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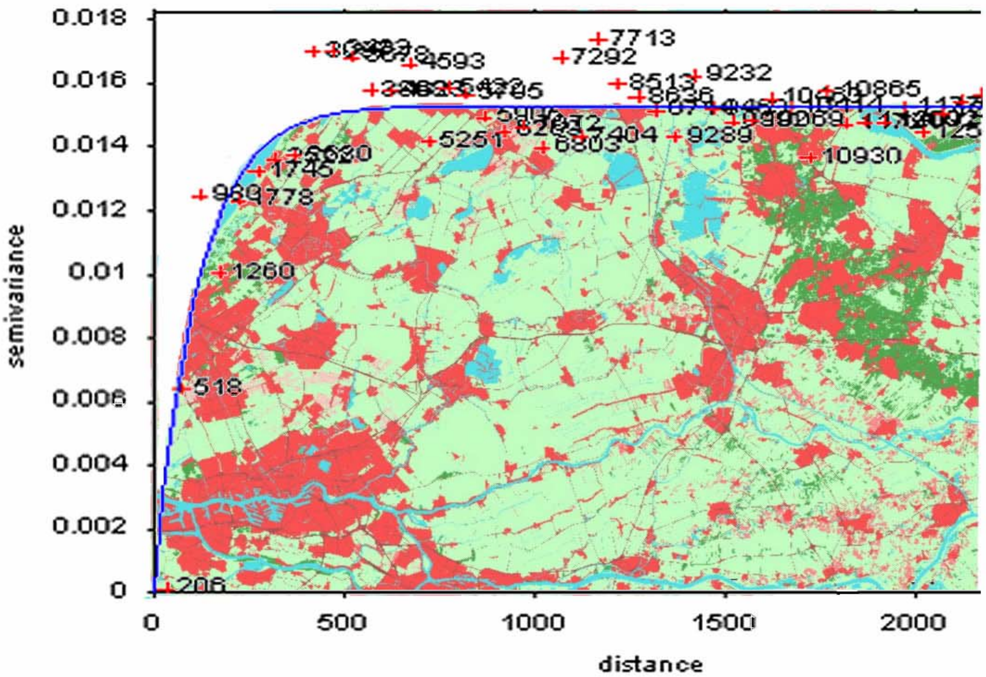
Is red 'red'?

A statistical quality assessment of a raster urbanisation map

Louise Willer



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A statistical quality assessment of a raster urbanisation map

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Abstract

This paper describes different methods to assess the quality of a remotely sensed urbanisation map of the southwest of the Netherlands, which is used for spatial planning. This map displays urbanisation between 1995-1999.
Firstly, the accuracy of an urbanisation map was quantified. The overall accuracy of urbanisation in the study area between 1995-1999 was reasonable. The rare and scattered urbanisation class showed a low map accuracy. Subsequently, the influence of the resolution size on the map accuracy was calculated. As expected, the global error decreased together with the map resolution. Finally, a geostatistical method, Sequential Indicator Simulations (SIS), was tested in its ability to estimate uncertainty in size of an urban patch, conditioned on reference data values. Despite of some shortcomings concerning the description of the spatial structure and a non-optimal hard data quantity, SIS was able to generate multiple realisations of the urbanisation map that can be used for uncertainty estimation.

Preface

This report is a product my thesis project at the Centre of Geo-information, Wageningen University and Research centre, done as part of my MSc program. After four months of dealing with *uncertainty*, I can certainly say that this thesis project has been a valuable experience in geostatistics.

I want to thank Sytze de Bruin and Allard de Wit for their patience, help and good suggestions.

Wageningen, 02-05-2003

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1 Introduction

Is ‘green’ giving way to ‘red’? This jargon is often heard when policymakers are discussing the spatial planning of the southwest of the Netherlands. This area includes the four largest cities of the Netherlands (Amsterdam, Rotterdam, The Hague, and Utrecht) and the Green Heart, a mainly natural and agricultural area situated in-between these cities (figure 1). This highly populated part of the Netherlands experiences a large pressure on the available land. The cities surrounding the Green Heart need space for expansion while environmental interest groups want to keep the Green Heart ‘green’ (VROM, 2003). The amount of, and rate in which, ‘green’ is disappearing can have its influence on whether new regulations concerning urban growth will be very stringent or more lenient.

For spatial planning purposes thematic land use maps, derived from satellite images, are often used. Even though, it is well documented that remotely sensed data are subject to errors in the remote sensing techniques and image processing (Goodchild et al, 1992; Fisher, 1997; De Bruin, 2000; Kyriakidis and Dungan, 2001), resulting in uncertainty of thematic classes. Especially thematic classes with small, scattered patches are likely to be subject to errors (Smith et al, 2003). In addition, remote sensing of urban surfaces is challenging because of the spatial variability and compositional heterogeneity (Mesev, 1997). It is therefore possible that different stakeholders, using the same urbanisation map, would derive different urbanisations rates that would benefit their own views because of the uncertainty range of the used map.

