An experiment on the Elevation Accuracy Improvement of Photogrammetrically derived DEM

Abstract

This paper focuses on a topic barely considered in the literature: how to improve the accuracy of a given Digital Elevation Model (DEM) irrespective of its lineage pointing out to its most suspicious values (also denoted here as outliers). Certainly, there exist methods tailored to a specific procedure and source (contour maps, remote sensing image, etc.), but they are not valid for other cases. This is a delicate problem for both the producer and end user. Here we reported the results of a comparison of two methods using six DEMs intended to be representative of different landscapes. Both methods have been applied to each DEM, producing a prescribed number of height candidates to be analyzed. Assuming that all candidates are wrong, their elevations have been blindly replaced by interpolated heights, simulating the behavior of the inexperienced user. The so improved (or degraded) DEM is compared against the ground truth, and updated accuracy figures are calculated. The experiment shows that the RMSE diminishes an amount between roughly 2 and 8 per cent of the original value by changing less than 1 per cent of the elevations in the dataset.

Keywords: DEM, accuracy assessment of source data, grid data, quality control

1. Introduction

There is a large body of current research towards management of uncertainty in GIS datasets (Lowell and Jaton 1999, Shi *et al.* 1999). This covers the characterization of uncertainties (i.e., recognize them and find means to specify it), the visualization of uncertain data, its storage, and models and strategies able to appropriately take it into account for GIS operations. This situation is common for all types of GIS data. Li and Chen (1999) suggested a "hierarchy of needs" of general applicability but in particular valid for error modeling in DEM. In fig. 1 the author identifies five basic needs, which can be organized in four levels. They are ordered, in the sense that higher levels are ignored unless all lower ones are considered satisfied. According with the author, the bottom level is the one that has received most attention in the literature. It covers the accuracy of original data, its density and distribution, the characteristics of the landscape, as well as the methods used to derive the DEM from the raw data. The second layer is concerned with errors inherent to such raw data, and its characterization. The third level analyzes the effects of the errors previously characterized in the DEM after considering the modeling methods of a particular application. An algorithm able to produce equally likely instances of the DEM with specified uncertainty might be in the future the standard way to accomplish this need (see Fisher 1998 for an example). It should be stressed that we restrict ourselves to the effect on the DEM itself, and not on derived products (see for example Fortin *et al.* 1998, Fisher 1991). The fourth level includes two basic needs, which share similar priority. Error management focuses on methods to deal with errors in output products. It usually takes the form of a specification of minimum accuracy levels, which are different for each application. Error reduction is concerned with methods for reducing or eliminating errors in output products. This paper is devoted to compare the performance of specific methods to partially achieve such goal.

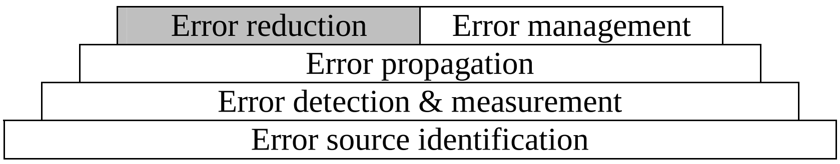

Figure 1. A "hierarchy of needs" for error modeling (modified from Li and Chen, 1999). In gray the topic considered in this paper.

According to Florinsky (1998), a Digital Terrain Model (DTM) can be defined as a digital representation of variables relating to topographic surface, such as Digital Elevation Models (DEM) and digital models of gradient, aspect, horizontal curvature and other topographic attributes. DEM are one of the most popular datasets in GIS applications, either as such or in derived form. They are used in visibility analysis, landslide evaluation, erosion, etc. all being different requirements with also different needs of accuracy. See Florinsky (1998) for a review of joint applications with remote sensing data, or Moore *et al.* (1991) for a broader range of typical applications. Recent efforts in the GIS community focused in the analysis of the propagation of errors for a given operation (Defourny *et al.* 1998, Fortin *et al.* 1998), or the establishment of the knowledge about how to cope with the inherent uncertainty of the dataset (Fortin *et al.* 1998). This will raise concerns among users about the effect of outliers on the final results, and motivate efforts to use reliable and effective "cleaning" tools (if available!).

According to Thapa and Bossler (1992) errors can be classified into three types: (1) gross errors and blunders, (2) systematic errors and (3) random errors. Gross errors and blunders are caused by carelessness or inattention of the observer in using equipment, reading scales or writing down readings, etc. Occasional malfunctioning of the equipment can also cause them. Observations affected by this kind of errors are useless, and should be eliminated. From a statistical point of view they cannot be considered as belonging to the same population as the other observations.

Systematic errors occur in accordance with some deterministic system which, if known, may be represented by some functional relationship. In a statistical sense, systematic errors introduce bias in the observations. Unlike gross errors, they cannot be detected or eliminated by repeated observations (the errors may be *precise*, but they will not be *accurate*). After removal of gross and systematic errors, differences still exist due to random errors. They cannot be removed by repeated observation, and they cannot be modeled with a deterministic relationship. If sufficient observations are taken, random errors posses the following characteristics: a) positive and negative errors occur with almost the same frequency b) small errors occur more often than large errors and c) large errors rarely occur.

Systematic errors have been considered in the literature, and can be attributed to many sources, including poorly selected control points, parameters and so on. The techniques to recover the DEM from them are highly dependent on the lineage (i.e. the methods and algorithms used for produce the DEM) so they are not generally valid. For example, Brown and Bara (1994) suggested a method for detect and correct the systematic error of the USGS 7 ½ minute DEMs.

Some of the references regarding error propagation assume that the DEM is contaminated with just errors following a normal distribution, which might not be the case in many particular DEMs. Most of the literature on accuracy improvement have been designed from the producer side, assuming that the system "...*warns the operator about suspicious values*..." and some correction measure can be taken. End users are left alone, because they do not have access to the original sources (aerial photographs, control points, etc.) or they lack of specialized equipment. Error surfaces stating the expected range of variation for a given confidence level (which are commonplace in the geostatistics community) are barely presented together with the DEM. Thus, if the application is sensitive to the accuracy of the DEM, there is little help for the end user, because a) no tool to pinpoint for unlikely values are available and b) once selected and confirmed that some elevation points are unrealistic, there is no help to estimate reliable values.

Regarding the first aspect, there are few references in the literature. A deterministic approach was used in an early paper by Hannah (1981), who detects non-systematic errors by applying constraints to the slopes and to the changes in slope at each point. Felicísimo (1994) analyzed the differences between the elevation and an interpolated value from the neighbors. Assuming Gaussian distribution of the errors, he analyzed the differences by means of a standard Student t test. No experimental results were given. López (1997) described a method based in the decomposition of the regular grid DEM into strips, and consider it as a multivariate table. Standard statistical techniques have been applied to select the unlikely elevations. He illustrated the performance of the method using synthetic errors only. López (2000) extended his previous method and showed results using two independent DEMs of different accuracy, illustrating hilly terrain. Its ability for other landscapes remains unknown. All of the three abovementioned methods are valid disregarding the lineage of the DEM, i.e. irrespective if it has been generated by direct photogrammetric measurements, digitizing contour lines, field survey, etc. In theory they filter out systematic errors, which are usually related with the generation procedure.

The problem of the most appropriate interpolation procedure has been extensively considered in the literature for DEM generation, and will not be analyzed here. However, their ability in this context has not been addressed. This paper will compare two of the available methods for detecting outliers in six different landscapes; in some sense, it can be complementary to the work of López (2000). In a recent paper (Durañona and López, 2000) a computer implementation of both methods was presented.

The present paper is organized as follows: section 2 describes the DEM data used in the test. Section 3 briefly covers the methods applied, while section 4 presents the numerical results. Section 5 contains the discussion, while acknowledgements and references are included at the end.

2. Data

We will use the set of DEMs for six test areas (see table 1 and figures 2 to 7) produced by the international working group III of the ISPRS in 1983, described by Torlegård *et al.* (1986). They were chosen to represent a variety of terrain types regarding land use, vegetation and surface roughness. For each of them, participants produced a DEM while the organizer produced one with higher accuracy using larger scale photographs. We will use one of the former as input, and make comparisons using the later as a reference. Despite the elevation data is located in a regular grid, there is no data in forest areas. Table 1 summarize the size (rows and columns) of each DEM, its grid size, the coverage (a measure of completeness) as well as maximum and minimum elevation. In Table 1 some statistics of the errors are reported. The headings *max, min, mean* stands for the maximum and minimum elevation, and the mean value over the DEM. The other values are related with the accuracy of the DEM relative to the reference one, which *in this experiment* can be calculated and not merely estimated. *RMSE* is the Root Mean Square of the elevation differences, while *p95* is the 95 per cent percentile of the same differences. The heading *outliers* stand for the estimated number of outliers, as defined by Torlegård *et al.* (1986). For each elevation point, they compare the absolute value of the difference between the error and the median of the errors in the 25 surrounding points. If this value is larger than three times the RMSE of the DEM the error is classified as outlier. Since the outliers affect the RMSE, the procedure is iterated once. The participants produced a number of DEM for the same area, so the heading *DEM id.* identifies which one was used in the analysis reported here (see Tolstoy *et al.* 2000 for further details).

#	*AREA (Country)*	*Size*	*Grid size (m)*	*Coverage (%)*	*Min/Max height ASL (m)*
1	*Spitze (Germany)*	*55x53*	*4.94*	*72.56*	*213/240*
2	*Sohnstetten (Germany)*	*20x104*	*11.37*	*90.96*	*576/640*
3	*Stockholm (Sweden)*	*45x46*	*11.97*	*91.40*	*0/27*
4	*Bohuslan (Sweden)*	*35x64*	*19.80*	*92.05*	*0/43*
5	*Uppland (Sweden)*	*69x36*	*23.20*	*93.16*	*12/45*
6	*Drivdalen (Norway)*	*45x57*	*28.28*	*80.66*	*-224/480*

Table 1 Summary of the characteristics of the available DEMs (from Torlegård et al. 1986). Size stands for the number of columns and rows, and coverage accounts for the missing values.

