thus allowing fewer interactions with terrain errors along the path.

For many applications, the decision maker is more concerned with conditional probabilities than with the expectations as shown in the previous tables. That is, how

trustworthy is the map for a particular application? In some applications, such as finding good sites for air defense placement, decisions are made based on predicted visibility: that is, the decision maker wishes to know whether the areas predicted to be visible will, in fact, actually be visible when the system is deployed. In other applications, such as finding routes where an aircraft might be masked from air defense sites, the issue is the reliability of the predicted masking. Table 3 shows the values of Table 2 expressed as conditional probabilities. One significant feature emerges from these tables: the areas predicted to be masked are highly likely to be masked, but the prediction of visibility is suspect. This is corroborated by the data reported in Fisher (1992). This sug-

TABLE 1. PREDICTED AND EXPECTED VISIBILITIES: REFERENCE CASES

Observer height:	3 m AGL	Target height:	60 m AGL
Database error:	15 m (90%)	Correlation length:	1.2 km
Coverage radius:	25 km	Grid size:	100 m
Vertical exaggeration:	1.0		

Table 1a. Mountain site (374,1807)				Table 1b. Plains site (267,1888)			
Predicted	Expected		Total Pred.	Predicted	Expected		Total Pred.
	Visible	Masked			Visible	Masked	
Visible	0.248	0.094	0.342	Visible	0.321	0.085	0.406
Masked	0.006	0.652	0.658	Masked	0.001	0.593	0.594
Total Exp.	0.252	0.746		Total Exp.	0.322	0.678	



TABLE 2. PREDICTED AND EXPECTED VISIBILITIES: SENSITIVITY TO DATABASE ERRORS

Observer height: 3 m AGL  
 Coverage radius: 25 km  
 Vertical exaggeration: 1.0

Target height: 60 m AGL  
 Correlation length: 1.2 km  
 Grid size: 100 m

Table 2a. Mountain site

Error = 2m (90%)			
Predicted	Expected		Total Pred.
	Visible	Masked	
Visible	0.337	0.005	0.342
Masked	0.002	0.656	0.658
Total Exp.	0.340	0.660	

Error = 7m (90%)			
Predicted	Expected		Total Pred.
	Visible	Masked	
Visible	0.313	0.029	0.342
Masked	0.005	0.653	0.658
Total Exp.	0.318	0.682	

Error = 15m (90%) (Ref)			
Predicted	Expected		Total Pred.
	Visible	Masked	
Visible	0.248	0.094	0.342
Masked	0.006	0.652	0.658
Total Exp.	0.252	0.746	

Error = 30m (90%)			
Predicted	Expected		Total Pred.
	Visible	Masked	
Visible	0.178	0.164	0.342
Masked	0.006	0.652	0.658
Total Exp.	0.184	0.746	

Table 2b. Plains site

Error = 2m (90%)			
Predicted	Expected		Total Pred.
	Visible	Masked	
Visible	0.404	0.002	0.406
Masked	0.001	0.593	0.594
Total Exp.	0.405	0.595	

Error = 7m (90%)			
Predicted	Expected		Total Pred.
	Visible	Masked	
Visible	0.401	0.005	0.406
Masked	0.001	0.593	0.594
Total Exp.	0.402	0.598	

Error = 15m (90%) (Ref)			
Predicted	Expected		Total Pred.
	Visible	Masked	
Visible	0.321	0.085	0.406
Masked	0.001	0.593	0.594
Total Exp.	0.322	0.678	

Error = 30m (90%)			
Predicted	Expected		Total Pred.
	Visible	Masked	
Visible	0.081	0.325	0.406
Masked	0.001	0.593	0.594
Total Exp.	0.082	0.918	

gests strongly that the reliability of the database in predicting masking is extremely high, but the ability to predict visibility is highly sensitive to both database error and terrain roughness, and extreme care must be taken in decisions based on predicted visibility.

