JANNEKE ROOS-KLEIN LANKHORST, SJERP DE VRIES, ARJEN BUIJS

MAPPING LANDSCAPE ATTRACTIVENESS

A GIS-BASED LANDSCAPE APPRECIATION MODEL FOR THE DUTCH COUNTRYSIDE

6.1 INTRODUCTION

Offering people scenic beauty is one of the most frequently mentioned landscape services. In the Netherlands it also has become an explicit policy goal: "we want a beautiful country to live and work in" (LNV, 2000: 3). However, instruments to help policy makers and spatial planners to implement this relatively new goal are largely lacking. Where do people like the landscape in their living environment and where do they not? And which physical characteristics influence this appreciation and to what extent? To provide such information in a cost-efficient way, a model was developed to map, monitor, and simulate precisely this: the GIS-based Landscape Appreciation Model (GLAM). The model predicts the attractiveness of the landscape based solely on nationally available GIS-data on its physical aspects for each 250 x 250 metre cell. In this article, we describe the theoretical background to GLAM, the attributes in the current version of the model, the final steps in calibrating the model, as well as its validation. We conclude with a discussion on the usefulness of GLAM for spatial policy.

6.2 THEORETICAL BACKGROUND

Ever since the 1970s, the attractiveness of landscapes has been an issue in landscape and environmental management. It was one of the driving forces behind the emergence of environmental psychology as a discipline. In the mean time a vast amount of research has been conducted in explaining or describing environmental preferences of both experts and lay people (for an overview, see Aoki, 1999). Different theories have emerged, ranging from strongly evolutionary to more cultural explanations of environmental preferences. A dominant paradigm since the 1980's has been the cognitive view of landscape perception. It focuses on subjective, psychological categories. Most notably is the theory of Kaplan and Kaplan (1989), with its emphasis on mystery, complexity, legibility and prospect. Many studies have focused on the link between these psychological categories and landscape attributes, but this has proven to be rather difficult (Strumse, 1994).

Another paradigm, the psychophysical one, has been present in environmental psychology from the start. Within this paradigm, preferences for and attractiveness of a specific landscape are supposed to be based in its physical attributes. Although it does not deny the importance of exploring the psychological mechanism behind these relationships, its focus is very much on the physical landscape. It is therefore particularly suited for modelling landscape preferences using geographic data of the physical landscape (see for other examples e.g. Bishop and Hulse, 1994; Real et al., 2000). From the psychophysical as well as from the cognitive paradigm, a large array of attributes has been evaluated since the 1980's (Ulrich, 1983; Zube, 1987; Kaplan and Kaplan, 1989; Purcell and Lamb, 1998; Strumse, 1994; Aoki, 1999). It is from this body of knowledge that we derived attributes for the GLAM model to predict landscape preferences in the Netherlands.

The initial GLAM model consisted of three positive indicators: *Naturalness*, *Relief*, *Historical Distinctiveness*, and three negative indicators: *Skyline Disturbance*, *Urbanity* and *Noise Level*. The choice of these indicators was the result of the mentioned literature and previous research results of a prototype version of GLAM (Vries and Gerritsen, 2003). One of the changes resulting from this previous research is that 'Variety', an attribute that is prominently present in the literature (see e.g. Hunziker and Kienast, 1999), was dropped because of its high correlation with Naturalness in the Dutch situation. The non-visual attribute Noise Level was included in the attribute set of our model because studies in the Netherlands (Goossen et al., 2001) proved noisiness, especially from traffic, to be a very important factor for the appreciation of the landscape. Moreover, noise level may also be considered as a proxy for visual fragmentation and disturbance of an area by (rail)roads.