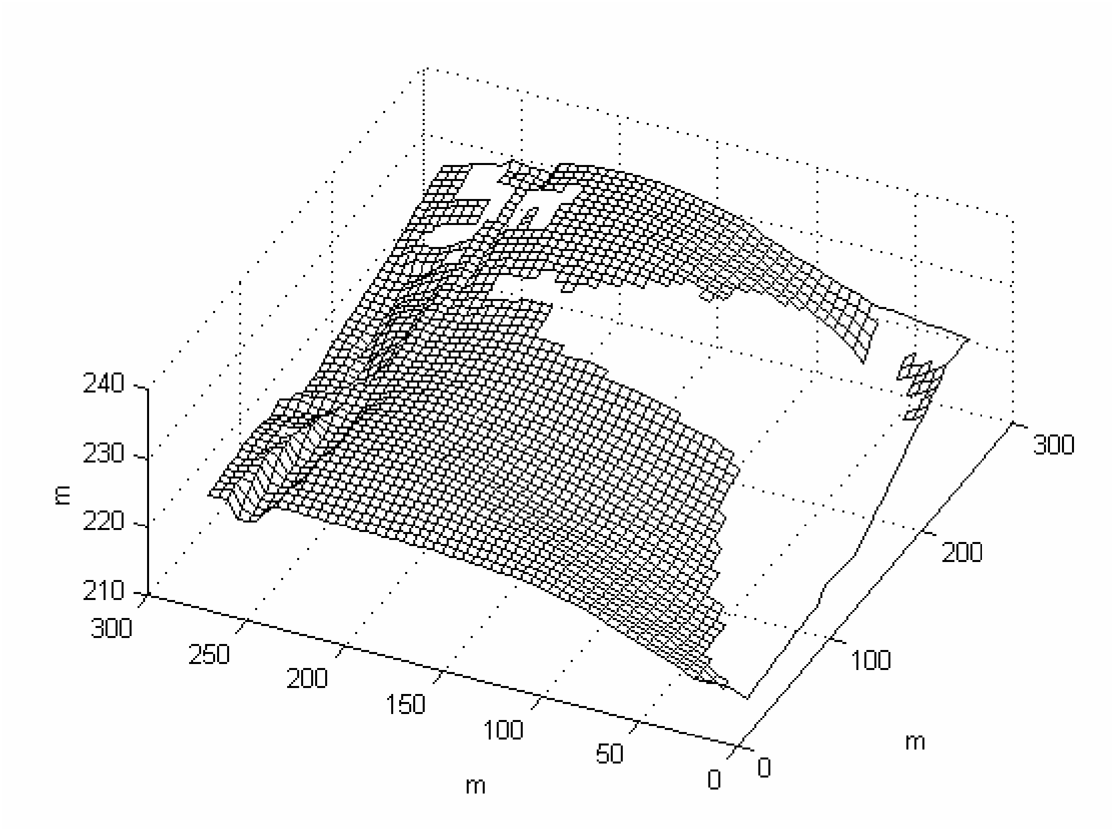

Figure 2 Mesh plot for Spitze. Missing values are not represented

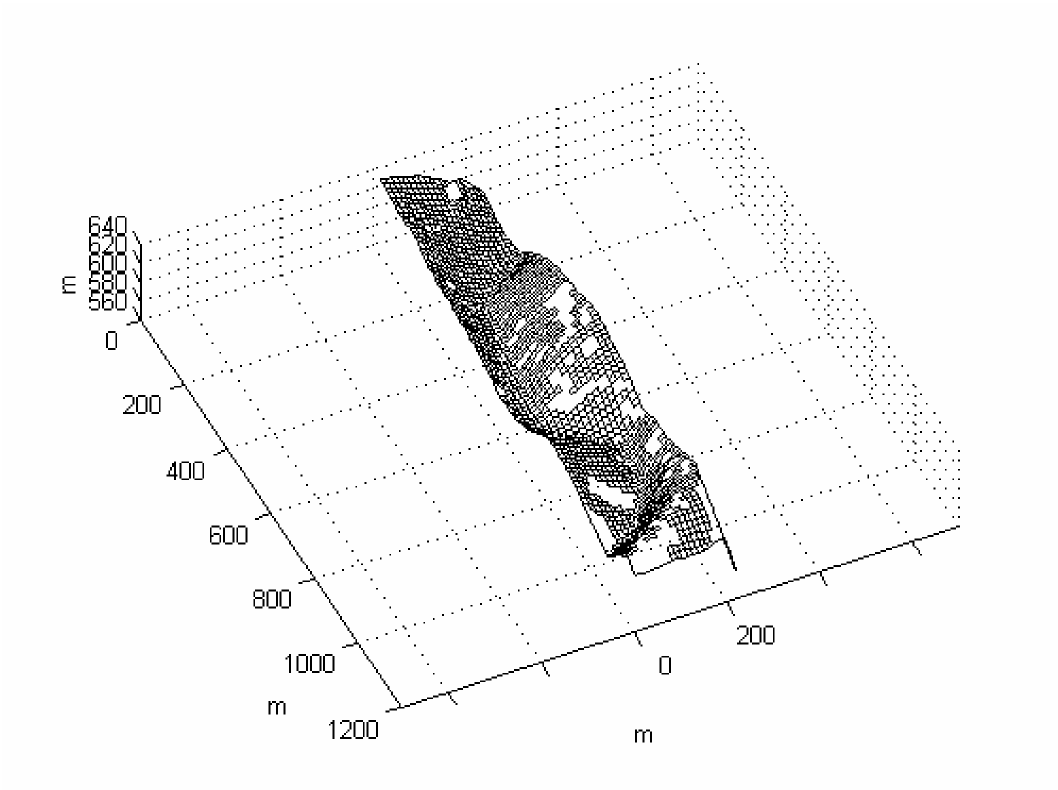

Figure 3 Mesh plot for Sohnstetten. Missing values are not represented

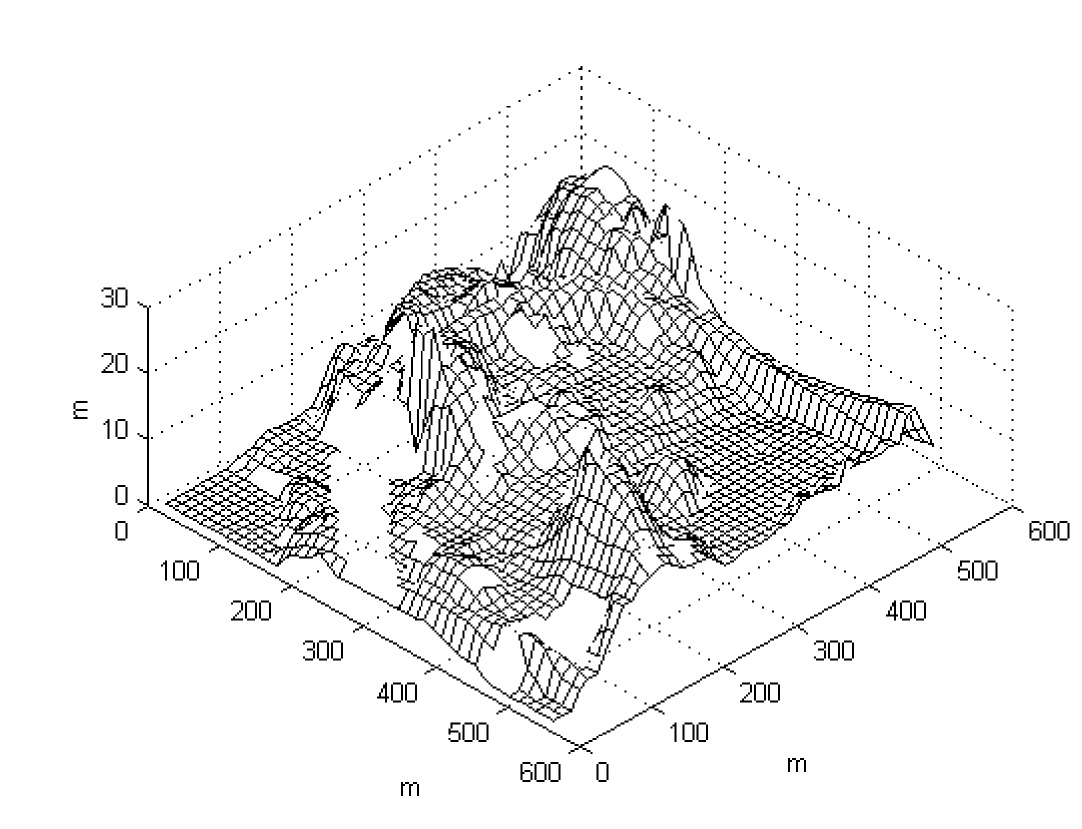

Figure 4 Mesh plot for Stockholm. Missing values are not represented

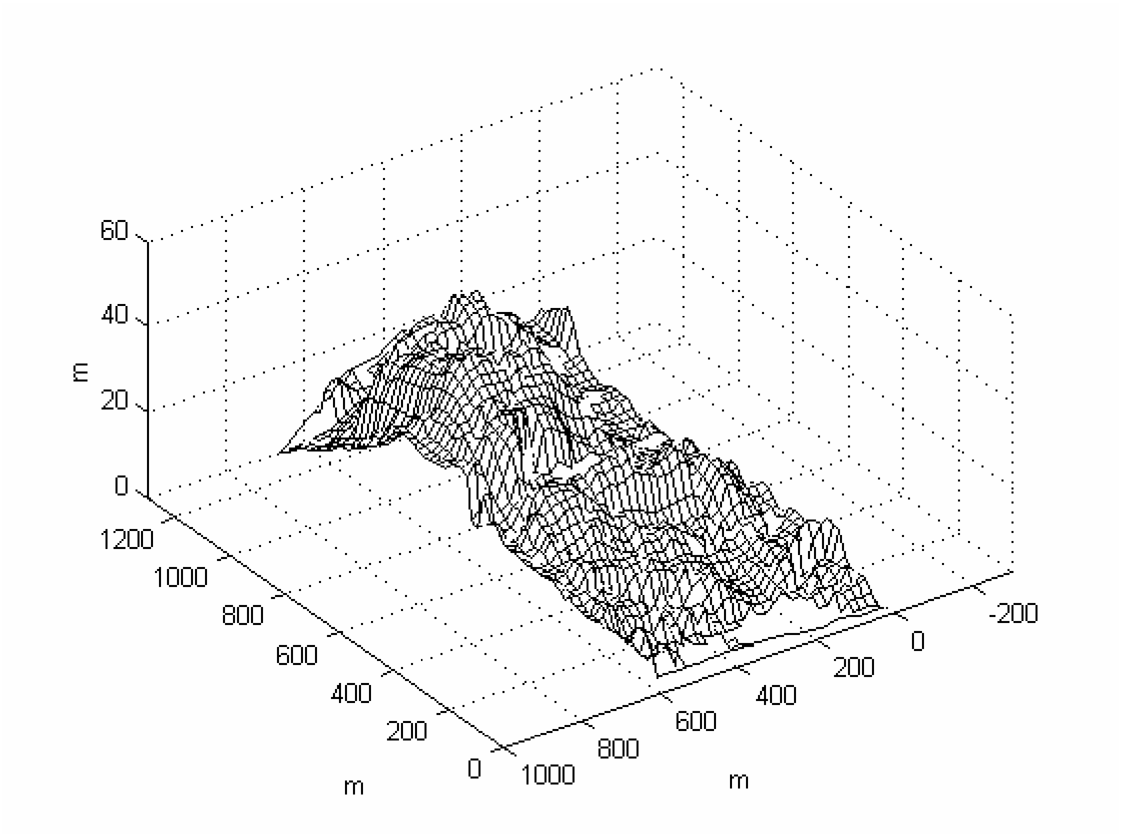

Figure 5 Mesh plot for Bohuslan. Missing values are not represented

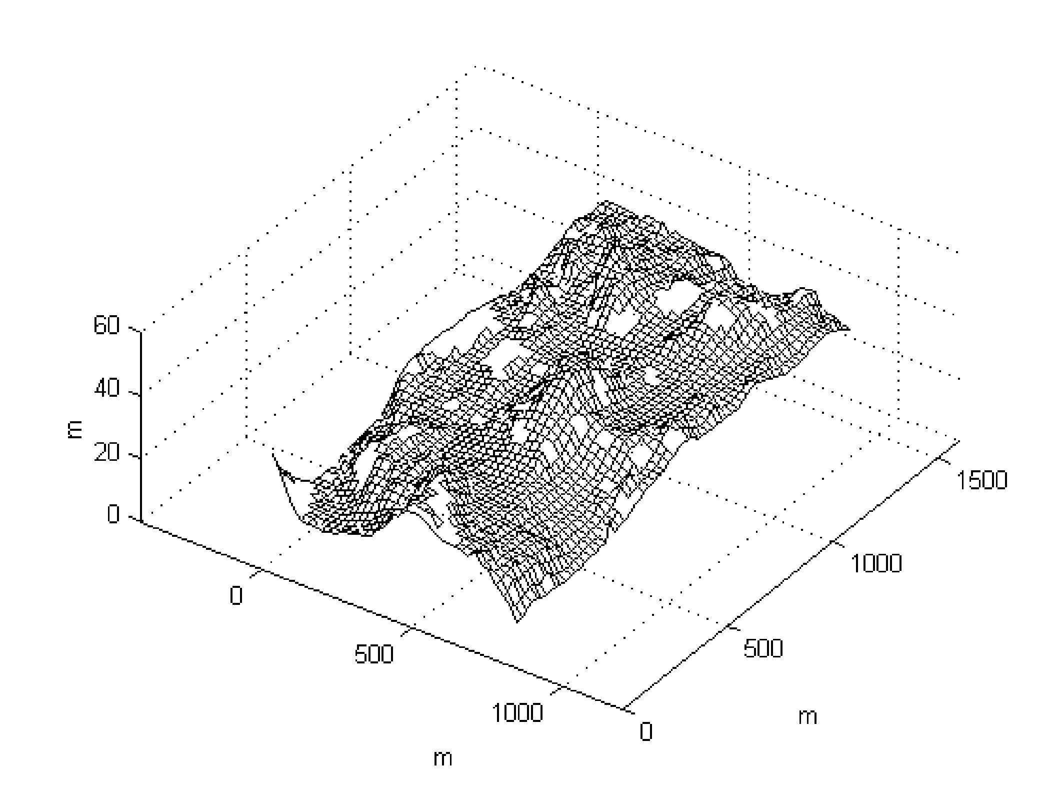

Figure 6 Mesh plot for Uppland. Missing values are not represented

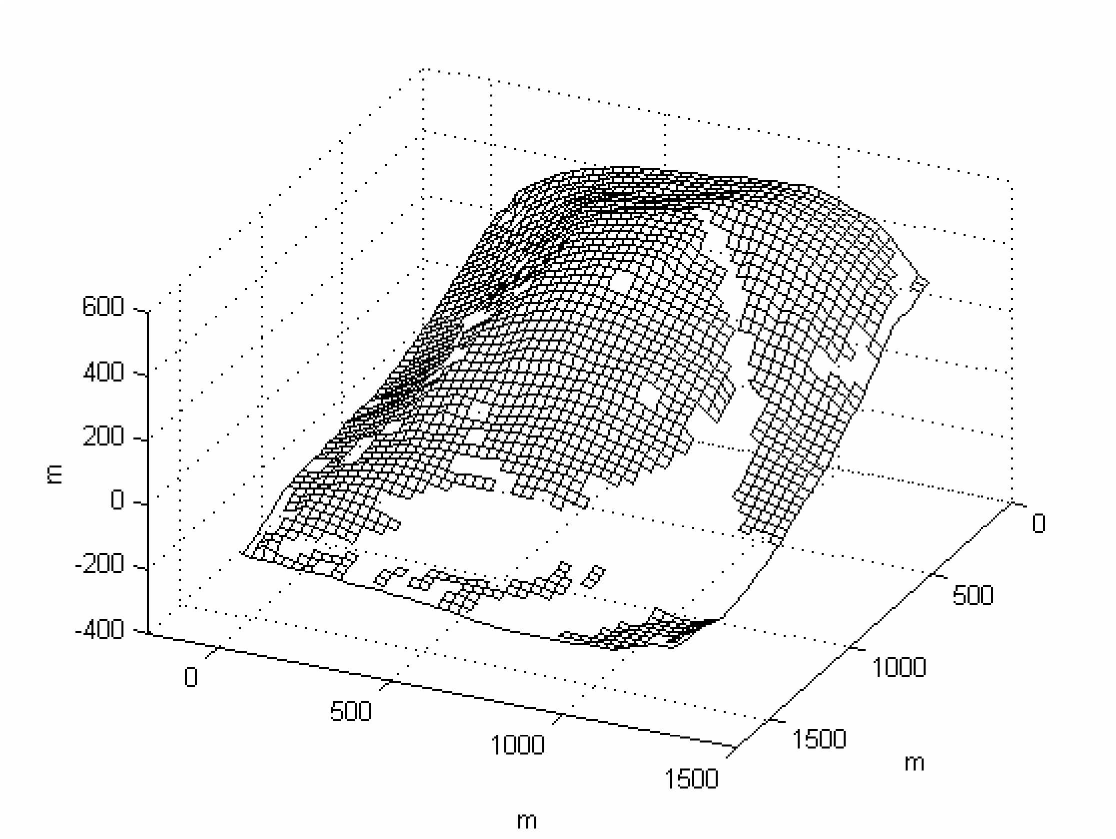

Figure 7 Mesh plot for Drivdalen. Missing values are not represented

According to Östman (1987) the Spitze area is a rural one and very smooth. The Sohnstetten one is also rural, but with undulated hills of moderate height. Sparse trees dominate the landscape, but few areas with denser cover are also present. As a mixed urban and natural sparse cover example we have the Stockholm area. It has also some water bodies in the north. The Bohuslan is an example of rough terrain, with sparse vegetation cover. The Drivdalen area has vegetation cover highly correlated with height: over a prescribed level there is almost no coverage.