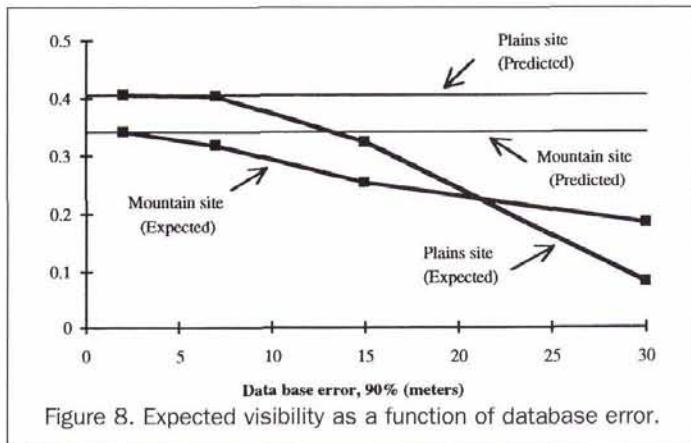
This apparent asymmetry is, however, logical. In order to have visibility of a target, all elevation points along the profile must lie below the line joining the observer and the target. Increasing the error increases the probability that one of these points may extend above the line, and hence mask the target. If a point is predicted masked, however, in order for it to become visible, the point(s) that mask it must all lie below the line of sight, and all other points must remain below the line of sight. While increasing the error allows for this to occur (the error may be negative as well as positive), it also increases the probability that other points may extend up and block visibility. The points that could be visible despite being predicted masked are those on the very fringe of the masked area, where the height error may extend the target above the cumulative shadow. This is a very important observation, because it suggests that databases of extreme accuracy may not be required if the application depends on finding masked areas, such as the penetrator mission. In fact, as the error increases, the estimate of masking becomes better, in the sense that more of the areas predicted visible will also be masked.

#### Terrain Roughness

To provide a test of how the terrain roughness affects sensitivity to error, the terrain was altered by multiplying the database elevations by a constant, called the exaggeration factor. It simply stretched or compressed the database vertically. Two factors were used: 0.2 (to reduce roughness) and 3.0 (to increase roughness). Table 4 shows the uncertainty matrices for the two reference positions for these exaggeration factors, as well as for the reference cases. All other parameters (i.e., observer height, target height, etc.) assumed their reference values. At both sites, as expected, the predicted visibility decreased with increasing roughness (exaggeration).

The values in these tables also are consistent with the results observed in the previous cases. First, as the roughness increases, the visibility predictions become more reliable, in the sense that the fraction of points predicted visible but expected masked decreases. Second, the prediction of masking continues to be robust over all tested roughness values: if a point is predicted to be masked, the probability that it will actually be masked from an observer in the field is extremely high.

Several cases were run with different database errors for the two additional roughness values, in order to observe how terrain roughness affects the sensitivity of the visibility predictions to database error. Three trends emerged from these



studies. First, as roughness (as defined above) increases, visibility decreases. Second, as roughness increases, sensitivity to database error decreases. Third, the predictions of *masking* are robust in all cases, but the sensitivity of predicted *visibility* to database errors is highly dependent on roughness: the rougher the terrain, the more reliable the visibility predictions.

### Other Sensitivities

A large number of cases were run for different locations, and also with different values of several parameters: observer height, target height, grid spacing, correlation length, etc. Space precludes a complete discussion of these results.

### Discussion

If databases are to be used for planning purposes, it is important to be able to assess the potential effects of database errors on system performance. There are actually two separate questions involved in this assessment. First, when a database is used in support of some aspect of the mission, what confidence does the user have that the actual values to be observed in the field will match the values predicted by using the database? Second, how sensitive is the actual system performance to this uncertainty? An example here is helpful. Suppose a database is to be used as an aid in a penetration mission for both threat avoidance and for target acquisition, and suppose that the elevation error in the database is 10 metres. The database is used to predict regions of visibility and masking from various points along a candidate path. The probability statistics associated with these visibility maps can be calculated, using the methods described in this paper. This addresses the first question, because it relates expected values to predicted values. For the second question, we must consider the use to which these intervisibility maps will be put. As was indicated above, even with large errors, the data-