6.3 OPERATIONALISING THE GLAM

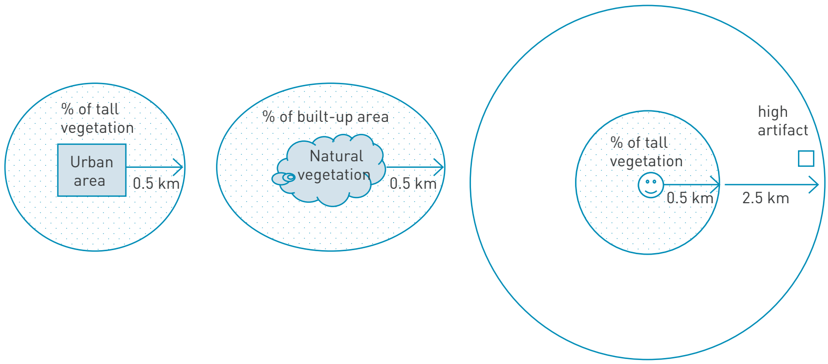
The GLAM model has been built in a dedicated modelling environment, named Osiris (Verweij, 2004) that supports the building and running of qualitative spatial models. Osiris enables the user to store qualitative expert knowledge in tables with which new grid maps are generated from two or three existing grid maps. It also enables the user to store and run map algebra scripts. It uses ArcView version 3.3 for the viewing of grid data and executing the grid algebra scripts.

6.3.1 Input data and computations

The most important dataset we use, is the digital topographic map 1:10,000 of the Netherlands, containing polygons representing e.g. forests, housing blocks, high-rise buildings (higher than 35 metre or 10 storeys), glass houses and water bodies, point elements such as power pylons and wind turbines, and lines of trees and ditches. Nevertheless, on pragmatic grounds we use grid maps with a resolution of 250 x 250 metre. Grid map computations are faster than vector-based computations, and indicator maps in grid format are easier to combine into one 'landscape attractiveness' map (without causing sliver polygons or inconsistencies in results due to differences in polygon boundaries). The grid cell size of 250 x 250 metre is generally viewed as a convenient size for national studies in the Netherlands.

Since in open landscapes larger areas are visible than the grid cell itself, we used neighbourhood operations to take a wider environment into account and to deduce the visibility of characteristics. Although specific algorithms exist to compute visibility in an accurate way, these tend to be very time consuming. We decided to use focal mean operations to compute to what extent urban areas were surrounded by vertical vegetation, and areas of natural vegetation were surrounded by buildings (see figure 1). For the high-rise artefacts of Skyline Disturbance we computed the openness of the surroundings of the observer, and not of the surroundings of the artefacts themselves. Such artefacts are usually higher than the surrounding trees and buildings, and are thus visible from a large distance if the observer has a clear view.

In open landscapes with clear weather, visibility of buildings and glass houses can be as far as 5 kilometres and for high artefacts like wind turbines even more than 10 kilometres. However, validation results (comparing maps with different neighbourhood distances with preference ratings by respondents) and field surveys suggested both that a distance of 2 to 3 kilometres is appropriate for Skyline Disturbance for high artefacts, and 0.5 kilometres for urban areas. For the indicator Historical Distinctiveness we used neighbourhood operations to merge grid cells containing monuments and nearby grid cells into larger areas that we considered to be of a more historical nature than areas further away from historical monuments. This neighbourhood operation was not only based on visibility considerations, but also on the assumption that the area surrounding a historical feature is more likely to have historical qualities itself.



The visibility of urban areas (low buildings) is deduced by calculating the amount of surrounding tall vegetation within 0.5km

The visibility of natural vegetation is deduced by calculating the amount of surrounding built-up area within 0.5 km

The visibility of high artifacts within 2.5km of the observer is deduced by calculating the amount of tall vegetation surrounding the grid cell of the observer within 0.5 km

Figure 1
Neighbourhood operations used for the indicators Naturalness, Urbanity and Skyline Disturbance

6.3.2 Preference levels per GIS-indicator

Given the broad definition of most physical characteristics, encompassing different elements, defining indicator levels was not simply a matter of counting the incidence of relevant elements. It had to be decided which (combinations of) elements were preferred or disliked to a similar degree and thus could be combined in one level. So, a given level of an indicator does not indicate mere presence, but an evaluation of this presence in terms of its expected contribution to landscape attractiveness. Originally these operational decisions were made based on a literature review, insights gained from previous studies (Coeterier, 1996; Goossen and Langers, 2000; de Boer et al., 1999) and interviews conducted during the project. However, GLAM also has a strong empirical basis. It was developed in interaction with the results of a national survey in landscape appreciation among almost 3000 Dutch residents (de Vries and van Kralingen, 2002), which will be described in more detail later on.