Area	*max(m)*	*min(m)*	*mean(m)*	*RMSE(m)*	*p95(m)*	*outliers(%)*	*DEM id.*
Spitze	*1.135*	*-2.716*	*0.075*	*0.162*	*0.278*	*0.51*	*5*
Sohnstetten	*3.465*	*-2.211*	*0.150*	*0.478*	*0.923*	*1.83*	*6*
Stockholm	*8.505*	*-10.636*	*0.813*	*1.274*	*2.370*	*0.72*	*5*
Bohuslan	*3.946*	*-5.795*	*-0.776*	*1.311*	*2.551*	*0.18*	*6*
Uppland	*5.996*	*-4.741*	*-0.119*	*0.973*	*1.969*	*1.01*	*5*
Drivdalen	*30.922*	*-32.151*	*4.284*	*6.746*	*11.514*	*0.44*	*6*

Table 1 Initial values of the traditional accuracy measures. See the text for explanations

The pattern of missing elevations is irregular, being rather isolated spots or contiguous areas, as illustrated in Fig. 8. In order to apply the methods, the datasets need to be complete, and thus they have been imputated with bilinear functions. Such locations have been masked later in order not to select them as candidates to be outliers.

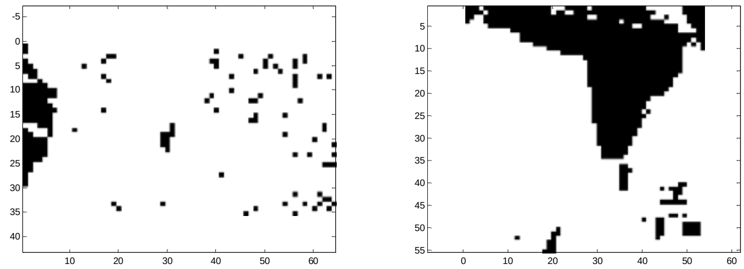

Figure 8 Example of an isolated (Spitze, left) and contiguous (Bohuslan, right) pattern of missing elevations, denoted in black.

3. Methods

For the sake of completeness we will describe briefly the methods of Felicísimo (1994) and López (2000). In addition, we will introduce the metrics of success applied for both methods.

3.1 *The method of Felicísimo (1994)*

This method is based upon very simple ideas. It assumes that outliers are only locally spatially correlated. Thus, they build a statistics calculated as the difference between the given value and an estimate from its immediate neighbors. If such difference has a Gaussian distribution, a Student's t test can be applied to analyze every elevation in the dataset. The mean and standard deviation are estimated from the population, so the outliers themselves might affect them. Given a confidence level, and estimates of the mean and standard deviation, the author describe how to calculate a threshold value in order to decide whether or not the elevation at a given location belongs or not to the overall population. For example, for a confidence level of α=0.001, the outliers are highlighted if the given elevation and the estimate differ more than 3.219 times the standard deviation.

How to obtain the estimate itself is not part of the method. In this work, we applied a best-fit approximation with a biquadratic polynomial using the eight closest neighbors. The author states that even though a significantly high difference does not necessarily imply an outlier, it is an excellent alarm sign. The method appears to be extremely simple and is parameter free (i.e., no tuning phase is required). The method does not require a DEM described in a regular grid.

Since we are analyzing methods to progressively refine the DEM, we must suggest an order among the candidates, being the most unlikely first. Such order is build according the normalized difference $t_{i,j} = \left(\delta_{i,j} - \overline{\delta}\right) / s_\delta$ being $\delta_{i,j}$ the difference between the given elevation value $z_{i,j}$ and the estimated guess $\hat{z}_{i,j}$, being $\overline{\delta}$ and s_δ the mean and standard deviation of the population of $\delta_{i,j}$. The latter values can be severely affected by gross errors. A possible approach is to correct just the worst values, recalculate the mean and standard deviation, and reevaluate the remaining elevation points. If the worst values cannot be classified as outliers, other candidates could be selected. It should be mentioned that there are better strategies (denoted collectively as high breakdown methods) which have in common the ability to extract the "right" estimate of the mean and standard deviation even with a population severe contaminated with outliers of arbitrary size (see Hadi 1992, 1994).

3.2 *The method of López (2000)*

The author first describes a procedure to find unlikely values in elongated DEMs, with length n and width w, being w<<n. Each one of the n cross sections has w elevation values, which can be regarded as the coordinates of points in R^W space. Each one of the w profiles of length n is associated with a coordinate axis in R^W space. Once described in such way, a number of well known methods from statistics can be applied to highlight those points which do not behave as the rest of the cloud (Hadi 1992, 1994, Hawkins 1974, 1993a, 1993b).

Assuming multivariate gaussian distribution, the author uses a modification of the method of Hawkins (1974) based upon Principal Component Analysis (PCA) to calculate a Mahalanobis-like distance from each point to the bulk of the cloud. Those points in R^W (cross sections) with Mahalanobis-like distances larger than a preset value suggest the existence of an outlier in the section.

Notice that the error location procedure directly analyzes the cloud of points in R^W, disregarding any order among points. This is an important assumption, since the concept of spatial self-correlation *based upon geometric distance* looses completely all significance in the cloud. Adjacent profiles (of length n) need not to be in any special order, since they are coordinate axes in the space R^W. However, an unique feature of the method is that it captures some sort of *direction-wise correlation*; if the nxw DEM has two or more profiles (of length n) which are very similar, their mutual correlation will be high and any difference due to outliers will be easily detected. Depending upon its lineage and terrain characteristics, some DEMs are more prone to show high direction-wise correlation than others.

Once the point in R^W is selected, it is necessary to identify which one of the w elevation values makes it unlikely. There might be more than one value, and they are identified after a sensitivity analysis of the Mahalanobis distance. We refer to the original reference for further details.

The requirement n>>w is crucial for having enough points in R^W to properly estimate the correlation matrix. Any given nxm DEM of n rows and m columns might not be so elongated for this method, but it can be divided into strips of size nxw, and the method applied in each one. If m is not an exact multiple of w the strips might overlap in order to consider the whole DEM. The candidates obtained in each strip can be grouped and designated hereinafter as *row-wise* candidates for the whole DEM. The same procedure can be applied to column-wise strips of size wxm, and a different set of *column-wise* candidates can be obtained. The elevation values belonging to both sets are the first ones to be considered as outliers.

As before, the method should be applied in steps, because the outliers might adversely affect all the statistics. The process is supposed to stop when some criteria are fulfilled. In this paper, we continue until a prescribed number of elevations are edited, which is a measure of the effort required to improve the

DEM accuracy. The overall procedure is clearly more complex than the one of Felicísimo (1994), and it requires some user-supplied parameters described in the original reference. In addition, it can be applied only on DEMs defined over a regular grid.

3.3 *The metrics of success*

Let's define a *perfect inspector* as the one which, given a location, can provide a perfectly accurate elevation value for it. Here *perfectly accurate* should be regarding in reference to the correct value with a given technology; such value is also assumed unique. Notice that, by definition, control points are those obtained by a perfect inspector. This hypothesis has some interesting properties while comparing methods. If a given imputation method behaves as a perfect inspector, after selecting 100 per cent of the elevations the RMSE must decrease 100 per cent also down to zero. Thus, if we select at random which elevation value should be corrected, after editing 1 per cent of the elevations we diminish the RMSE just 1 per cent on average. Clever choice of the elevations to edit should render a better improvement, so the relative change of RMSE (in per cent) will be greater than the number of the elevations inspected (also in per cent).

A perfect inspector imputation is certainly possible, but is usually expensive. So, the effort required for editing 100 per cent of the elevations is not considered as a choice, but a limited one might be. Thus, we will define as *effort* the fraction of the whole DEM that we might accept to edit/imputate (with any method, not necessarily the perfect one) in order to improve the accuracy. The effort is expressed in per cent. In real situations (either in the producer or the user role) we must limit our reprocessing of the DEM due to budget, time or other constraints. Let's consider first the producer side. In some cases we can assign *a monetary value* to the accuracy: we have to compare the cost of reworking (usually proportional to the effort) vs. the value of the DEM (usually a decreasing function of the RMSE). The equilibrium point can be calculated, and it will define the effort limit. End users define an effort limit, but for other reasons. They probably are not willing to edit a significant part of the DEM. They might accept at most to be warned by software, and after some inspection, use an estimate instead of the given data. In both cases, the effort limit should be agreed before and will quantify the commitment to make changes in the given DEM.

In this experiment we have at hand the perfect inspector elevations. However, to represent a realistic situation, we imputated the elevations using bilinear interpolation from the neighbors of the candidate point. This procedure is available both to the DEM producer and the end user, since it does not require unavailable information. The procedure is not part of the accuracy improvement method: it simply attempts to mimic the behavior of an inexperienced user. Other users will go to every candidate, display the data and the neighborhood, and take a decision whether or not to change the given value. Here, we decided to accept every candidate as suggested by the methods, and change the elevation as described. Notice that, with this imputation method, there is neither no guarantee nor arguments to claim that after 100 per cent effort all the errors will be eliminated, and it is also hard to argue that the RMSE must even decrease. The interpolated value might be worse than the original one.

For both methods, we will select up to a prescribed number of elevation spots, related with the effort limit and the size of the DEM itself. As presented before, if the relative change of the accuracy is larger than the effort, we are performing better than mere chance. A similar argument can be raised for the percentile 95 per cent of the errors.

The process is as follows: the methods were applied, and they selected a small set of candidates representing some effort. Once edited, new accuracy figures can be calculated up to that effort. The process continues until we exceeded the specified effort limit. Then, we interpolate the accuracy figures to prescribed stations, like [0.25, 0.50, 1.00] per cent. Unlike other authors, and since the RMSE is badly affected by even few outliers, we have also considered the percentile 95 per cent of the absolute errors as a significant accuracy figure.

The 1 per cent effort limit was chosen following Torlegård *et al*. (1986), and is of the order of the number of outliers found in the DEMs. Their estimate of the initial number of outliers for the six DEM models has been presented in Table 1.

4. Results

We want to summarize some results in Table 2, while more details will be given in Table 3. Almost all the entries in Table 2 are over 1.000 and some clearly over, which shows that both methods are better than the mere chance. Only for the Bohuslan area and for the p95 statistics the values are lower than 1.000, which must be interpreted that (on average) the method behaves worse than random selection of the candidates. Notice that no negative entries arise, so the combined (error detection + simple interpolation) strategy did not degrade the accuracy.

It should be stressed that the accuracy in this experiment is always *calculated* (not *estimated*) by comparing against the respective reference DEM for *all* elevation values. In real situations this is not possible; the accuracy is just estimated (not *calculated*), and the estimation is performed by comparing elevations from higher accuracy sources (typically field values) against the given DEM.

The worst values correspond to Bohuslan. According to Torlegård *et al*. (1986), this DEM has just 0.18 per cent outliers (as defined by them), which is significantly less than 1 per cent. If they were right, this implies that we are editing not only blunders but also regular errors, which is a situation outside the hypothesis for both methods. The case of Uppland is unique in the sense that, in terms of the RMSE, F1994 is better, but the situation is the opposite for the percentile 95 per cent. This shows that L2000 is more prone to pick in this case the worst values while F1994 picks a bunch of not-too-extremely-large errors. The methods applied to the Stockholm DEM show better performance by F1994. The area is very complex, with a number of roads and urban areas, which might require further analysis. The other DEMs shown better or clearly better performance for L2000, for smooth and rugged terrain as well. However, all the statistics should be analyzed with caution, because the DEM test are rather small (i.e. few elevation points) to derive strong conclusions. The L2000 method is more sensitive than F1994 to this aspect, because it requires an undefined "large" number of rows and columns, which is not the case in any of the samples (for Sohnstetten there are only 20 rows for the analysis!). In addition, the missing elevations have been interpolated, and both methods were applied after the interpolation, deriving statistics that might not reflect well the original variability of the data. This explains why, despite good, the performance is not as good as reported before (López, 2000). For accuracy as RMSE, and for 1 per cent effort, the author reported a RMSE decrease of 4.701 per cent for a rugged mountain area, while for the method F1994 the same figure is 3.675 per cent.

We want to stress that both methods were designed to pick just outliers. If a significant part of the initial RMSE error of a given DEM is due to outliers, a substantial improvement can be obtained even by a limited editing effort, as shown in this paper. If the bulk of the errors arise from systematic reasons, the methods will not contribute significantly to any accuracy improvement.

Figures 9 and 10 show the evolution of the accuracy vs. effort for the case of the RMSE and the percentile 95 per cent for Drivdalen. The dashed area shows the lower boundary for the behavior of *any possible* method. The limit curve is obtained by selecting one at a time the largest outlier in the DEM, imputating it with the perfect inspector's elevation value and repeating until a given effort is accomplished. No method can do better. All the required information to proceed this way is available for this experiment, but not in real cases. Notice that the perfect method requires both a *perfect outlier location method* and a *perfect inspector* in order to imputate the values. At the 1 per cent effort, this perfect method is able to decrease significantly the RMSE, showing that there is still room for improvement.

Four additional curves are shown: one for the method of Felicísimo (1994) and three for the other method, corresponding to different number of Principal Components dropped from the Mahalanobis distance calculation (see López, 2000 for further details). As suggested in the reference, we estimated "2" as the best value for Drivdalen, and Table 3 summarizes the results for such option. If we go further with the effort (beyond 1 per cent) we might notice that the performance (RMSE decrease vs. effort) degrades significantly. This fact (not shown in the figure) confirms the assertion of Torlegård *et al.* (1986) regarding the small number of outliers in the dataset.