This paper describes different statistical methods to assess the quality of a remotely sensed urbanisation map of the southwest of the Netherlands. A common method to assess the accuracy of a raster map is to compare the total urbanisation with the urbanisation rate of a reference set, and to quantify misclassifications of pixel class labels, based on validation points. The accuracy of the urbanised class is likely to be low, as the urbanised patches of this urbanisation map are relatively small. Aggregating data to a lower resolution may decrease classification errors, resulting in a higher accuracy for the urbanised class.

Besides quantifying the overall accuracy of a map it is also possible to calculate uncertainty of a pixel value that takes into account spatial correlation of error estimates. Spatial -or multiple point-uncertainty assesses uncertainty of attribute values at many locations simultaneously (Goovaerts, 2001). Spatial uncertainty in categorical maps is commonly assessed with stochastic simulation. Stochastic simulation aims at the production of realisations that all honour the same data and match reasonably well the same global statistics, like variograms and class proportions (Goovaerts, 1999). Map classes, assigned to a pixel, are considered certain if they are seen in all realisations. Sequential Indicator Simulation (SIS) (Deutsch and Journel, 1998), is a frequently used algorithm for stochastic simulation of categorical variables (e.g. Kyriakidis and Dungan, 2001;Goovaerts, 2001; Murray et al, 2002). In this paper the SIS method was tested for its ability to estimate uncertainty in the areal extent of an urbanised patch. These area estimates are based on uncertain remotely sensed data and hard reference data. The suitability of spatial uncertainty models, like SIS, depends on decisions made during the modelling process. The influence of one decision, the hard data amount, is evaluated in this paper. The aim of the evaluation is to explore if SIS, based on 1% hard data points, is able to reproduce the global input statistics accurately. If not, will the accuracy improve when using 0.5% or 2% hard data points.

The following questions will be discussed in this paper;

- How accurate is the urbanisation map of the southwest of the Netherlands, based on the total urbanisation rate and pixel misclassifications?
- What is the influence of the resolution size on the mean error, so accuracy, of this urbanisation map?
- How suitable is the SIS approach for an uncertainty assessment in the areal extent of an urban patch?
- Related to the previous question, how many reference points are required for a suitable SIS use?

Figure 1 The Netherlands with its four largest cities and the Green Heart border, the study area of this project is indicated with the dark grey shading

2 Data & Methodologies

2.1 Land use data

The land use map of the Netherlands, Landelijk Grondgebruiksbestand Nederland (LGN) was used in this study. LGN maps are based on satellite data together with other geographical databases, like agriculture-statistics maps, and have a resolution of 25 x 25 meter (LGN, 2003). LGN maps are updated approximately every five years, in this way LGN maps provide recent information about land use in the Netherlands. LGN is regularly used by governmental agencies as a tool for land use planning. Because of the uniform mapping methodology of LGN3 (1995) and LGN4 (1999/2000), land use changes, like urbanisation, can be monitored by using LGN maps (De Wit & Thunnissen, 2001). Urbanisation is the process of proportional expansion of build-up areas in a certain area.

2.2 Reference set

To be able to assess the quality of the LGN urbanisation map, an exhaustive reference set was created. This reference dataset displayed urbanisation for the same time span as the LGN urbanisation map and fully covered the study area. More detailed sources were used for the development of this reference map, namely, TOP10 vector maps (1:10 000) from 1995, and aerial orthophotographs from 2000 (2 meter resolution). The extent of urban areas on both maps was visually interpreted, compared, and the difference was mapped. Urban areas were classified according LGN4 definitions of ‘urban area’ (LGN, 2003).

The used orthophotographs dated from 2000, while the used satellite images were from 1999.To account for this time difference, urbanised patches at the othophotographs, which were obviously not present at the satellite image, were not included in the reference map. The total area that corrected for the time difference was less than 1% of the total urbanised area.

After mapping of urbanised areas, the vector reference urbanisation map was rasterised to a 25 x 25 meter resolution raster map, and perfectly matched the LGN urbanisation map. Class assignment was based on the category with the largest area in the cell. The reference map consisted out of two exclusive classes; urbanised and non–urbanised areas.

2.3 Accuracy calculations

The total overall urbanisation rate of the study area between 1995-1999 of the LGN map was compared with the exhaustive reference set. Differences between the two sets indicate a possible over- or underestimation of the new urban areas by LGN.

To quantify global accuracy of the urbanisation map, the user’s and overall accuracy (Congalton, 1991) were computed with the aid of a confusion matrix. The user’s accuracy indicates the probability that a cell from a LGN class is classified correctly according to the reference map. The overall accuracy is the probability that a random cell of LGN is classified right. The LGN urbanisation map was cell-by-cell compared with the total reference map.