Each of the six indicators has five levels, ranging from 0 (no or very small presence of appropriate physical characteristics) to 4 (strong visible presence of appropriate physical characteristics). For the positive indicators 0 means ‘least preferred’, and 4 ‘most preferred’, for the negative indicators, 4 means ‘least preferred’. The five levels per indicator should be interpreted as a semi-interval scale. The computation method per indicator is briefly described below, beginning with for the three positive ones. In table 1 a description of the levels per indicator is given.

The score for Naturalness depends on the amount and type of vegetation, the presence of natural water and the amount of built-up area within 500 metres. The amount of natural vegetation forms the basis. However, if there is less than 5% nature (e.g. heath, dunes, swamp, forest) but over 50% of grassland, the grid cell scores a point extra; grid cells with less than 50% natural vegetation also score an extra point if they contain a shoreline of natural waters (rivers, brooks, pools, lakes, sea). Big water bodies themselves are left out of the maps: the model is restricted to landscapes on land. On the other hand, if there is a lot of built-up area and few trees within 500 metres, the grid cell looses 1 point. The resulting score remains within the 0 - 4 range.

The score for Relief depends on the presence of the most valued type of relief in the grid cell: the more variety in altitude, the higher the score. For this indicator we used the Dutch geomorphology map, indicating different landforms, which we classified from flat areas to large hills.

For Historical Distinctiveness, the score depends on the presence or vicinity of nationally protected historical (clusters of) buildings or sites.

The score for Urbanity depends on the amount of built-up area within the cell, within 500 metres from that cell, and the area of trees within 500 metres (because of visibility). Glass house areas score less (because they are semi-transparent and generally lower than solid buildings) and (clusters of) office buildings more (these are considered to score the most negative). The calculation is quite complex. A grid cell scores e.g. 0 for urbanity if it contains less than 1% built-up area or less than 10% glass houses. But a grid cell also scores 0 if it contains 1-5% buildings, on the condition that the average built-up area within 500 metres is less than 1%. A grid cell also scores 0 if it contains 5-10% buildings but these are less visible because the average area of trees within 500 metres is more than 50%. At the other extreme, a grid cell scores 4 for urbanity if it contains more than 20% buildings and has less than 10% of trees within 500 metres. A grid cell also scores 4 if it contains only 1-5% buildings but the average built-up area within 500 metres is larger than 10% (these are densely built-up areas) and visibility is not reduced by trees. However, the city centres themselves are left out of the map: the model is restricted to the appreciation of the countryside.

For Skyline Disturbance the score of the focal cell depends on the type of visible man-made artefacts within a 1 kilometre to 2.5 kilometre radius; from the most to the least disturbing these are: high-rise, power pylons, wind turbines. Their visibility depends on the amount of nearby vertical vegetation from the focal cell (observer's position). We realise that these artefacts are not always negative: they can form important landmarks that make the landscape readable and help to orientate oneself, which most often receives a positive appreciation. We also realise that high buildings, for example, may be appreciated because of architectural quality. But no

Table 1

Map legends for the six GIS indicators

Indicator	Legend of indicator map
Naturalness	0 < 0.1% nature and < 50% grassland and no natural water 1 0.1-5% nature, or nature < 0.1% and > 50% grassland or natural water 2 5-10% nature and < 50% grassland, or 0.1-5% nature and > 50% grassland or water 3 10-50% nature or 5-10% nature and water 4 > 50% nature (e.g. heath, dunes, swamps, forests) or 10-50% nature and natural water If there is a lot of built-up area visible within 500m, grid cells scoring >1 loose 1 point.
Relief	0 flat areas, man-made relief 1 nearly flat, old man-made mounds (for housing) 2 sloping 3 hilly (or dunes) 4 larger hills
Historical Distinctiveness	0 > 1 km from grid cells with nationally protected historical (clusters of) buildings or sites 1 < 1 km from grid cells with nationally protected historical (clusters of) buildings or sites 2 next to grid cells with single historical buildings / sites or within 500 m of a cluster 3 next to grid cells with clusters of historical buildings 4 grid cell containing nationally protected historical (clusters of) buildings or sites
Urbanity (negative)	0 1-5 % in grid cell and average <1% in surrounding 500m or <1% built-up area visible in grid cell and average 1-5% in surrounding 500m 1 1-5% visible built-up area in grid cell and average 1-5% in surrounding 500 m or <1% visible in grid cell and average >5% in surrounding 500m. 2 5-10% built-up area visible in grid cell and <5% in surrounding 500m, or 1-5 % visible in grid cell and average >5% in surrounding 500m 3 10-20% built-up area visible within grid cell and average <5% in surrounding 500m, or 5-10% visible in grid cell and average >5% in surrounding 500m 4 >20% built-up area visible within grid cell and average <5% in surrounding 500m or 10-20% visible within cell and average >5% in surrounding 500m Visible means here: less than 10% trees in the surrounding 500m of the buildings
Skyline Disturbance (negative)	0 no disturbing high-rise artefacts visible within 2.5 km 1 wind turbines visible within 2.5km or other artefacts not very visible 2 visible power pylons/high buildings > 1km < 2.5km, or < 1km but not very visible 3 visible power pylons < 1km or high buildings < 1km but not very visible 4 visible high buildings < 1km (higher than 35m or 10 storeys) Visible means here: less than 10% trees within 500m of the observer
Noise Level (negative)	0 quiet < 35 dB 1 not noisy: 35-45 dB 2 rather noisy: 45-55 dB 3 noisy: 55-65 4 very noisy: > 65 dB