AREA	*(RMSE(1%)-RMSE(0%)) / RMSE(0%)*		*(p95(1%)-p95(0%)) / p95(0%)*	
	F1994	*L2000*	*F1994*	*L2000*
Spitze	*1.235*	*8.642*	*1.439*	*1.439*
Sohnstetten	*4.393*	*4.812*	*2.600*	*3.034*
Stockholm	*2.198*	*1.962*	*5.612*	*1.350*
Bohuslan	*1.144*	*1.068*	*0.706*	*0.510*
Uppland	*4.111*	*2.878*	*1.574*	*1.727*
Drivdalen	*1.349*	*2.224*	*1.181*	*1.285*

Table 2 Summary of the results of the test. "RMSE(x%)" stands for accuracy (as RMSE) after editing x% of the elevations in the DEM, while "p95(x%)" stands for the percentile 95% of the absolute elevation error, etc. F1994 and L2000 stands for the methods applied. In gray those cases where F1994 outperforms L2000.

AREA	*max (1%) (m)*		*min (1%) (m)*		*mean(1%) (m)*		*RMSE(1%) (m)*		*p95(1%) (m)*	
	F1994	*L2000*	*F1994*	*L2000*	*F1994*	*L2000*	*F1994*	*L2000*	*F1994*	*L2000*
Spitze	*1.135*	*0.728*	*-2.716*	*-0.592*	*0.077*	*0.076*	*0.160*	*0.148*	*0.274*	*0.274*
Sohnstetten	*3.300*	*3.465*	*-2.211*	*-2.211*	*0.149*	*0.148*	*0.457*	*0.455*	*0.899*	*0.895*
Stockholm	*8.505*	*6.908*	*-10.636*	*-10.636*	*0.813*	*0.806*	*1.246*	*1.249*	*2.237*	*2.338*
Bohuslan	*3.946*	*3.946*	*-5.795*	*-5.795*	*-0.773*	*-0.770*	*1.296*	*1.297*	*2.533*	*2.538*
Uppland	*5.357*	*5.885*	*-3.923*	*-4.602*	*-0.116*	*-0.111*	*0.933*	*0.945*	*1.938*	*1.935*
Drivdalen	*30.922*	*30.922*	*-32.151*	*-29.167*	*4.308*	*4.325*	*6.655*	*6.596*	*11.378*	*11.366*

Table 3 Accuracy statistics reported after 1 per cent effort discriminated by method and area. Initial values were reported in Table 1

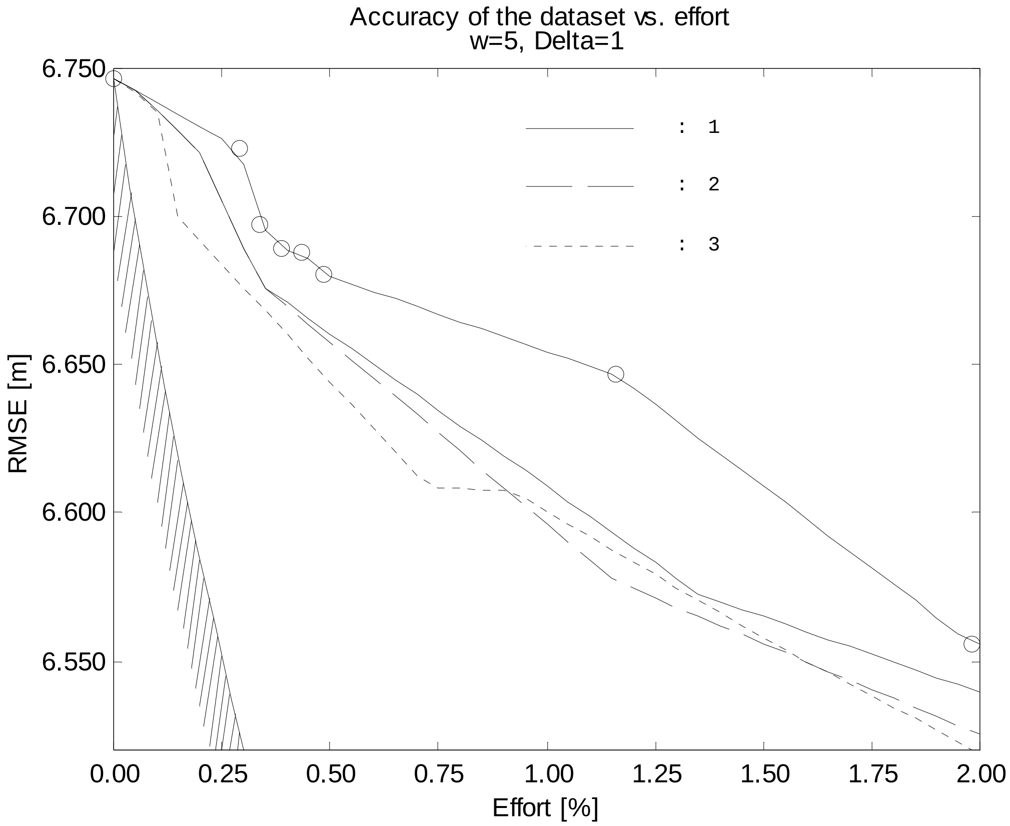

Figure 9 Evolution of the accuracy as RMSE up to an effort of 2.0 per cent for the case of Drivdalen. Symbol "-o-" denotes experimental points for method F1994. The others are for different parameters of method L2000. The border of the dashed region denotes the best possible operation line. All the curve values were obtained after linear interpolation between experimental points.

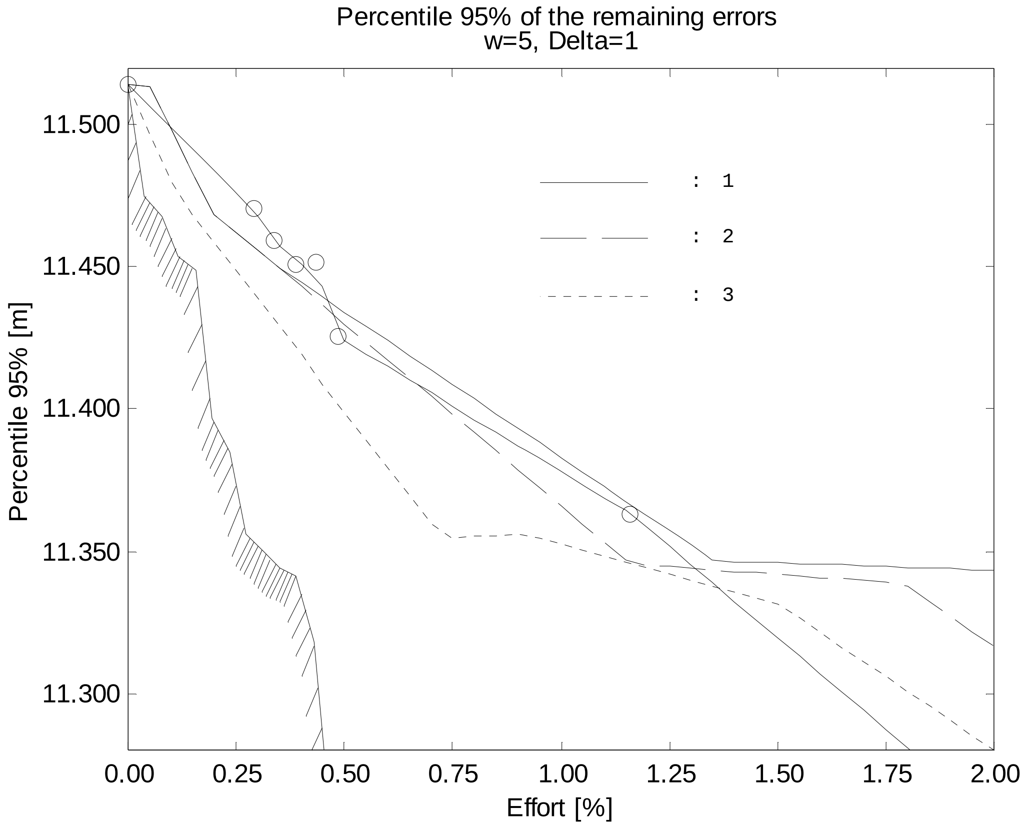

Figure 10 Evolution of the percentile 95 per cent of the error up to an effort of 2.0 per cent for the case of Drivdalen. Symbol "-o-" denotes experimental points for method F1994. The others are for different parameters of method L2000. The border of the dashed region denotes the best possible operation line. All the curve values were obtained after linear interpolation between experimental points.

5. Conclusions

Errors in any DEM might adversely affect its usefulness for a particular application, so they need to be modeled and taken into consideration. Usually, both the systematic and random errors are modeled jointly using a Gaussian distribution. Its parameters can be estimated using control points and the DEM itself provided that no outliers are present; otherwise they might be severely affected.

In this paper, we have presented preliminary quantitative results of the comparison of two methods for outlier detection for DEM applied over six cases representative of different landscapes. Systematic errors are not considered. Both methods produce an ordered set of location candidates to be outliers. In real cases, the operator will go through the list and decide whether or not a particular elevation is wrong. Here, we blindly imputated the elevation by bilinear approximation using its immediate neighbors, trying to mimic the behavior of automatic equipment or inexperienced operators. In any case, the process is iterative because outliers affect the statistics of the DEM and indirectly the numbers used by the methods themselves and continues until a prescribed fraction of the DEM has been edited. The results in terms of RMSE or percentile 95 per cent of the elevation error demonstrated that a significant improvement in the accuracy for both methods could be achieved. Previous papers on the subject lack for a comparison with different landscapes, which is the main contribution of this one. The best results were for the method by López (2000). In all but one case it diminished the RMSE more than 2 per cent irrespective of the landscape, while the performance of the method by Felicísimo (1994) were more irregular. These results should be taken with caution and can be regarded as conservative for the method described by López (2000) because the DEM samples were not particularly appropriate for its application due to its limited size.

For other DEMs, the significance of the accuracy improvement depends upon the number and size of outliers in the dataset: if they are known to contribute significantly to the accuracy, the methods might provide a good strategy for improvement. If most of the accuracy is due to systematic errors, the methods are of little use.

Acknowledgments

The author would like to thank Professors Kennert Torlegård of the Royal Institute of Technology, Stockholm, Sweden, Anders Östman of the Luleå Technical University, Luleå, Sweden, Miguel Águila, Ariel Pérez and Rocío Tolstoy of the University of the Republic, Montevideo, Uruguay, for their support while interpreting the ISPRS83 DEM dataset. This paper has benefited from the comments of two anonymous reviewers.

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Montevideo, April 24th, 2001

Dr. Peter Fisher

Midlands Regional Research Laboratory

Department of Geography

University of Leicester

Leicester LE1 7RH

United Kingdom

Dear Prof. Fisher

Attached you will find a paper for reconsideration. It has been rejected before by reasons I took into consideration in this (new) draft.

I should mention that a significantly shorter paper with the same title has already been presented at the Accuracy 2000 conference, held in Amsterdam last July. No other journal is currently reviewing this material.

Hope to hear from you soon

Best wishes

Carlos

Montevideo, June 6th, 2000

Dr. Peter Fisher

Midlands Regional Research Laboratory

Department of Geography

University of Leicester

Leicester LE1 7RH

United Kingdom

Dear Prof. Fisher

Attached you will find a paper for reconsideration. It has been rejected before. I have considered most of the observations from reviewer 3, as well as made my best regarding opinions of reviewer 2.

I should mention again that significantly shorter paper with the same title has been already been accepted for the conference Accuracy 2000, to be held in Amsterdam in July. The organizers claim that some selected papers will be considered for publication at IJGIS, and for personal reasons I want to review this as soon as possible. No other journal is currently reviewing this material.

Hope to see you again soon

Best wishes

Carlos

Montevideo, February 16th, 2000

Dr. Peter Fisher

Midlands Regional Research Laboratory

Department of Geography

University of Leicester

Leicester LE1 7RH

United Kingdom

Dear Prof. Fisher

Attached you will find a paper for your consideration. A significantly shorter paper with the same title has been already been accepted for the conference Accuracy 2000, to be held in Amsterdam in July. The organizers claim that some selected papers will be considered for publication at IJGIS, and for personal reasons I want to review this as soon as possible. No other journal is currently reviewing this material.