2.4 Scale analysis

This analysis was accomplished by making a map consisting out of pixel blocks of multiple LGN cells. Each map was put on top of the LGN changes and reference map. Per pixel block, the urbanisation ratio of the LGN map was compared to the urbanisation ratio of the reference map. This has been done for four different pixel block resolutions; 250, 1250, 2500 and 3750 meter. A Root Mean Square Error (RMSE) analysis was used to measure the goodness-of-fit of the two maps at the different pixel block sizes. RMSE was calculated by:

$$\text{RMSE} = \sqrt{\frac{\sum (x-y)^2}{n}}$$

With x and y as urbanised proportions of the reference and LGN urbanisation map, respectively and n being the number of pixel blocks.

The lower the RMSE the better the goodness-of-fit between both maps.

2.5 Spatial uncertainty simulation

Spatial uncertainty simulation was used to estimate uncertainty in the areal extent of an urbanised patch. Area estimation is subject to spatial uncertainty as it depends on the surrounding land use. To address this question, we focussed on one municipality in the study area, Haarlemmermeer (figure 2). In the example area of this municipality four reference points indicated urbanisation, but no urbanised patch was present at the LGN map. We tested SIS for its ability to estimate the size and its uncertainty of this urbanised patch by generating multiple realisations. The size of the patch was estimated by calculating the mean amount of connecting cells around four the urbanised hard data points. An urbanised cell was considered connected to another urban cell if it was one of its eight neighbouring cells. A set of 50 realisations calculated with SIS provided an uncertainty model of the spatial distribution of the urbanisation class. Cell values were considered certain if they were seen in all realisations and visa versa.

The following global map characteristics of Haarlemmermeer were used as conditions for the generation of different realisations (De Bruin *et al*, submitted), 1) proportions of map categories should resemble the specified global distribution, 2) accuracy of simulated maps should be similar to the accuracy of the original map, 3) spatial continuity of map categories should satisfy the given model.

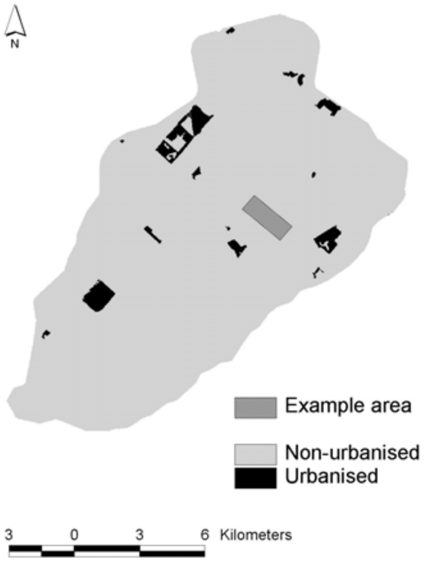

Figure 2 Fragment of the LGN urbanisation map; Haarlemmermeer, with the example location for the uncertainty assessment

SIS calculates conditional cumulative probabilities for each raster cell from which values were drawn. The calculation of conditional cumulative probability distribution was, in this case, based on indicator kriging with varying local priors. This form of indicator kriging makes an optimal weighting of neighbouring soft data, prior probability data, and hard indicator data (0 or 1 for respectively absence and presence of a map class). A value of this distribution is drawn using the Monte Carlo sampling technique, which randomly generates values for uncertain variables.

SIS uses the following procedure to simulate a categorical map (Kyriakidis and Dungan, 2001):

1) Random path through all cells to be simulated is defined, visiting all cells only once.
2) At each cell along this path:
    a) The indicator kriging algorithm is used to compute the conditional cumulative probability distribution of a categorical random variable given conditioning data within a certain neighbourhood.
    b) Via Monte Carlo sampling a value for the random variable is generated. This value is added as a hard data point to the conditioning data set to be used in all subsequent cells along the random path.

After moving to the next cell along the random path, step 2 is repeated.

The realisation is completed when all cells have been given a simulated value.

50 Realisations were made using the `sisim` program of public domain GSLIB software (Deutsch and Journel, 1998). This program was modified according to De Bruin et al (submitted) for this application; details are explained in section 2.5.1.

2.5.1 Quadtree method

To stimulate the reproduction of the global input conditions, as mentioned above, a regional quadtree method was used (De Bruin et al, submitted).

Quadtree segmentation is a successive subdivision of square raster segments into four equally sized quadrants. If a segment does not exist of homogeneous cells then the segment will subdivide into quadrants, this will going on until entirely homogeneous segments are obtained (Samet, 1990). Each level of subdivision is called a leave of the quadtree. With level 0 for the smallest subdivision, the raster cell size. The highest leave number indicates the largest homogeneous area (see figure 3). All cells were labelled according to their leave level, using software developed by Gorte (1998).

The quadtree segmentation method has been used to deal with heterogeneous probabilities. Calculating the user's accuracy for a certain class, with the aid of confusion matrixes, probabilities are given to all cells within that class considered. However, in heterogeneous complex landscapes not all cells will have the same accuracy. It is likely that cells clustered together will have a higher accuracy then single cells surrounded by cells of a different class. For each leave level the user accuracies were calculated, these accuracies were used as local priors in the sequential indicator simulation.