TABLE 3. CONDITIONAL PROBABILITIES OF VISIBILITY AND MASKING:\* SENSITIVITY TO DATABASE ERRORS

Observer height:	3 m AGL	Target height:	60 m AGL
Coverage radius:	25 km	Correlation length:	1.2 km
Vertical exaggeration:	1.0	Grid size:	100 m

Error = 2m (90%)			
Predicted	Expected		Total Pred.
	Visible	Masked	
Visible	0.985	0.015	0.342
Masked	0.003	0.997	0.658

Error = 2m (90%)			
Predicted	Expected		Total Pred.
	Visible	Masked	
Visible	0.995	0.005	0.406
Masked	0.002	0.998	0.594

Error = 7m (90%)			
Predicted	Expected		Total Pred.
	Visible	Masked	
Visible	0.915	0.085	0.342
Masked	0.008	0.992	0.658

Error = 7m (90%)			
Predicted	Expected		Total Pred.
	Visible	Masked	
Visible	0.988	0.012	0.406
Masked	0.002	0.998	0.594

Error = 15m (90%) (Ref)			
Predicted	Expected		Total Pred.
	Visible	Masked	
Visible	0.725	0.275	0.342
Masked	0.009	0.991	0.658

Error = 15m (90%) (Ref)			
Predicted	Expected		Total Pred.
	Visible	Masked	
Visible	0.791	0.209	0.406
Masked	0.002	0.998	0.594

Error = 30m (90%)			
Predicted	Expected		Total Pred.
	Visible	Masked	
Visible	0.520	0.480	0.342
Masked	0.009	0.991	0.658

Error = 30m (90%)			
Predicted	Expected		Total Pred.
	Visible	Masked	
Visible	0.200	0.800	0.406
Masked	0.002	0.998	0.594

\*Values shown in the tables are the fraction of points expected visible and masked, given that they were predicted visible or masked from the database. For example, Table 3a (15m) shows that 34.2 percent of the area was predicted visible; of this area, 72.5 percent would be expected to be visible in the field, while 27.5 percent would be masked.



TABLE 4. PREDICTED AND EXPECTED VISIBILITIES: SENSITIVITY TO TERRAIN ROUGHNESS

Observer height:	3 m AGL	Database error:	15 m (90%)
Target height:	60 m AGL	Coverage radius:	25 km
Grid size:	100 m	Correlation Length:	1.2 km

Table 4a. Mountain site			
Vertical exaggeration = 0.2			
Predicted	Expected		Total Pred.
	Visible	Masked	
Visible	0.246	0.319	0.565
Masked	0.011	0.424	0.435
Total Exp.	0.257	0.743	

Table 4b. Plains site			
Vertical exaggeration = 0.2			
Predicted	Expected		Total Pred.
	Visible	Masked	
Visible	0.156	0.377	0.533
Masked	0.001	0.466	0.467
Total Exp.	0.157	0.843	

Table 4a. Mountain site			
Vertical exaggeration = 1.0 (Ref)			
Predicted	Expected		Total Pred.
	Visible	Masked	
Visible	0.248	0.094	0.342
Masked	0.006	0.652	0.658
Total Exp.	0.252	0.746	

Table 4b. Plains site			
Vertical exaggeration = 1.0 (Ref)			
Predicted	Expected		Total Pred.
	Visible	Masked	
Visible	0.321	0.085	0.406
Masked	0.001	0.593	0.594
Total Exp.	0.322	0.678	

Table 4a. Mountain site			
Vertical exaggeration = 3.0			
Predicted	Expected		Total Pred.
	Visible	Masked	
Visible	0.257	0.032	0.289
Masked	0.002	0.709	0.711
Total Exp.	0.259	0.741	