Hope to see you again soon

Best wishes

Carlos

band1

DELTA =

1

Metodo de Felicisimo. 1994

abscisa	SKEW	MU	SD	P95	MAX	MIN	accuracy
0.000;	0.898;	0.075;	0.144;	0.278;	1.135;	-2.716;	0.162
0.250;	0.878;	0.075;	0.143;	0.277;	1.135;	-2.716;	0.162
0.500;	0.857;	0.076;	0.142;	0.276;	1.135;	-2.716;	0.161
1.000;	0.804;	0.077;	0.142;	0.274;	1.135;	-2.716;	0.160
2.000;	0.851;	0.078;	0.141;	0.273;	1.135;	-2.716;	0.159
2.500;	0.844;	0.078;	0.141;	0.273;	1.135;	-2.716;	0.159
3.000;	0.818;	0.078;	0.140;	0.272;	1.135;	-2.716;	0.158
5.000;	0.804;	0.078;	0.139;	0.269;	1.135;	-2.716;	0.156
10.000;	0.570;	0.079;	0.134;	0.260;	0.507;	-2.716;	0.147

1 sin controlar y w=5

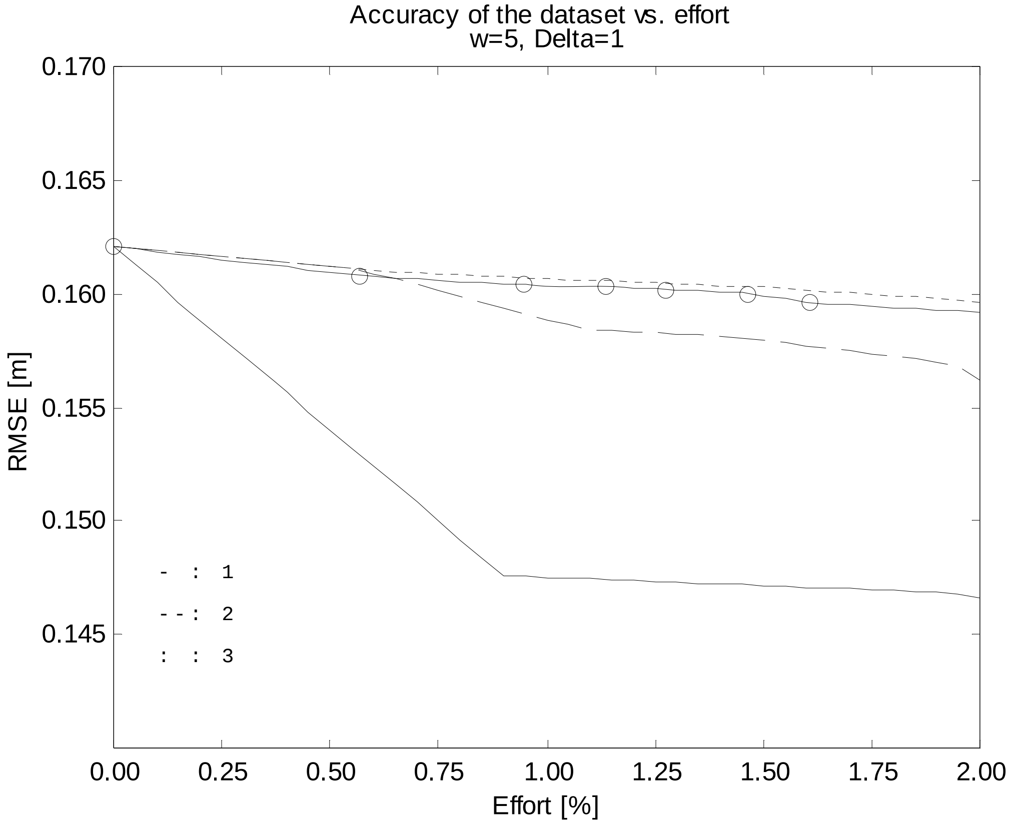
abscisa	SKEW	MU	SD	P95	MAX	MIN	accuracy
0.000;	0.898;	0.075;	0.144;	0.278;	1.135;	-2.716;	0.162
0.250;	0.964;	0.075;	0.139;	0.277;	1.022;	-2.125;	0.158
0.500;	1.030;	0.076;	0.135;	0.276;	0.908;	-1.534;	0.154
1.000;	1.135;	0.076;	0.127;	0.274;	0.728;	-0.592;	0.148
2.000;	1.118;	0.076;	0.127;	0.274;	0.728;	-0.584;	0.147
2.500;	1.041;	0.077;	0.126;	0.273;	0.728;	-0.544;	0.146
3.000;	1.054;	0.077;	0.125;	0.272;	0.728;	-0.544;	0.145
5.000;	1.013;	0.078;	0.123;	0.268;	0.728;	-0.544;	0.142
10.000;	0.804;	0.080;	0.121;	0.265;	0.728;	-0.544;	0.137

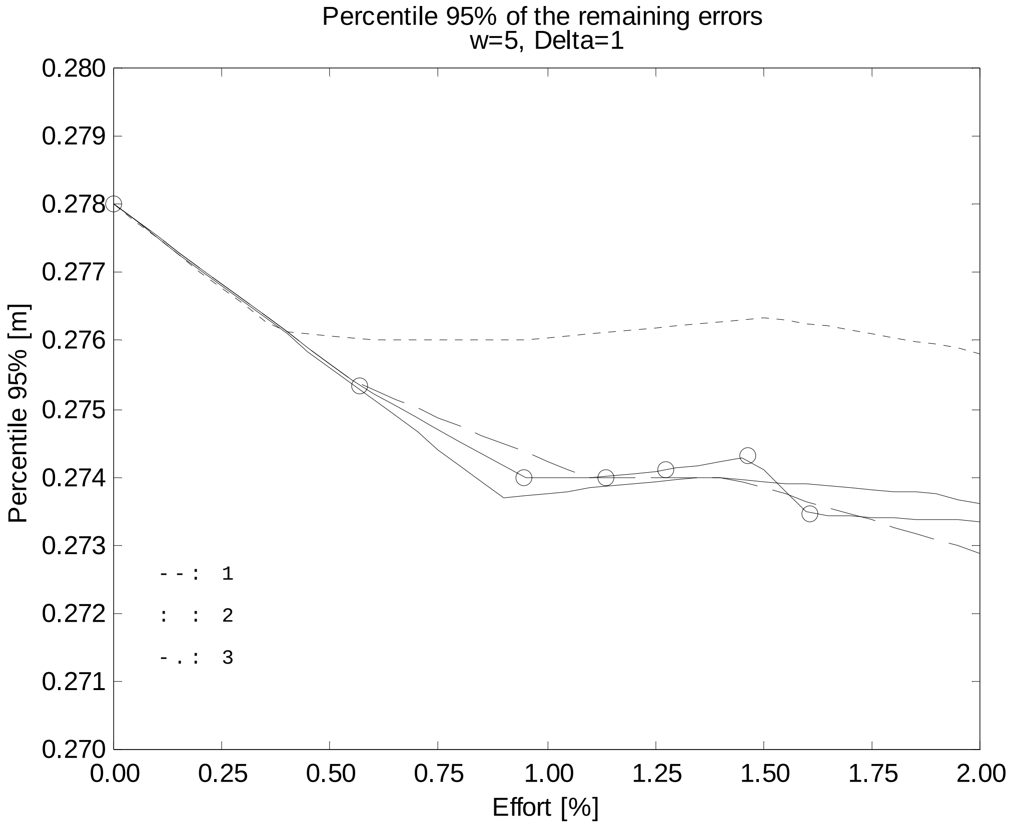
2 sin controlar y w=5

abscisa	SKEW	MU	SD	P95	MAX	MIN	accuracy
0.000;	0.898;	0.075;	0.144;	0.278;	1.135;	-2.716;	0.162
0.250;	0.878;	0.075;	0.143;	0.277;	1.135;	-2.716;	0.162
0.500;	0.857;	0.075;	0.143;	0.276;	1.135;	-2.716;	0.161
1.000;	0.851;	0.074;	0.141;	0.274;	0.796;	-2.716;	0.159
2.000;	0.864;	0.074;	0.139;	0.273;	0.728;	-2.593;	0.156
2.500;	0.973;	0.075;	0.132;	0.272;	0.728;	-1.595;	0.150
3.000;	1.082;	0.076;	0.126;	0.271;	0.728;	-0.596;	0.145
5.000;	1.033;	0.077;	0.123;	0.269;	0.728;	-0.519;	0.142
10.000;	0.757;	0.080;	0.120;	0.263;	0.728;	-0.501;	0.136

3 sin controlar y w=5

abscisa	SKEW	MU	SD	P95	MAX	MIN	accuracy
0.000;	0.898;	0.075;	0.144;	0.278;	1.135;	-2.716;	0.162
0.250;	0.867;	0.075;	0.143;	0.277;	1.135;	-2.716;	0.162
0.500;	0.851;	0.075;	0.143;	0.276;	1.135;	-2.716;	0.161
1.000;	0.851;	0.075;	0.143;	0.276;	1.135;	-2.716;	0.161
2.000;	0.804;	0.075;	0.143;	0.276;	1.124;	-2.716;	0.160
2.500;	0.804;	0.075;	0.141;	0.274;	0.733;	-2.716;	0.157
3.000;	0.804;	0.075;	0.140;	0.274;	0.728;	-2.716;	0.157
5.000;	0.749;	0.076;	0.138;	0.272;	0.728;	-2.716;	0.154
10.000;	0.709;	0.078;	0.137;	0.268;	0.728;	-2.716;	0.150





10.000; 0.756; 0.080; 0.120; 0.263; 0.728; -0.499; 0.136

band2

DELTA =

1

llegue para las graficas con los resultados de felicisimo. 1994

Metodo de Felicisimo. 1994

abscisa	SKEW	MU	SD	P95	MAX	MIN	accuracy
0.000;	1.850;	0.150;	0.454;	0.923;	3.465;	-2.211;	0.478
0.250;	1.796;	0.151;	0.453;	0.923;	3.466;	-2.211;	0.476
0.500;	1.799;	0.150;	0.449;	0.918;	3.429;	-2.211;	0.473
1.000;	1.729;	0.149;	0.435;	0.899;	3.297;	-2.211;	0.457
2.000;	1.691;	0.149;	0.434;	0.898;	3.300;	-2.211;	0.454
2.500;	1.667;	0.149;	0.433;	0.896;	3.289;	-2.211;	0.452
3.000;	1.628;	0.150;	0.431;	0.888;	3.317;	-2.211;	0.449
5.000;	1.524;	0.150;	0.408;	0.831;	2.632;	-2.211;	0.424
10.000;	1.428;	0.157;	0.397;	0.815;	2.674;	-2.211;	0.405

1 sin controlar y w=5

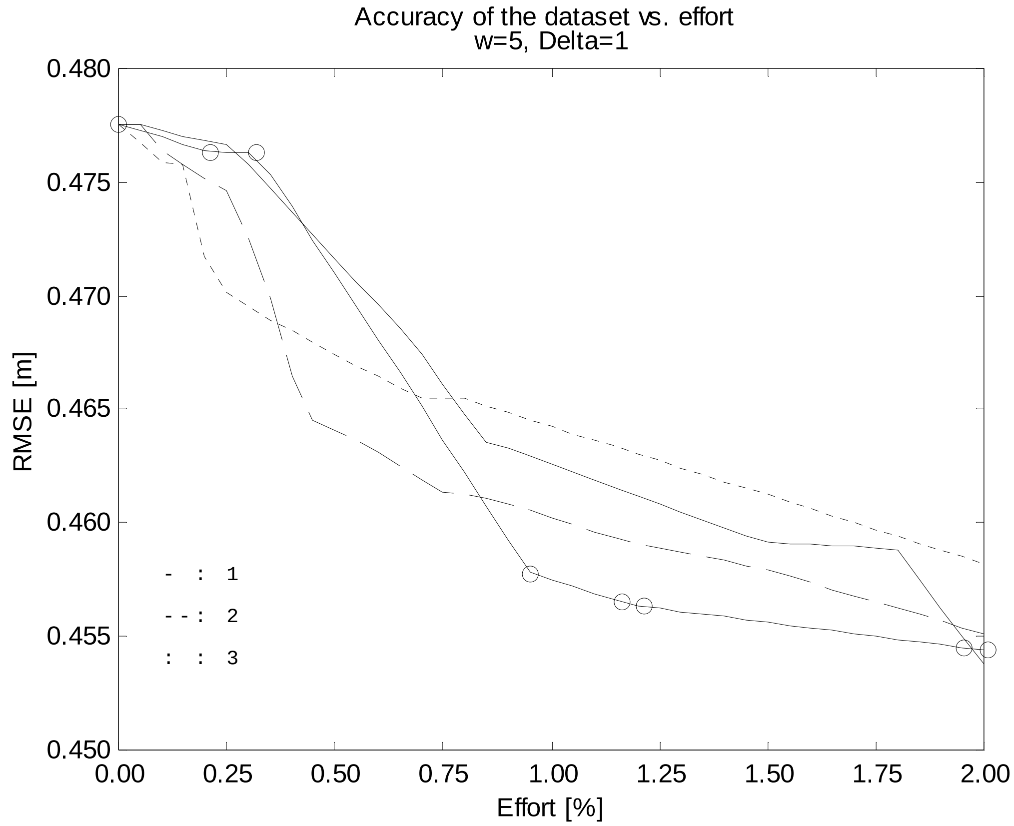
abscisa	SKEW	MU	SD	P95	MAX	MIN	accuracy
0.000;	1.850;	0.150;	0.454;	0.923;	3.465;	-2.211;	0.478
0.250;	1.797;	0.151;	0.453;	0.923;	3.465;	-2.211;	0.476
0.500;	1.782;	0.150;	0.448;	0.916;	3.417;	-2.211;	0.471
1.000;	1.732;	0.149;	0.435;	0.900;	3.300;	-2.211;	0.457
2.000;	1.691;	0.149;	0.434;	0.898;	3.300;	-2.211;	0.454
2.500;	1.661;	0.149;	0.433;	0.894;	3.300;	-2.211;	0.452
3.000;	1.631;	0.150;	0.431;	0.887;	3.300;	-2.211;	0.449
5.000;	1.526;	0.150;	0.409;	0.833;	2.674;	-2.211;	0.425
10.000;	1.427;	0.157;	0.397;	0.815;	2.674;	-2.211;	0.405