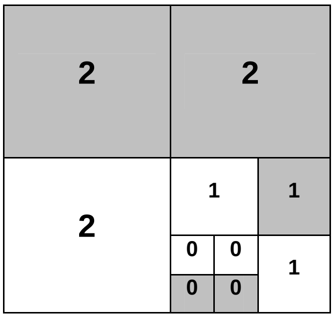

Figure 3 Example, quadtree with leave level numbers, in gray the urbanised and in white the non-urbanised cells

Besides accounting for different user's accuracies, the quadtree method was used to modify the visiting sequence during the simulations.

Within SIS, leave levels were used as input for simulation paths. The `sisim` program has been modified so that cells with the highest leave levels were simulated first, according the procedure as describe earlier in this paper. De Bruin *et al* (submitted) showed that this affected the simulations in a positive way. The SIS method assigns a value to a cell depending on input data and values of the already simulated surrounding cells. So when the cells with the highest accuracy of their input data are simulated first, the surrounding cells will get a more accurate value. Another advantage of a simulation path based on quadtree levels is that they can be used also to improve variogram reproduction. The largest leave levels were simulated first, which correspondences with large-scale variogram structures, ending with the smallest leave levels for the small-scale structures.

To avoid border-effects, quadtree levels have been calculated for a larger area then the area to be simulated. This because the quadtree method divides the study area into quarters until a homogeneous area is reached. As the study area has an irregular shape, this will often lead to an underestimation of homogenous areas. LGN was available for the whole Netherlands, enabling the inclusion of a larger area.

2.5.2 Variogram

To describe spatial continuity of the urbanisation map, a variogram was used as input for SIS. Variograms display dissimilarity between points within a certain distance. From a random sample of 3000 points of the focus area Haarlemmermeer, residuals per point (indicator hard data minus local priors) were calculated. Hard data values were derived directly from the reference data set. The used soft data were the priors calculated with the quadtree confusion matrixes. Only one variogram was needed to describe both urbanised and non-urbanised structures, as these map classes were exclusive.
In GSTAT (Pebesma, 2001) a model describing the variogram of the sample data was interactively created.

2.6 SIS evaluation

The evaluation of spatial uncertainty assessment by SIS was based on the reproducibility of global features and statistics, seen in the output realisations; namely, 1) proportions of urbanised cells, 2) user's accuracy, 3) variograms of the residuals.
A way to evaluate these statistics is by looking at the precision (the uncertainty) and accuracy (inclusion of the input statistics) of the output statistics (Goovaerts, 2001). This evaluation was done for simulations based on 0.5%, 1% and 2% hard data points of the total Haarlemmermeer urbanisation map.

Evaluating the user's accuracies and map proportions of the realisations, the exhaustive reference data of Haarlemmermeer was used. We considered an input statistic 'accurately reproduced' when the input value was included in the cumulative 10-90 percentile range of output statistics of the 50 realisations. The standard deviation of the accuracy and map proportion of the 50 realisations was used as indicator for the precision. Besides this, a 5% 2-tailed t-test was used to test if the mean urbanised proportions and accuracies equalled the desired values.
Variogram reproduction was evaluated based on residual variograms of all 50 realisations (indicator values minus soft priors). A random sample of 3000 data points was used to compute these experimental variograms. Note that this 3000-point sample was different than the hard sample used in the SIS calculations, if not the variograms of the realisations would perfectly match the input variogram. The fit of the realisation variograms was evaluated visually with the input variogram.

3 Results

3.1 Accuracy

The LGN urbanisation map showed a total urbanisation rate of 0.9% in the southwest of the Netherlands between 1995 and 1999. The exhaustive reference map displayed 0.7 % urbanisation.

The global accuracy of the LGN map was calculated with a confusion matrix. Probabilities of correctly classified cells of the LGN urbanisation map are listed in table 1. The user's accuracy of the urbanised class is low; there is a probability of approximately 0.52 that an urbanised cell of the LGN map is correctly classified. The overall accuracy of the LGN urbanisation map is very high, 0.9929.

Table 1 Confusion matrix, shown the LGN accuracies per class and overall accuracy

		Reference data		
		Urbanised	Non- urbanised	
LGN changes map	Urbanised	0.5190	0.4810	
	Non-urbanised	0.0030	0.9970	
	Overall			0.9929

3.2 Scale analysis

The low user's accuracy of the urbanised class (table 1) indicated that at the present resolution of LGN , 25 X 25 meter, it is not possible to give a very reliable representation of urbanisation in the study area. To explore at which resolution the LGN map gives a more accurate representation of the urbanisation rate, different resolutions were tested (figure 4).