distinction has been made in this respect; due to lack of data and the fact that these preferences may well differ between individuals.

Finally, for Noise Level the score depends on the amount of noise according to a model computing decibels depending on traffic intensity and type of industry (Jabben et al., 2000).

The maps of the 6 indicators, including the topographic map we used as input, were checked in the field, using a field computer with GPS. While driving through the countryside we could see our movements on the maps, making it quite easy to compare the maps with the real landscape. Although we found some inconsistencies in the data (sometimes existing tree lines did not appear on the maps) we found the indicator maps quite accurate. The accuracy of the Skyline Disturbance map varied strongly with weather conditions: the visibility of the high artefacts change dramatically depending on the amount of moisture in the air.

Interrelationships between the six GIS-indicators were calculated at the grid-cell level for the whole of the Dutch countryside (n = 545,652). All correlations (Pearson's) are below 0.30, except the one between Naturalness and Relief: r = 0.34. This was considered acceptable. The predicted landscape attractiveness was calculated as a linear combination of these indicators, using regression weights. This will be explained later in more detail. More detailed information on GLAM can be found in Roos-Klein Lankhorst and colleagues (2005).

6.4 CALIBRATION OF GLAM

The model generates predictions for each and every 250 x 250 metre grid-cell of countryside in the Netherlands (excluding built-up areas and large water surfaces). However, the primary aim of the model is not to predict the attractiveness of the landscape at this detailed level, but rather the attractiveness at the broader level of the landscape surrounding one's place of residence. This was also the question asked in the survey that was used to calibrate the model: "how attractive do you find the landscape surrounding your place of residence?" In the study, the Netherlands was divided into 15 regions that were thought to be reasonably homogeneous with regard to dominant landscape type. Within each of these regions the sample was stratified by level of urbanity: non-urban versus at least somewhat urban. Within each stratum the chance to be included in the sample was proportional to the size of the postcode area. Due to the sampling design, the sample cannot be expected to be representative for the Dutch population: the design was focused more on sampling (ratings of) landscapes than on sampling people.

The aim was to have about 100 filled-in postal questionnaires for each of the strata, with a grand total of 3000 respondents. This goal was reached (n = 3006), with response rates being lower in the more urban strata (21%) than in the non-urban strata (28%). There were no significant differences in response rates between landscape regions. In the final sample males are overrepresented (61%), people below 30 years of age are underrepresented (7%). Typically the questionnaire was answered by a head of the household (90%). Of the respondents 48% characterises him-/herself as being full-time employed, 10% as part-time employed, 23% as being on retirement, and 14% as full-time homemaker. Since no special measures were taken, ethnic minorities are likely to be underrepresented. For more information on this sample, see de Vries and van Kralingen (2002).

No specific delineation of the landscape was given: it was left to the respondents what they considered the relevant area to be rated. The model's predictions can be scaled up by averaging the predicted values for a given area. At first instance 'the landscape surrounding one's place of residence' seems like a rather difficult spatial unit to delineate. However, research on the prototype version of GLAM has shown that in practice this constitutes less of a problem (de Vries and van Kralingen, 2002). Averages were calculated for circles around the midpoint of one's postcode, with different radii. The correlation between averaged predictions and the (average) rating by inhabitants proved to be remarkably consistent for radii between 2.5 and 7.5 kilometres. Therefore we have chosen to use the average of the model values for the countryside cells within 5 kilometres as predictor for the rating by inhabitants.