2 sin controlar y w=5

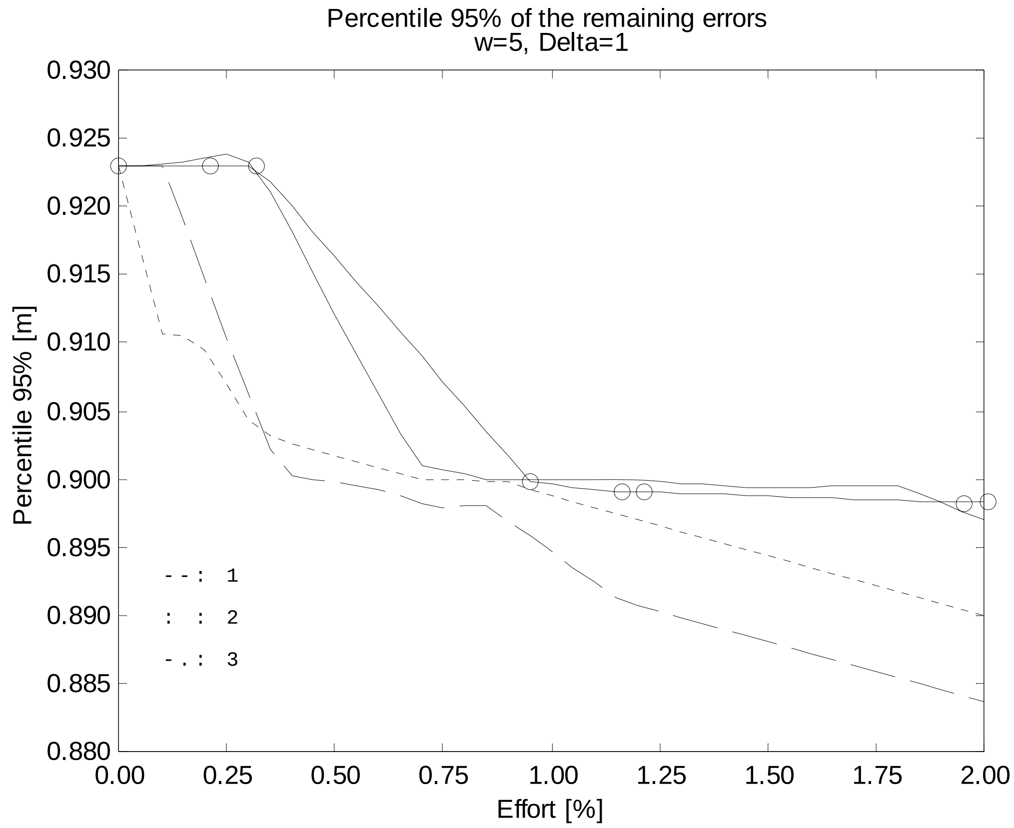
abscisa	SKEW	MU	SD	P95	MAX	MIN	accuracy
0.000;	1.850;	0.150;	0.454;	0.923;	3.465;	-2.211;	0.478
0.250;	1.749;	0.151;	0.451;	0.910;	3.465;	-2.211;	0.475
0.500;	1.797;	0.149;	0.441;	0.900;	3.465;	-2.211;	0.464
1.000;	1.718;	0.148;	0.438;	0.895;	3.465;	-2.211;	0.460
2.000;	1.648;	0.149;	0.435;	0.884;	3.465;	-2.211;	0.455
2.500;	1.606;	0.149;	0.433;	0.879;	3.465;	-2.211;	0.452
3.000;	1.565;	0.150;	0.431;	0.875;	3.465;	-2.211;	0.450
5.000;	1.425;	0.151;	0.424;	0.854;	3.465;	-2.211;	0.439
10.000;	1.303;	0.157;	0.411;	0.824;	3.465;	-2.100;	0.417

3 sin controlar y w=5

abscisa	SKEW	MU	SD	P95	MAX	MIN	accuracy
0.000;	1.850;	0.150;	0.454;	0.923;	3.465;	-2.211;	0.478
0.250;	1.831;	0.149;	0.447;	0.907;	3.465;	-2.211;	0.470
0.500;	1.745;	0.150;	0.444;	0.902;	3.465;	-2.211;	0.467
1.000;	1.744;	0.149;	0.442;	0.899;	3.465;	-2.211;	0.464
2.000;	1.701;	0.149;	0.438;	0.890;	3.465;	-2.211;	0.458
2.500;	1.662;	0.149;	0.436;	0.884;	3.465;	-2.191;	0.455
3.000;	1.611;	0.150;	0.432;	0.877;	3.465;	-2.155;	0.450
5.000;	1.533;	0.151;	0.426;	0.866;	3.465;	-2.100;	0.441
10.000;	1.268;	0.148;	0.417;	0.839;	3.465;	-2.100;	0.420



Accuracy of the dataset vs. effort
w=5, Delta=1
RMSE [m]
Effort [%]
- : 1
- - : 2
: : 3



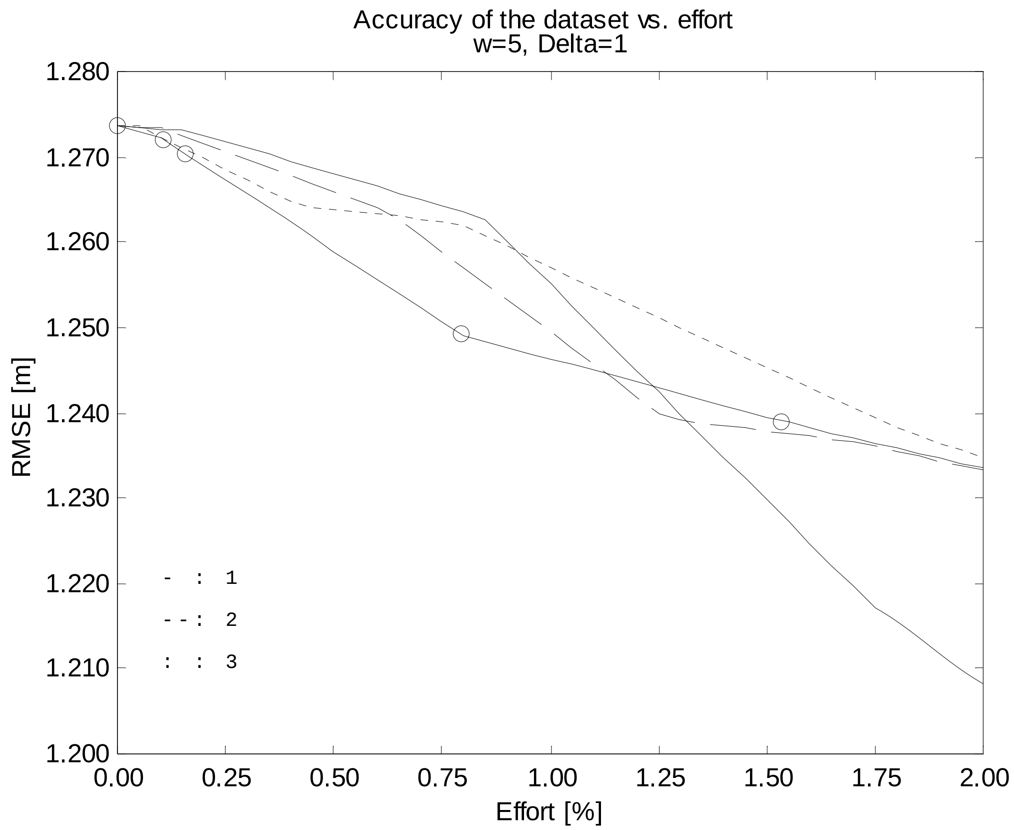
Percentile 95% of the remaining errors
w=5, Delta=1
Percentile 95% [m]
Effort [%]
- - : 1
: : 2
- . : 3

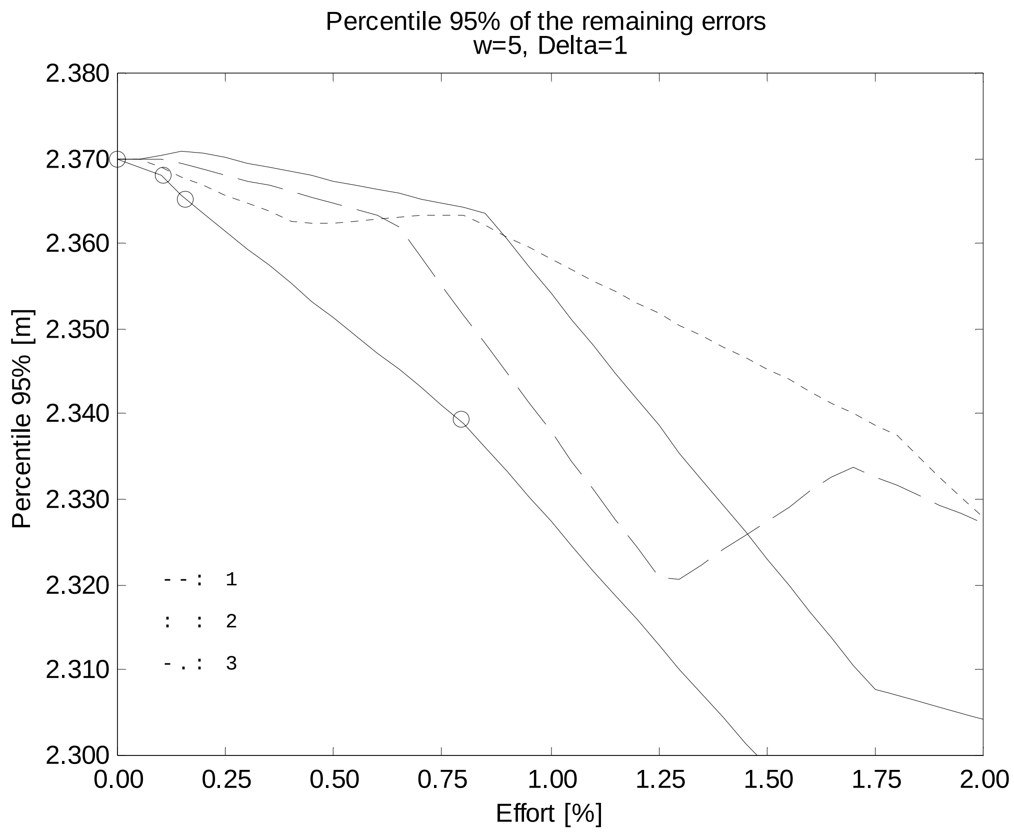
band3

```
Metodo de Felicisimo. 1994
  abscisa   SKEW      MU       SD    P95     MAX     MIN
accuracy
   0.000;  1.321;  0.813;  0.981;  2.370;  8.505;-10.636;
1.274
   0.250;  1.329;  0.811;  0.976;  2.361;  8.505;-10.636;
1.267
   0.500;  1.350;  0.812;  0.966;  2.351;  8.505;-10.636;
1.259
   1.000;  1.359;  0.813;  0.953;  2.327;  8.505;-10.636;
1.246

   2.000;  1.292;  0.810;  0.947;  2.296;  8.505;-10.636;
1.233
   2.500;  1.268;  0.808;  0.946;  2.296;  8.505;-10.636;
1.228
   3.000;  1.268;  0.806;  0.946;  2.296;  8.505;-10.636;
1.224
   5.000;  1.395;  0.821;  0.898;  2.294;  8.505;-10.636;
1.186
  10.000;  1.194;  0.819;  0.824;  2.272;  6.873; -4.683;
1.102
1 sin controlar  y w=5
  abscisa   SKEW      MU       SD    P95     MAX     MIN
accuracy
   0.000;  1.321;  0.813;  0.981;  2.370;  8.505;-10.636;
1.274
   0.250;  1.314;  0.813;  0.981;  2.370;  8.505;-10.636;
1.272
   0.500;  1.295;  0.811;  0.979;  2.367;  8.505;-10.636;
1.268
   1.000;  1.278;  0.809;  0.968;  2.354;  8.029;-10.636;
1.255
   2.000;  1.385;  0.812;  0.911;  2.304;  5.736; -9.714;
1.208
   2.500;  1.510;  0.816;  0.887;  2.297;  5.736; -7.912;
1.190
   3.000;  1.511;  0.816;  0.881;  2.293;  5.736; -7.588;
1.182
   5.000;  1.406;  0.812;  0.872;  2.280;  5.736; -7.588;
1.161
  10.000;  1.216;  0.803;  0.861;  2.252;  5.736; -7.588;
1.117
2 sin controlar  y w=5
  abscisa   SKEW      MU       SD    P95     MAX     MIN
accuracy
   0.000;  1.321;  0.813;  0.981;  2.370;  8.505;-10.636;
1.274
   0.250;  1.307;  0.812;  0.980;  2.368;  8.505;-10.636;
1.271
   0.500;  1.282;  0.809;  0.978;  2.365;  8.505;-10.636;
1.266
   1.000;  1.299;  0.806;  0.963;  2.338;  6.908;-10.636;
1.249
```

```
   2.000;  1.299;  0.806;  0.950;  2.327;  5.736;-10.636;
1.233
   2.500;  1.262;  0.805;  0.948;  2.316;  5.736;-10.636;
1.228
   3.000;  1.226;  0.804;  0.946;  2.305;  5.736;-10.636;
1.222
   5.000;  1.163;  0.798;  0.941;  2.284;  5.736;-10.636;
1.202
  10.000;  1.057;  0.789;  0.923;  2.244;  3.861;-10.636;
1.152
3 sin controlar  y w=5
  abscisa   SKEW      MU       SD    P95     MAX     MIN
accuracy
   0.000;  1.321;  0.813;  0.981;  2.370;  8.505;-10.636;
1.274
   0.250;  1.293;  0.810;  0.978;  2.366;  8.505;-10.636;
1.269
   0.500;  1.268;  0.808;  0.976;  2.362;  8.505;-10.636;
1.264
   1.000;  1.279;  0.808;  0.972;  2.358;  7.934;-10.636;
1.257
   2.000;  1.309;  0.808;  0.950;  2.328;  5.736;-10.636;
1.235
   2.500;  1.277;  0.807;  0.943;  2.304;  5.736;-10.636;
1.226
   3.000;  1.243;  0.806;  0.938;  2.296;  5.736;-10.636;
1.218
   5.000;  1.216;  0.805;  0.932;  2.290;  5.736;-10.636;
1.200
  10.000;  1.057;  0.805;  0.929;  2.283;  5.736;-10.636;
1.166
```