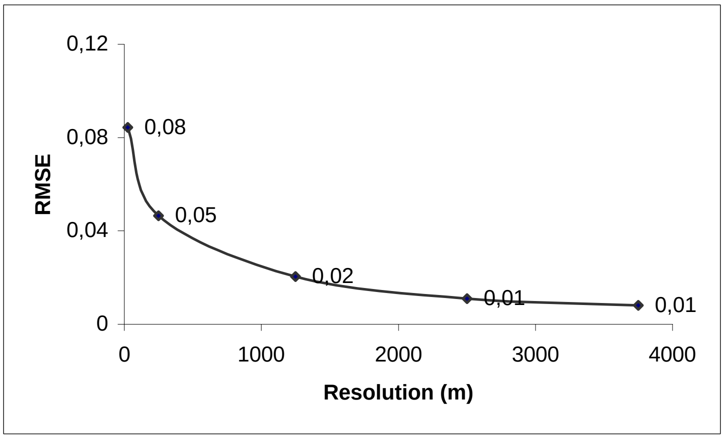

Figure 4 Relation between resolution and goodness-of-fit (RMSE) of the urbanised class, between LNG and reference map.

The present resolution of LGN, raster cells of 25 x 25 meter, showed a RMSE of the urbanised class of 0.08. Lowering the resolution with a factor 100 resulted in a substantial reduction of the mean error (RMSE= 0.01).

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3.3 Spatial uncertainty simulation

3.3.1 Quadtree method

The user’s accuracy has been calculated for each leave level, using the complete Haarlemmermeer map. For low leave levels a positive relation with the leave levels was visible. This trend was less pronounced for in the higher leave levels (Figure 5).

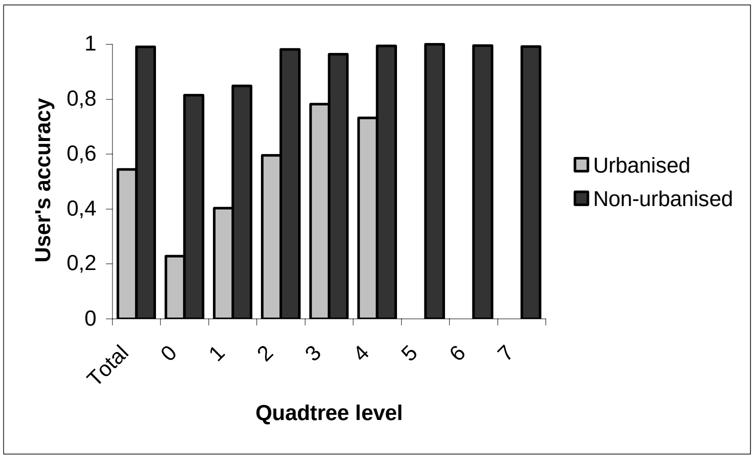


Figure 5 User’s accuracy of the urbanised and non-urbanised classes for total Haarlemmermeer and for each leave level

Accuracies were assigned to cells depending on its leave level and class. Leave level 5, 6, and 7 were merged together, as they had an almost similar accuracy. The accuracies were used as local priors in the sequential indicator simulation.

3.3.2 Variogram

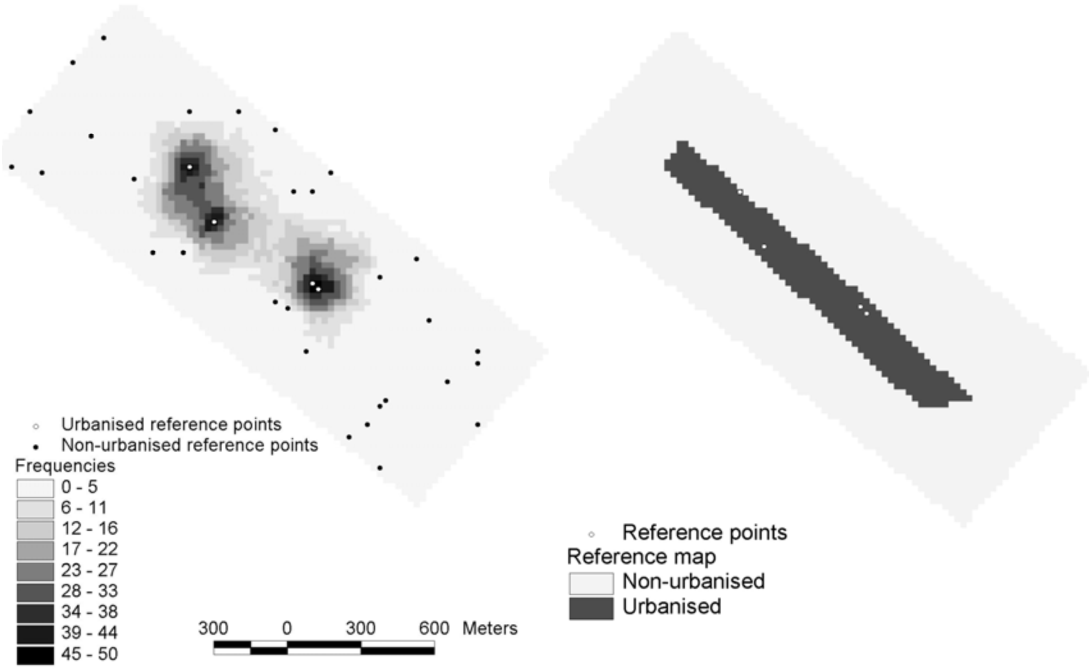
In GSTAT (Pebesma, 2001) an onmidirectional semi-variogram with its model was interactively created. The maximum distance where spatial correlation was taken into consideration, the cut-off value, was set on 2500 meter. The width of the lag, the step size of distance intervals, was set on 50 meters.