Relations between predictions and actual ratings become stronger to the degree the actual ratings are averaged over more respondents judging the same environment: individual differences are averaged out to a larger extent. Unfortunately many postcode areas had very few respondents. We decided to use only those postcodes that had at least three respondents to calibrate the GLAM model ($n = 277$). The correlations between averaged GIS indicator values for 5 kilometre radius circles of the selected postcodes are given in table 2.

Correlations are especially high for Noise and Urbanity and for Relief and Historical Distinctiveness. But even in those cases, less than 50% of the variance in one indicator is 'explained' by the other indicator, implying there is quite a lot of unique variation left. A rule of thumb is that correlations above 0.80 constitute a serious multi-collinearity problem (Gujarati, 1995), which is not the case here. We started the calibration of the GLAM model with a calculation of the relations between GIS-indicators and the averaged attractiveness ratings. All six GIS-indicators show significant correlations ($p < 0.001$) with the averaged overall attractiveness rating of the landscape and all in the expected direction (table 3). The correlations are strongest for Naturalness and Skyline Disturbance. The multivariate regression analysis shows four of the six indicators have a significant unique predictive contribution: Relief and Noise Level do not. Together the remaining four indicators 'explain' 36% of the variance in averaged attractiveness scores (adjusted R^2). The standardised regression weights are similar for Urbanity, Naturalness and Historical

Table 2

Pearson's correlations between averaged GIS indicator values for 5 kilometre radius circles (n = 277)

	Historical Distinctive-ness	Relief	Urbanity	Skyline Disturbance	Noise
Naturalness	0.13 *	0.53 **	-0.11	-0.41 **	-0.12 *
Historical Distinctiveness		0.60 **	0.38 **	0.06	0.19 **
Relief			0.08	-0.31 **	-0.10
Urbanity				0.48 **	0.68 **
Skyline Disturbance					0.47 **

* : significant at 0.05-level

** : significant at 0.01-level

Distinctiveness, but lower for Skyline Disturbance. This is a different pattern than observed for the bivariate correlations with attractiveness, in which Skyline Disturbance has one of the highest correlations. This is likely to be due to the interrelations of Skyline Disturbance with Naturalness (negative) and Urbanity (positive; table 2). Historical Distinctiveness shows a reversed pattern: its standardised regression weight is higher than its bivariate correlation. Tracing the stepwise build-up of the regression equation shows that it is only after Urbanity has delivered its negative contribution, that Historical Distinctiveness can make its positive contribution. These indicators have a positive interrelation: historical monuments and features are more likely to be found in or near urban areas. But whereas urbanity in general has a negative effect on the surrounding countryside, historical monuments and historical features do indeed have a positive effect on the environment.

Table 3

Relations between GIS indicator values for 5 kilometre radius circles and averaged attractiveness rating of surrounding countryside (n = 277)

	Bivariate (Pearson's) correlation	Standardized regression weight (Beta)	Raw regression weight (B)
Naturalness	0.45 **	0.31	0.44
Historical Distinctiveness	0.20 **	0.30	0.57
Relief	0.34 **	ns	ns
Urbanity	-0.32 **	-0.32	-0.81
Skyline Disturbance	-0.42 **	-0.16	-0.21
Noise Level	-0.32 **	ns	ns
Constant			7.36