Accuracy of the dataset vs. effort
w=5, Delta=1
RMSE [m]
1.280
1.270
1.260
1.250
1.240
1.230
1.220
1.210
1.200
- : 1
- - : 2
: : 3
0.00
0.25
0.50
0.75
1.00
1.25
1.50
1.75
2.00
Effort [%]


Percentile 95% of the remaining errors
w=5, Delta=1
Percentile 95% [m]
2.380
2.370
2.360
2.350
2.340
2.330
2.320
2.310
2.300
- - : 1
: : 2
- . : 3
0.00
0.25
0.50
0.75
1.00
1.25
1.50
1.75
2.00
Effort [%]

band4

Metodo de Felicisimo. 1994

abscisa	SKEW	MU	SD	P95	MAX	MIN	accuracy
0.000	1.261	-0.776	1.057	2.551	3.946	-5.795	1.311
0.250	1.273	-0.773	1.054	2.541	3.946	-5.795	1.305
0.500	1.292	-0.772	1.052	2.537	3.946	-5.795	1.301
1.000	1.328	-0.773	1.048	2.533	3.946	-5.795	1.296
2.000	1.358	-0.777	1.046	2.534	3.946	-5.795	1.289
2.500	1.350	-0.776	1.045	2.533	3.946	-5.795	1.285
3.000	1.326	-0.774	1.043	2.527	3.946	-5.795	1.279
5.000	1.309	-0.770	1.032	2.506	3.946	-5.795	1.255
10.000	1.212	-0.778	1.025	2.505	3.946	-5.795	1.220

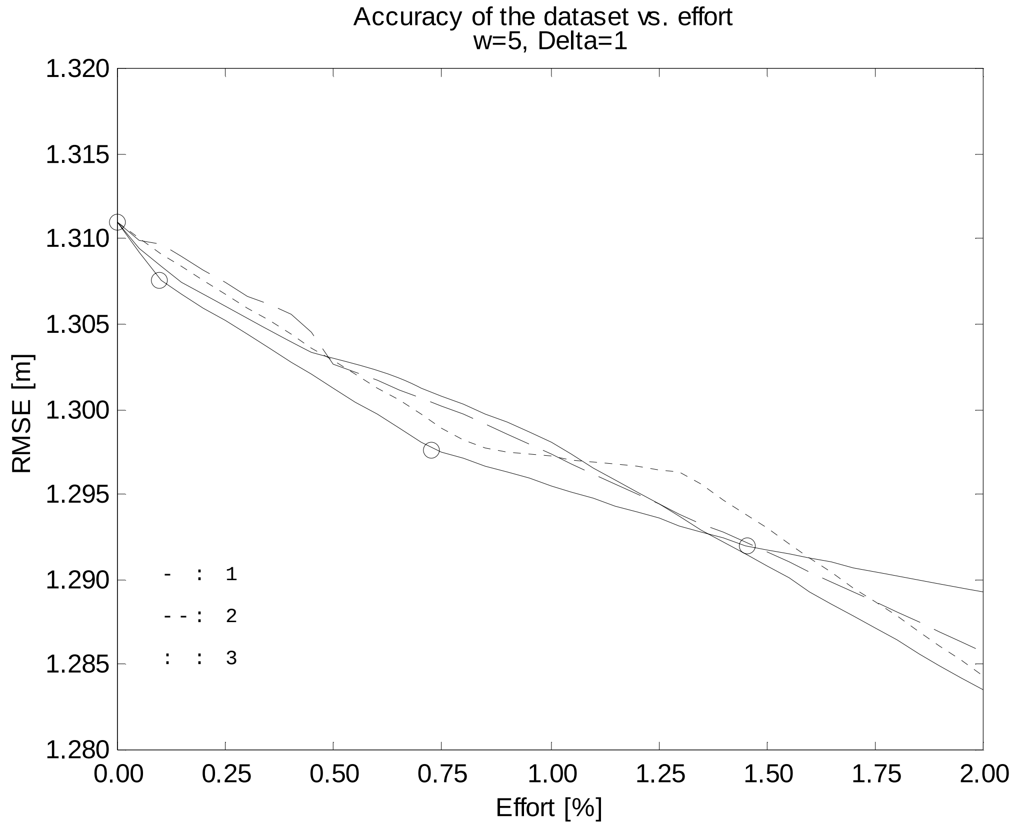
1 sin controlar y w=5

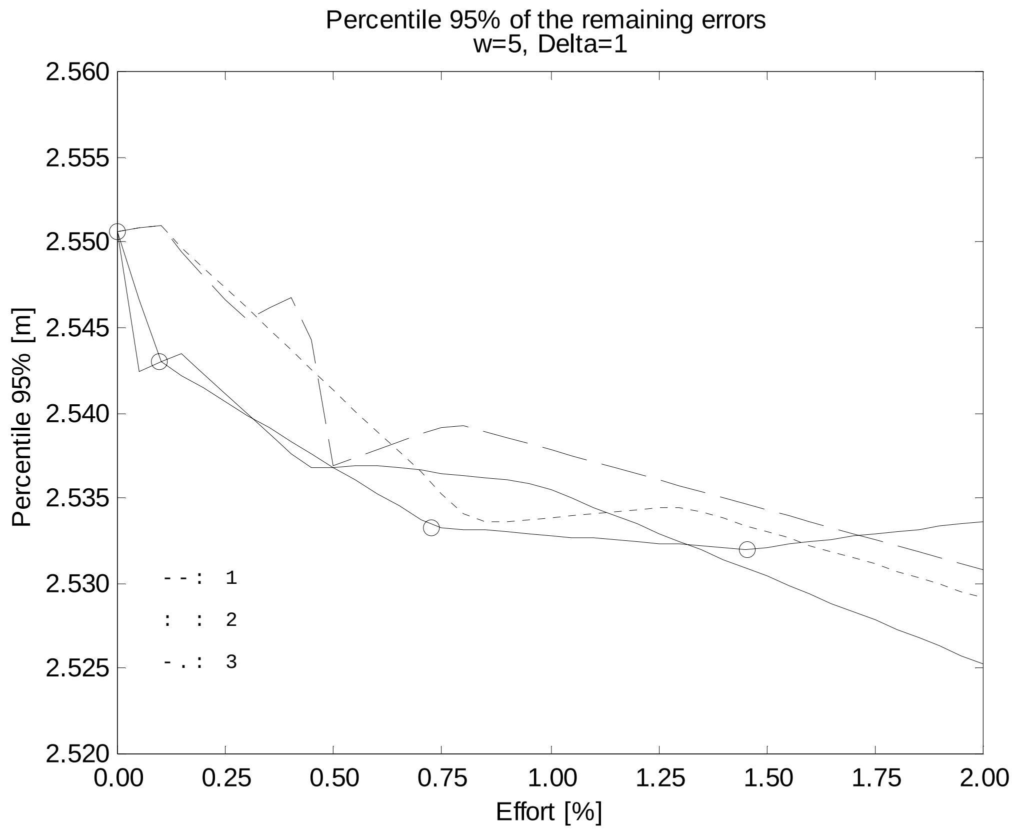
abscisa	SKEW	MU	SD	P95	MAX	MIN	accuracy
0.000	1.261	-0.776	1.057	2.551	3.946	-5.795	1.311
0.250	1.261	-0.772	1.055	2.541	3.946	-5.795	1.306
0.500	1.261	-0.771	1.055	2.537	3.946	-5.795	1.303
1.000	1.262	-0.769	1.054	2.535	3.946	-5.795	1.298
2.000	1.310	-0.765	1.047	2.525	3.946	-5.795	1.284
2.500	1.334	-0.763	1.043	2.520	3.946	-5.795	1.276
3.000	1.358	-0.761	1.040	2.515	3.946	-5.795	1.269
5.000	1.261	-0.762	1.023	2.510	3.946	-4.743	1.244
10.000	1.195	-0.753	1.000	2.457	3.946	-4.381	1.187

2 sin controlar y w=5

abscisa	SKEW	MU	SD	P95	MAX	MIN	accuracy
0.000	1.261	-0.776	1.057	2.551	3.946	-5.795	1.311
0.250	1.261	-0.774	1.056	2.547	3.946	-5.795	1.307
0.500	1.261	-0.771	1.054	2.537	3.946	-5.795	1.303
1.000	1.253	-0.770	1.053	2.538	3.946	-5.795	1.297

```
   2.000;  1.219; -0.769;  1.047;  2.531;  3.946; -5.795;
1.286
   2.500;  1.234; -0.768;  1.043;  2.527;  3.946; -5.617;
1.279
   3.000;  1.269; -0.767;  1.038;  2.524;  3.946; -5.336;
1.271
   5.000;  1.252; -0.769;  1.027;  2.517;  3.946; -5.006;
1.250
  10.000;  1.088; -0.769;  0.993;  2.484;  3.946; -4.381;
1.192
```



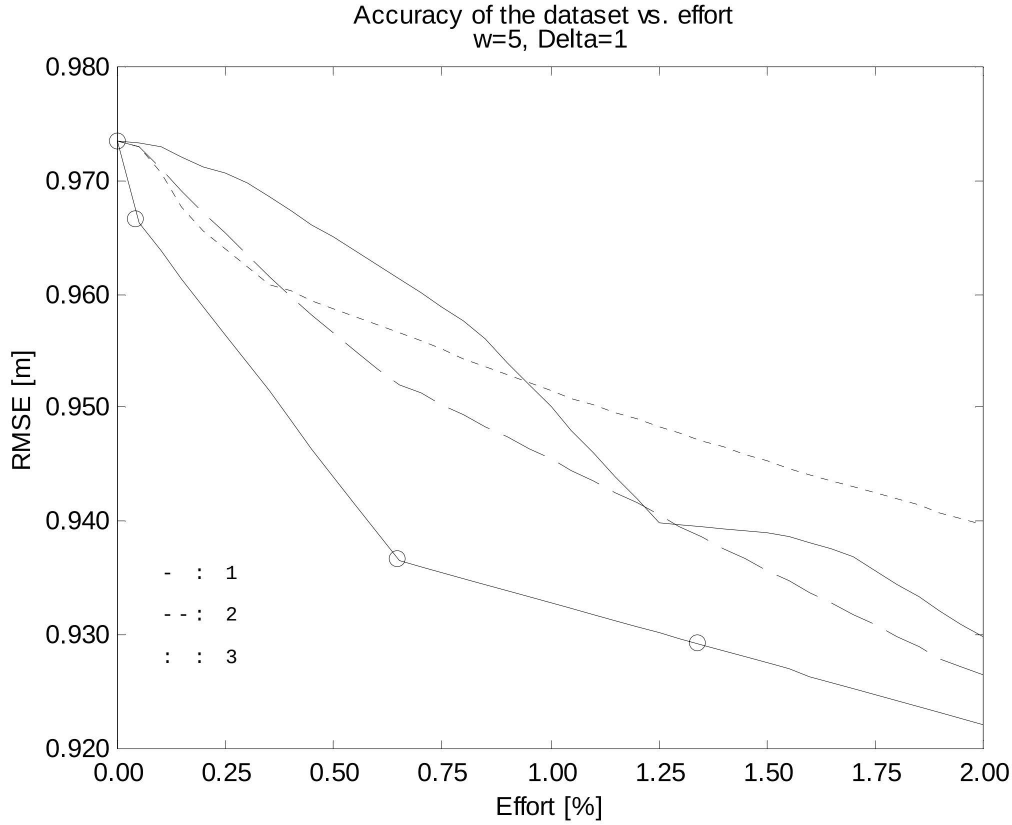

Percentile 95% of the remaining errors
w=5, Delta=1
2.560
2.555
2.550
2.545
2.540
2.535
2.530
2.525
2.520
Percentile 95% [m]
0.00
0.25
0.50
0.75
1.00
1.25
1.50
1.75
2.00
Effort [%]
- - : 1
: : 2
- . : 3