With a weighted least square fit, the model of this semi-variogram could be expressed as: 0.0163 Exp (135.99). The first factor of the model indicates the sill, the highest semi-variance between two points. Exponential models, like this one, have an asymptotically sill. The second number of the model shows the one third of the effective range, which is the distance where the semi-variance reaches 95 % of it’s maximum (Isaaks and Srivastava, 1989).

The sill, model shape, and effective range are input values for SIS to describe the spatial continuity of the LGN urbanisation map.

3.3.3 SIS realisations

SIS was used to assess uncertainty of the estimation of the size of an urban patch, of which only random urban reference points were known. Figure 6 displays the frequency of the non-urbanised cells of the LGN map that show up as urbanised in the realisations.



a

b

Figure 6 a) Frequencies of urban cells after 50 realisations b) Reference map

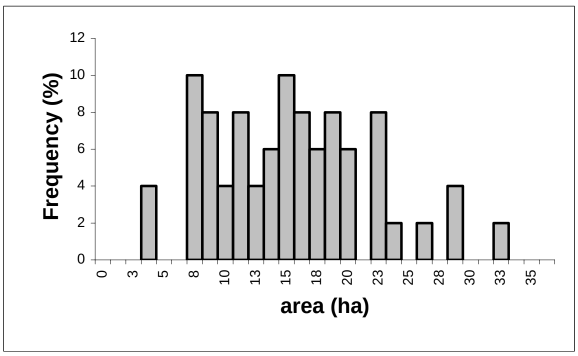


Figure 7 Histogram of the sum of the connected areas around the four sampling points per realisation

The average size of the urban patch around the four reference points is 15.9 ha with a standard deviation of 6.5 ha. Figure 7 shows a histogram displaying the total urban area per realisation. The mean of this normal distribution is an estimate of the true urbanised area, the standard deviation is a measure of the uncertainty. The size of this urban patch according to the reference map is 25.25 ha.

3.4 SIS evaluation

The evaluation of the spatial uncertainty simulations by SIS was based on the reproducibility of the global statistics, seen in the realisations. These are 1) proportion of urban areas, 2) the user's accuracy, 3) variograms of the residuals.

SIS calculations in this paper were done using 3000 random hard data points, 1% of the Haarlemmermeer data set. The aim of this evaluation was to explore if these 3000 points were able to reproduce the global input statistics.

The map proportions and user's accuracy have been evaluated using the exhaustive reference set, see table 2. The means of user's accuracy and urban area of the 1% hard data simulations were both rejected by a 5% 2 tailed t-test, meaning that these global statistic values where significant different from these means. The rejection of means could not be solved by using a half or a double amount of hard data.

Nevertheless, the LGN map accuracy and reference map area extent were both included in the 10-90 percentile range of the realisations based on 1% hard data points.

The uncertainty, expressed as SD, in area estimates decreased when a larger hard data quantity was used. So the variation in accuracy and area proportion decreased with a higher hard data amount.

Table 2 Map statistics of the urbanised class of 50 realisations based on 0.5%, 1 % and 2% hard data values, compared to the LGN urbanisation and reference map

Hard data points	0.5% (1500)	1% (3000)	2% (6000)	LGN
User's Accuracy				
Mean	0.5048*	0.5692*	0.6516*	0.5442
SD	0.0324	0.0217	0.0183	
90-percentile	0.5474	0.5974	0.6718	
10-percentile	0.4596	0.5386	0.6256	
Area (ha)				Reference
Mean	449.60**	483.98**	481.76**	463.13
SD	31.71	27.13	23.23	
90-percentile	480.75	517.31	510.69	
10-percentile	396.75	456.88	454.75	

* H_0: Realisation mean = LGN, rejected by 5% 2 tailed t-test

** H_0: Realisation mean = Reference, rejected by 5% 2 tailed t-test

Variograms of the residuals of the realisation and input variogram were compared visually, see figure 8. The range and sill of the realisations based on 3000 hard data points, were both reasonable reproduced, although, one realisation showed an extremely low range.

Variograms of the 1500 hard data point sample realisations did show some improvements. The reproduction of the input variogram of realisations based on a 6000 hard data sample was worse, the average sill and the range differed both for the input variogram.