Table 4b. Plains site			
Vertical exaggeration = 3.0			
Predicted	Expected		Total Pred.
	Visible	Masked	
Visible	0.326	0.009	0.335
Masked	0.002	0.663	0.665
Total Exp.	0.328	0.672	

base predictions may be very useful during the penetration phase by finding areas masked from threats, and these computations appear to be robust, even in the face of large errors. For the acquisition portion, however, the predictions of visibility may be totally unacceptable because of the large uncertainties. Thus, the step of assessing the effects of database errors on system performance is an entirely separate issue from evaluating the statistics themselves, and must be evaluated in the context of each system.\*

The current study addresses the first of these questions with respect to the use of terrain databases to predict intervisibility, although some limited inferences may be made regarding the second question. A terrain database covering an area approximately 40 by 40 km was used for the analysis. It contains a variety of terrain types, from very smooth to very rough. Two reference sites were selected: one in the mountainous area and one on the plains. Calculations were done from each site to assess the predicted visibility (using the database) as well as the expected visibility based on errors between the database and the true terrain. A number of sensitivity studies were done to show the dependence of expected visibility on database error, and also the dependence of both predicted and expected visibility on the various parameter values.

Hard conclusions are difficult to draw in a study of this nature, based as it is on so limited a set of cases. However, several trends emerged that are worth noting. First, the prediction of *masking* is robust across all variations in error, ter-

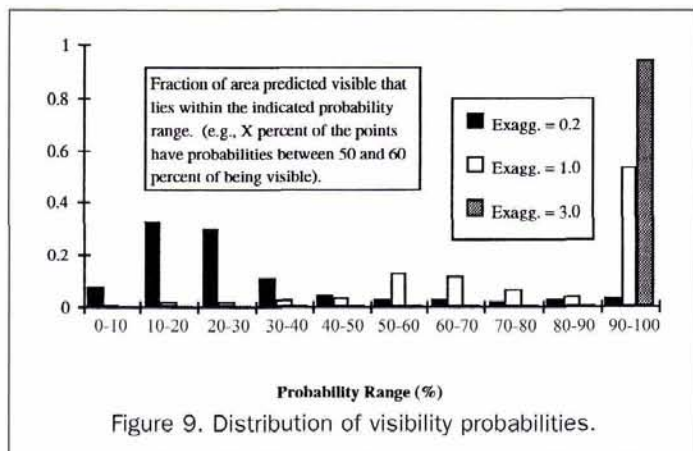
\*These types of evaluations are often made in the context of utility theory. For databases, the analyst evaluates the *utility* of a database of a given accuracy (or feature content, perhaps) in support of the system. From this, the decision maker can determine whether existing databases are acceptable, or whether new databases must be developed.

rain types, and parameter values. That is, the areas predicted (from the database) to be masked are highly likely to be masked in the field. This implies that systems that use the database to find regions of masking (e.g., penetrating aircraft looking for threat avoidance paths) may be able to use databases with moderate to large errors. The amount of error tolerance lies, of course, with the individual system. This result is supported by the results cited by Fisher (1992).

Second, the reliability of visibility predictions is highly dependent on terrain type. The rougher the terrain, the more reliable is predicted visibility. This is because as terrain becomes rougher, the error is proportionally smaller as a contributor to masking. The effect of roughness was evaluated for the plains site by using three exaggeration factors: 0.2 (much smoother), 1.0 (reference), and 3.0 (much rougher). The probability of visibility was also calculated at each terrain point using the methods described above. These probability values for all points predicted visible were then grouped. Figure 9 shows the histogram of these grouped probabilities for all three roughness values. For the rough terrain, most of the points (93 percent) lie in the highest probability band. This means that 93 percent of the points predicted visible have a very high probability of actually being visible in the field. For the smooth terrain (exaggeration = 0.2), most of the points lie in the lower probability regions, and there are very few points that have a high probability of being seen.

Third, both the visibility coverage map itself and its sensitivity to various types of errors are extremely site-specific, and observations or conclusions based on single-point visibility maps should be viewed with skepticism. The entire process is highly nonlinear, in that the sensitivity to a parameter value is dependent on values of other parameters. For example, the sensitivity to database height errors is much greater when either the observer or the target is at very low





altitude. Of particular importance is the effect of features, especially forests. Some current digital mapping techniques can lead to ambiguities with regard to tree height and terrain height.