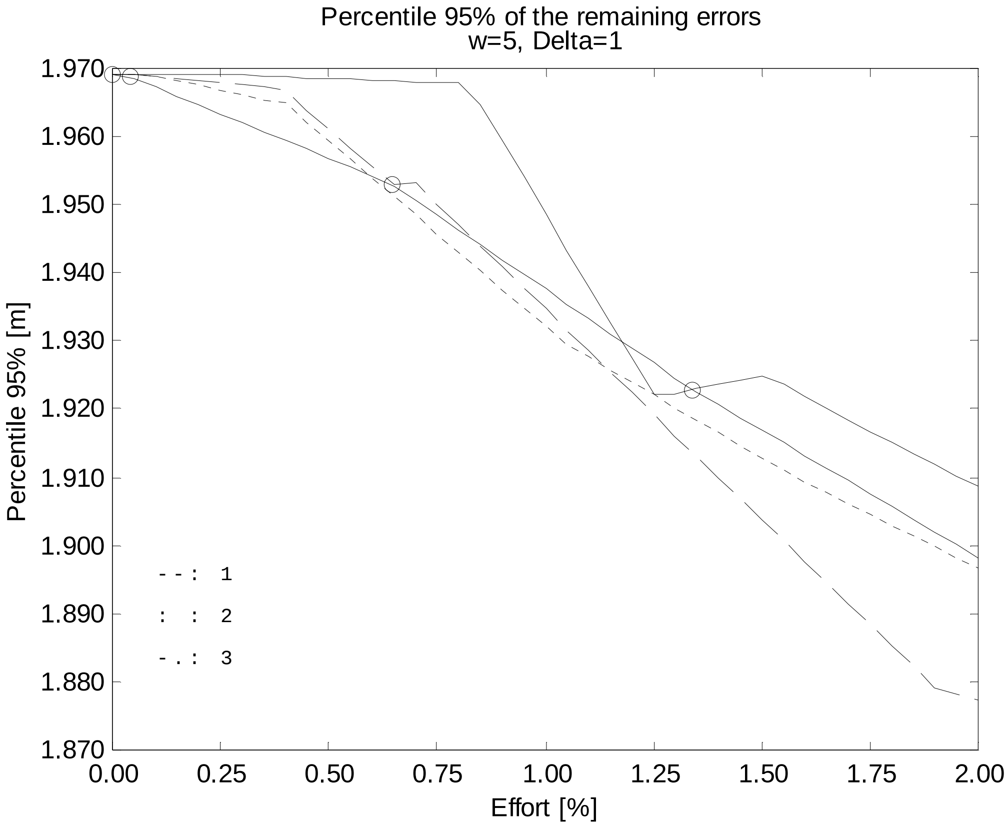
band5

```
Metodo de Felicisimo. 1994
  abscisa   SKEW      MU       SD    P95     MAX     MIN accuracy
  0.000;  0.994; -0.119;  0.966;  1.969;  5.996; -4.741;  0.973
   0.250;  1.009; -0.120;  0.950;  1.963;  5.778; -4.461;  0.956
   0.500;  1.027; -0.118;  0.939;  1.957;  5.514; -4.123;  0.944
   1.000;  1.015; -0.116;  0.931;  1.938;  5.357; -3.923;  0.933

   2.000;  0.994; -0.114;  0.925;  1.898;  5.357; -3.923;  0.922
   2.500;  1.009; -0.115;  0.923;  1.888;  5.357; -3.923;  0.918
   3.000;  1.030; -0.118;  0.921;  1.883;  5.357; -3.923;  0.914
   5.000;  1.087; -0.135;  0.893;  1.858;  4.012; -3.923;  0.880
  10.000;  0.961; -0.145;  0.867;  1.819;  3.732; -3.923;  0.834
2 sin controlar  y w=5
  abscisa   SKEW      MU       SD    P95     MAX     MIN accuracy
   0.000;  0.994; -0.119;  0.966;  1.969;  5.996; -4.741;  0.973
   0.250;  0.994; -0.115;  0.960;  1.968;  5.996; -4.666;  0.965
   0.500;  0.994; -0.112;  0.953;  1.961;  5.996; -4.602;  0.957
   1.000;  1.005; -0.111;  0.944;  1.935;  5.885; -4.602;  0.945

   2.000;  1.047; -0.112;  0.929;  1.877;  5.560; -4.602;  0.927
   2.500;  1.099; -0.111;  0.925;  1.869;  5.560; -4.602;  0.920
   3.000;  1.151; -0.109;  0.921;  1.860;  5.560; -4.602;  0.913
   5.000;  1.080; -0.112;  0.915;  1.844;  5.560; -4.602;  0.899
  10.000;  0.850; -0.116;  0.888;  1.793;  5.560; -4.602;  0.850
```




Percentile 95% of the remaining errors
w=5, Delta=1
1.970
1.960
1.950
1.940
1.930
1.920
1.910
1.900
1.890
1.880
1.870
Percentile 95% [m]
- - : 1
: : 2
- . : 3
0.00
0.25
0.50
0.75
1.00
1.25
1.50
1.75
2.00
Effort [%]

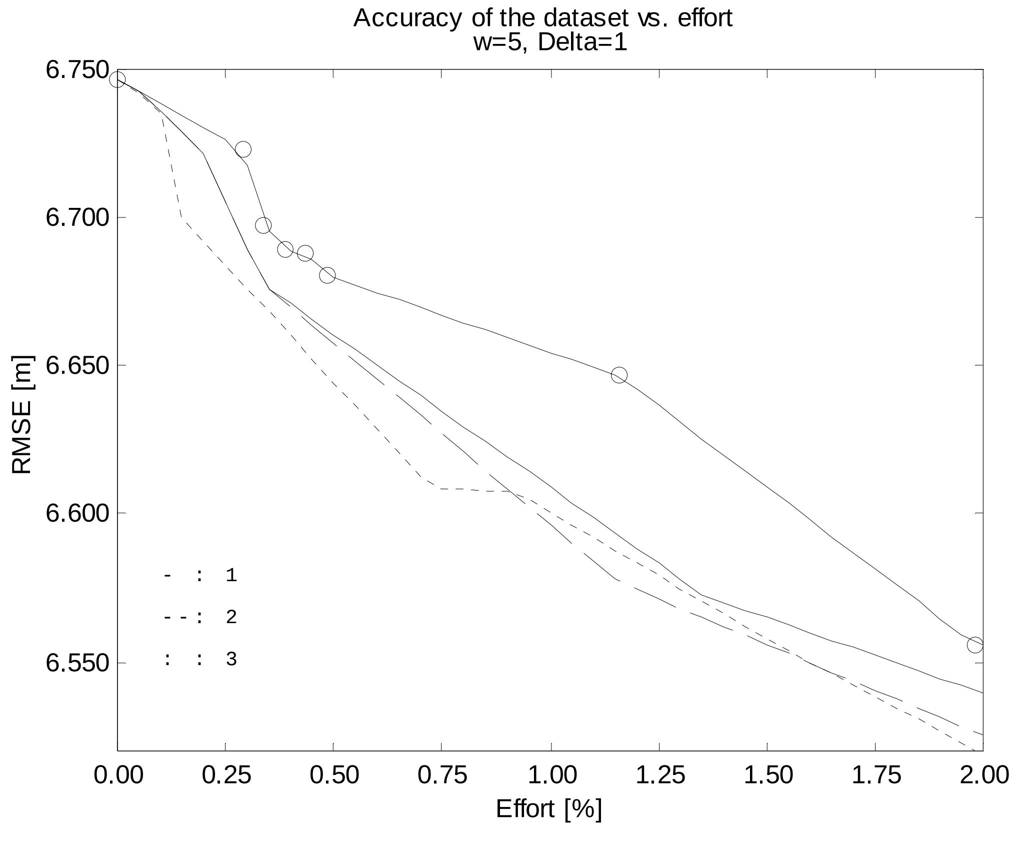
band6

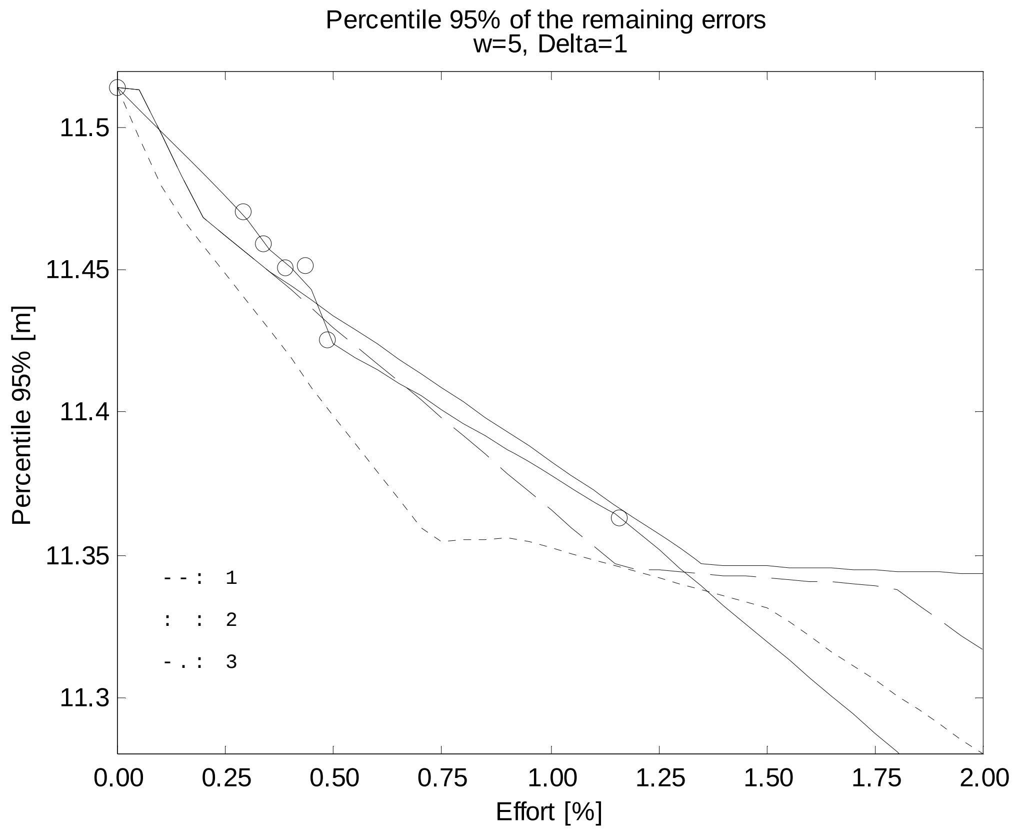
Metodo de Felicisimo. 1994

abscisa	SKEW	MU	SD	P95	MAX	MIN	accuracy
0.000;	1.595;	4.284;	5.213;	11.514;	30.922;	-32.151;	6.746
0.250;	1.553;	4.294;	5.189;	11.476;	30.922;	-32.151;	6.726
0.500;	1.547;	4.314;	5.123;	11.424;	30.922;	-32.151;	6.680
1.000;	1.547;	4.308;	5.117;	11.378;	30.922;	-32.151;	6.655
2.000;	1.498;	4.331;	5.011;	11.258;	30.922;	-32.151;	6.556
2.500;	1.475;	4.333;	4.986;	11.254;	30.922;	-32.151;	6.522
3.000;	1.449;	4.334;	4.960;	11.249;	30.922;	-32.151;	6.486
5.000;	1.125;	4.362;	4.715;	10.955;	30.922;	-32.151;	6.260
10.000;	0.967;	4.414;	4.585;	10.724;	30.922;	-32.151;	6.037

2 sin controlar y w=5

abscisa	SKEW	MU	SD	P95	MAX	MIN	accuracy
0.000;	1.595;	4.284;	5.213;	11.514;	30.922;	-32.151;	6.746
0.250;	1.566;	4.292;	5.164;	11.462;	30.922;	-30.985;	6.706
0.500;	1.566;	4.308;	5.099;	11.430;	30.922;	-29.167;	6.657
1.000;	1.478;	4.325;	5.026;	11.366;	30.922;	-29.167;	6.596
2.000;	1.342;	4.345;	4.958;	11.317;	30.922;	-29.167;	6.525
2.500;	1.314;	4.361;	4.926;	11.264;	30.922;	-29.167;	6.495
3.000;	1.274;	4.380;	4.885;	11.221;	30.922;	-29.167;	6.462
5.000;	1.118;	4.443;	4.759;	11.098;	30.922;	-29.167;	6.345
10.000;	0.931;	4.594;	4.517;	10.941;	30.922;	-19.266;	6.111




Percentile 95% of the remaining errors
w=5, Delta=1
11.5
11.45
11.4
11.35
11.3
Percentile 95% [m]
- - : 1
: : 2
- . : 3
0.00
0.25
0.50
0.75
1.00
1.25
1.50
1.75
2.00
Effort [%]

Hola Ana Ines
Te molesto porque necesitaria que me consiguieras una copia de los siguientes articulos (citados en desorden cronologico):

+Ritter. P. A vector based slope and aspect generation algorithm. PHOTOGRAMMETRIC ENGINEERING & REMOTE SENSING. 53 (8). 1109-1111. 1987

+Sharpnack. D.A. and Akin. G. An algorithm for computing slope and aspect from elevations. PHOTOGRAMMETRIC ENGINEERING & REMOTE SENSING 35. pag 247. 1969

+Hodgson. M.E. What Cell size does the computed slope/Aspect angle represent? PHOTOGRAMMETRIC ENGINEERING & REMOTE SENSING. 61(5). 513-517. 1995

+Bolstad. P.V. and Stowe. T. An evaluation of DEM accuracy: elevation. slope. and aspect. PHOTOGRAMMETRIC ENGINEERING & REMOTE SENSING 60(11). 1327-1332. 1994

+Lantner. D. and Veregin. H. A research paradigm for propagating error in layer-based GIS. PHOTOGRAMMETRIC ENGINEERING & REMOTE SENSING 58. 825-833. 1992

+Veregin. H. Integration of simulation modeling and error propagation for the buffer operation in GIS. PHOTOGRAMMETRIC ENGINEERING & REMOTE SENSING. 60. 427-435.1994

+Veregin. H. Error propagation through the buffer operation for probability surfaces. PHOTOGRAMMETRIC ENGINEERING & REMOTE SENSING 62. 419-428. 1996

+Kubik. K; Lyons. K and Merchant. D. Photogrammetric Work without blunders. PHOTOGRAMMETRIC ENGINEERING & REMOTE SENSING. 54. 51-54. 1988

+Kubik. K.; Merchant. D. and Schenk. T. Robust estimation in photogrammetry. PHOTOGRAMMETRIC ENGINEERING & REMOTE SENSING. 53. 167-169. 1987

Para los ultimos dos. las paginas aparecen repetidas. lo que no deja de ser curioso (y dudoso!). Espero que lo puedas localizar de todas formas.

Caso contrario. intenta ubicar a Mr. Kubik en Internet.
utilizando el titulo de los trabajos. Usualmente. encontraras
una pagina con sus publicaciones. y alli la referencia estara
(casi seguramente) correcta.

La otra cosa es rastrear la tesis de doctorado (PhD) del siguiente fulano: Shyue. S. W. El titulo es: High Breakdown point robust estimation for outlier detection in photogrammetry.
Fue presentada en 1989 en la Universidad de Washington. Lo que habria que hacer. es a) intentar localizar la pagina WEB del fulano. No creo que sea un apellido muy popular... b) conseguir la tesis (si es que esta disponible en linea) o bien conseguir el e-mail del fulano. el que me enviarias.
Sugiero usar yahoo!. altavista. etc. utilizando el apellido y/o partes del titulo (encerradas entre comillas) hasta que tengas suerte. La otra es intentar buscar por la universidad. pero eso puede ser mas problematico.