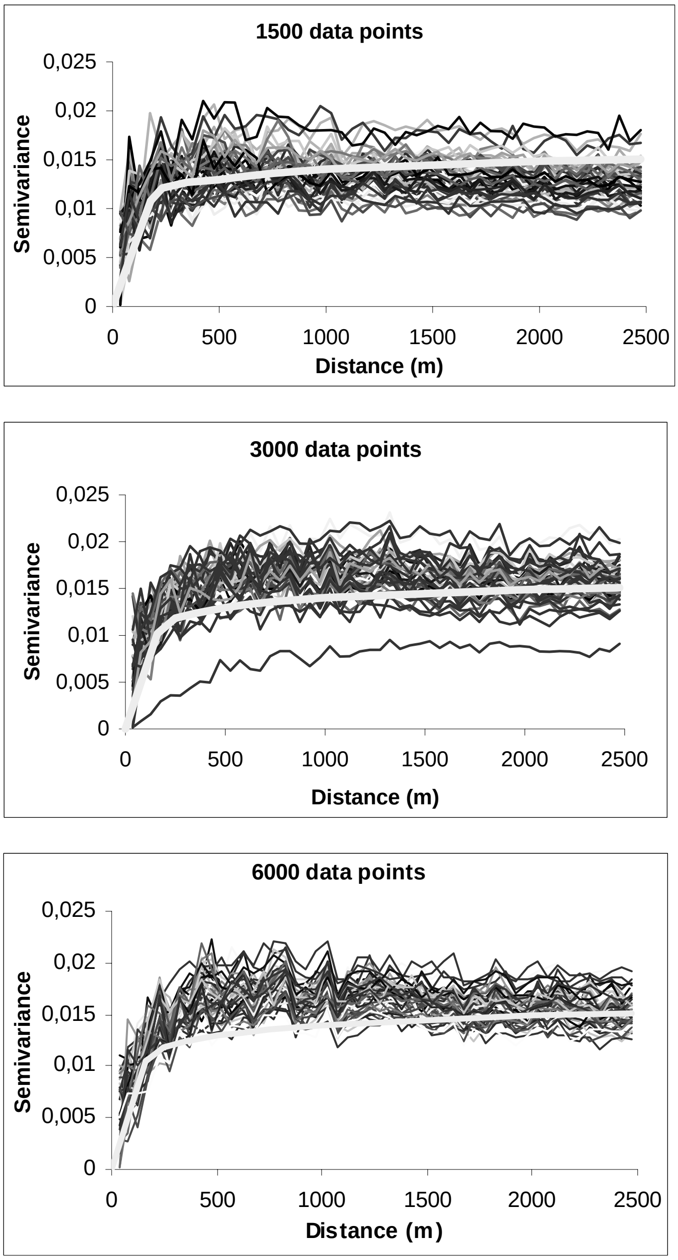


Figure 8 Variograms of the 3 different SIS runs, containing; 1500, 3000 and 6000 hard data points. The thin lines represent the experimental variograms of the realisations; the thick grey lines represent the input variogram

4 Discussion

4.1 Reference data

The methods described in this article were based on an exhaustive reference data set. The question is if these methods are still useful without a complete high quality reference set.

Table 3 displays the differences between the accuracies of the urbanisation maps based on the exhaustive reference set and 3000 random hard data points set. The difference in accuracy between the two reference sets is mainly observed in the rare urbanised class accuracy, the non-urbanised and overall accuracy is high.

Table 3 Global accuracies of the LGN urbanisation map based on the exhaustive reference set and a 3000 hard data points

	Exhaustive reference set	Sample reference set
User's accuracy		
Urbanised	0.5190	0.4752
Non-urbanised	0.9970	0.9907
Overall accuracy	0.9929	0.9733

For the uncertainty assessment in Haarlemmermeer we used the global classification accuracies per quadtree level based on the exhaustive reference set. Using 3000 reference points, instead of the total reference set, the accuracy calculations showed some shortcomings (figure 9). The user's accuracy of the urbanised class is at 3 leave levels lower, and at one leave level even zero. Increasing the amount of reference points to 6000 did not solve this problem (not shown here). This indicates that a practical amount of reference points poorly represents user's accuracies of the leave levels, so soft data values within SIS.