#### Position

The predicted visibility can be extremely sensitive to position, especially in rough terrain. This sensitivity can result from changing the geometry of the observer relative to obstacles and also changing the elevation of the observer. In one experiment, we found that translating the observer to an adjacent grid point having the same elevation resulted in a 75 percent reduction in predicted visibility. This points out again that all visibility estimates are extremely site-specific.

There is a subtle but significant point to be made from this result. Obviously, when out in the field, the observer will move around slightly to "fine tune" his location for best performance. If he is directed to a location for surveillance of a particular area, he will move around to find the place where he has the best line of sight. One cannot, however, move around as easily in the database to investigate all locations to evaluate line of sight. What the database user needs for this application is an efficient way to evaluate quickly the suitability not just of a point, but rather of a local area as a potential surveillance site. Fortunately, such a method exists, but its description is outside the scope of the current study.

There are many applications where terrain databases could serve a useful support function where intervisibility information is needed. However, the traditional methods of calculation that yield a result of visible/not visible at each point could be significantly misleading, especially if the application depends on the database's reliability in predicting visibility. The approach described in this paper offers a far more meaningful representation of the visibility map, yielding an estimate of the probability that a point will be visible.

The decision maker may thus narrow his choices only to those points where the probability of visibility is highest.

This study demonstrates the significant effects that database errors can have on terrain intervisibility estimation, and it further demonstrates both the value and feasibility of estimating probability of visibility. Further work should be expanded in two primary areas. First, a more rigorous analysis must be made of the computational methods involved in calculating probability of visibility. The methods used for these preliminary results used some approximations in certain areas, and these should be treated with greater rigor. As part of this analysis, better descriptions of the errors in the databases should be made available. This should include more precise descriptions of error correlations.

Second, there is a need for field studies to support the computations. Visibility calculations should be made from the database and then compared with field observations. One possible result of such field studies could be that the approximate methods used in this paper are sufficiently robust for direct use. This would be a highly desirable result, because the current methods are already implemented and are extremely efficient.

#### References

- Fels, J.E., 1992. Viewshed simulation and analysis: An interactive approach, *URISA Proceedings*, Urban and Regional Information Systems Association, 1:264-276.
- Fisher, P.A., 1991. First experiments in viewshed uncertainty: The accuracy of the viewshed area, *Photogrammetric Engineering & Remote Sensing*, 57:1321-1327.
- , 1992. First experiments in viewshed uncertainty: Simulating fuzzy viewsheds, *Photogrammetric Engineering & Remote Sensing*, 58:345-352.
- , 1993. Algorithm and implementation uncertainty in viewshed analysis, *International Journal of Geographical Information Systems*, 7:331-347.
- Lee, J., 1994. Digital analysis of viewshed inclusion and topographic features on digital elevation models, *Photogrammetric Engineering & Remote Sensing*, 60:451-456.
- Marlin, D.A., 1992. *Digital Terrain Evaluation Study*, Hughes Aircraft Co., Advanced Systems Planning, Los Angeles.
- Miller, R., and W.-N. Xiang, 1992. A knowledge-based GIS method for visual impact assessment in transmission line siting, *GIS/LIS Proceedings*, American Society for Photogrammetry and Remote Sensing, 2:577-584.
- Mills, K., G. Fox, and R. Heimbach, 1992. Implementing an intervisibility model on a parallel computing system, *Computers and Geosciences*, 18:1047-1054.
- O'Rourke, K.K., 1992. *Digital Terrain Database Resolution and Accuracy Analysis (DTDRAA)*, AD-B163471, Pacific Sierra Research Corporation, Los Angeles.
- Slocum, K., and M. Collins, 1991. When you can't see the ground for the trees, *Digital DataDigest*, (1), No. 4, USAETL, Ft. Belvoir, Virginia.

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