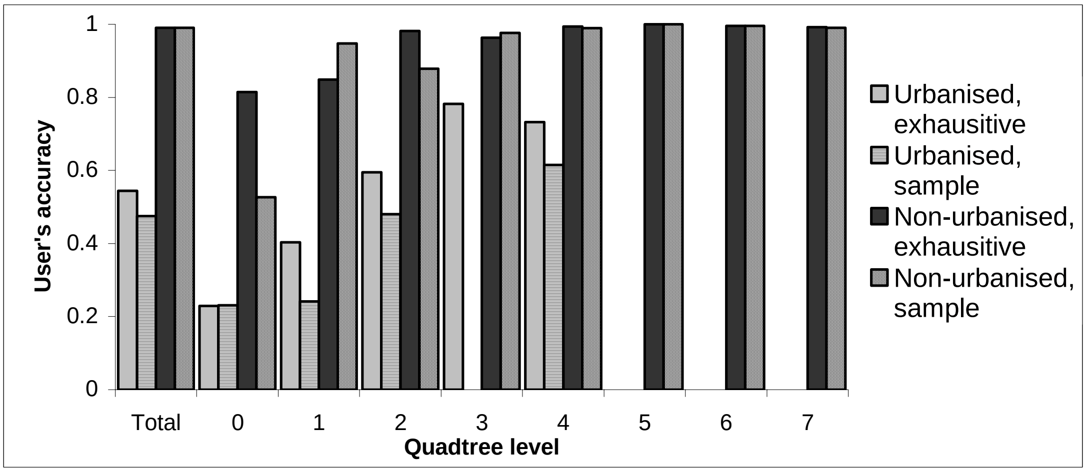


Figure 9 User's accuracies per quadtree level calculated with the exhaustive and sample reference set

As an alternative, global accuracies per quadtree level calculated for a detailed sub-area might be successfully extrapolated to the total study area.

4.2. Accuracy calculations

The user's accuracy of the rare LGN urbanisation class is low. Only 52% of the urbanised pixels are correctly classified. Even though the low pixel based accuracy of the urbanised class, a reasonable accuracy of the total urbanised area was found. The LGN map displayed an urbanisation between 1995-1999 of 0.9% while the reference map showed 0.7% urbanisation. Conform this accuracy difference, the scale analysis showed a decreasing classification error on lower resolutions. Based on these results it seems that the present resolution of LGN, 25 x 25 meter, assumes a higher data quality of the urbanisation class than is seen in the accuracy calculations.

Remarkable was the overestimation of the rare urbanisation class as small classes are more often underestimated in thematic data derived from remotely sensed imagery. A reason for this overestimation can be found in the classification of the urbanised areas. For instance; soil preparation for a new building is considered as a new urban area, agricultural soil preparations not. On a satellite image both activities are hard to distinguish, giving rise to the possibility that agricultural land was incorrectly classified as urban area, resulting in an overestimation of the urbanised area.

4.3 SIS method

As stated before, the suitability of SIS depends on decisions made during the modelling process.

One decision was to use an omnidirectional variogram to describe the spatial structure of the urbanisation map. With this type of variogram spatial features, other than circles, are less adequate simulated. As seen in figure 6, the shape of the simulated patches differed clearly from the reference map patch. Calculating variograms, it is possible to indicate a direction angle and direction tolerance (Isaaks and Srivastava, 1989). In this way ellipses can be simulated, but this will only benefit the description of the spatial structure if one expects that the indicted angle and tolerance account for the whole simulated area. In the Haarlemmermeer study area this was not the case (figure 2).

A general disadvantage of variograms is that they will always lack in modelling square features, which is a problem when dealing with urban areas, as they are often square. Since other methods to describe spatial structures were not available, SIS is at this moment probably more suitable to model spatial features that have rounder shapes, like natural vegetation patches or pollution spots. Future research could aim at the development of a model that is able to describe more square spatial structures.

Another decision was the amount of input hard data values for SIS. Looking at the accuracy of the different hard data sample sizes it can be concluded that the mean global statistics would have been reproduced the best by a hard data amount between 0.5% and 1%, instead of the used 1% (table 2). Although, simulations with a larger hard data quality have less variance within their global statistics, so a higher precision. A shortcoming of using SIS for area estimation is that the amount of hard data points needed to come to an optimal result cannot be defined on forehand. A less convenient trail-and-error method will have to reveal the right amount of hard data points required for the best accuracy and precision for a given setting.

5 Conclusions

This paper describes different methods to assess the quality of a remotely sensed urbanisation map of the southwest of the Netherlands.
Firstly, the accuracy of the urbanisation map was quantified. The overall accuracy of urbanisation in the study area between 1995-1999 was reasonable, with only a slight difference in the estimated urbanisation rate. The user's accuracy of the urbanised class with small, scattered patches was low. Approximately half the amount of urban cells was classified correctly. Subsequently, the influence of the resolution size on the map accuracy was calculated. Aggregating data to a lower resolution reduced the error of the urbanisation map compared to the reference data, indicating that the pattern of the urbanised patches of both maps was similar, even if the cell based accuracy was low. Based on these results it seems not recommendable to use the LGN urbanisation map at a local scale but on a regional scale as these results were found more reliable.
Thirdly, a geostatistical method, SIS, was tested in its ability to estimate the uncertainty of the size an urban patch, conditioned on hard data values. Based on the evaluation it can be concluded that multiple realisations generated by SIS can be used for estimation of the uncertainty of the size of an urban patch, although the shape of the patch was poorly simulated and the hard data quantity was not optimal. In order to deal with the uncertainty in areal estimates it is recommended to use multiple realisations when this information is needed as input for policy-models. Decision makers will in this way have a better idea about the real amount of 'green' and 'red'.

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