** : significant at 0.01-level

Note: regression weights (all p < 0.01) are from multiple regression analysis

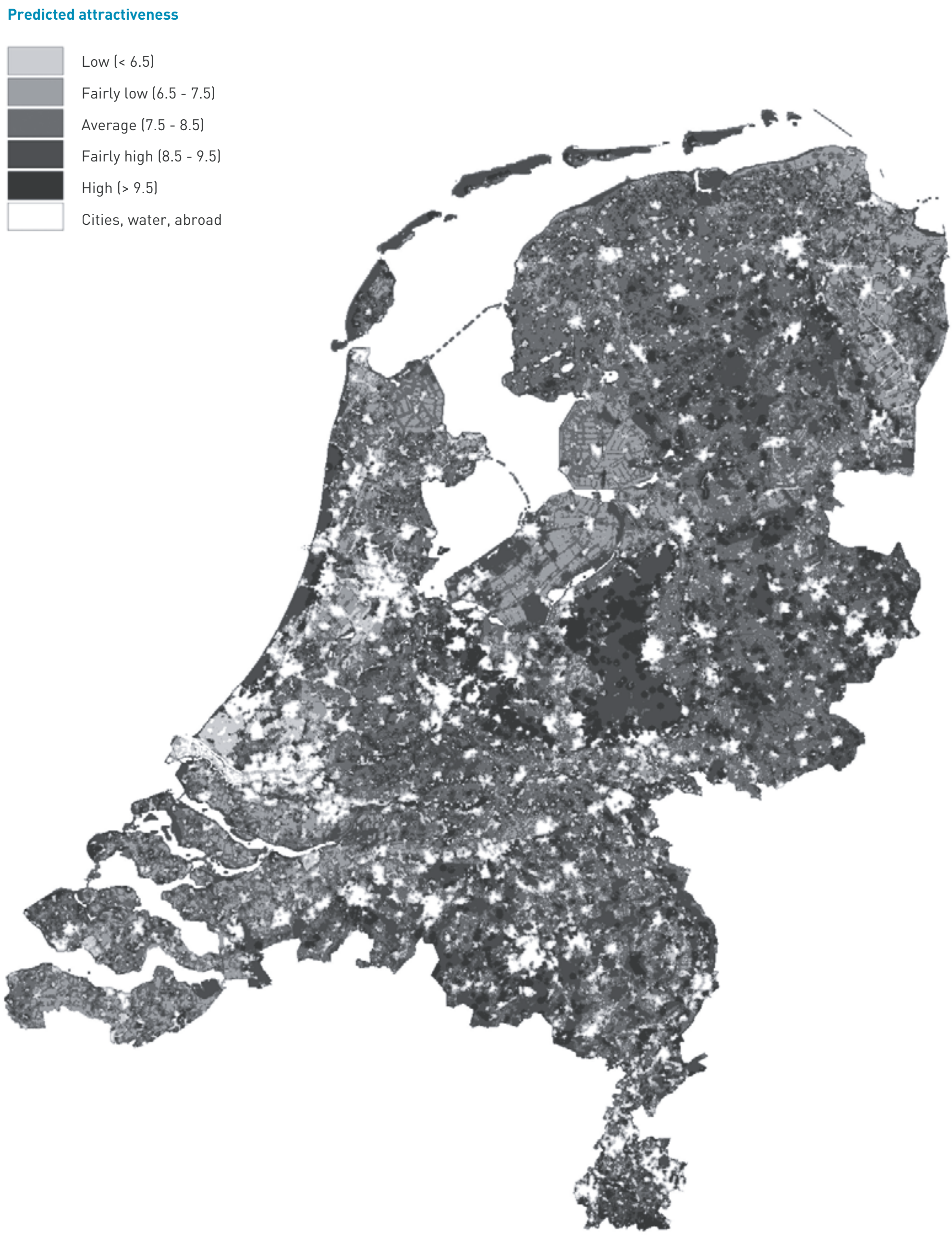


Figure 2

Predicted attractiveness, based on calibrated version of GLAM

Figure 2 shows the attractiveness of the landscape, as predicted by the calibrated version of GLAM, applying the raw regression weights in table 3 (B's). Note that the map gives results at the grid cell level, while the calibration and validation took place at the level of averages within 5-kilometre circles.

6.5 VALIDATION OF GLAM

Whereas the calibration shows the fit of the model, these results could not be used to validate the model, because the weights are optimised for the dataset. To validate the model, independently acquired data from another study on landscape appreciation were used (SNM, 2005). Although this study was not set up to validate GLAM, the questionnaire was quite similar to the one that was used to calibrate the model. Most of the questions were identical in formulation and answering scale. The study differed on some other aspects. To start with, 52 areas were selected that landscape experts considered being of high quality. That is: the area was considered a good example of a certain type of landscape, or otherwise attractive. The size of the areas ranged between 500 and 9000 hectares. One or sometimes two (4-digit) postcodes were selected in the vicinity of each of these areas. Within the postcodes attached to each of the 52 areas 670 unaddressed questionnaires were randomly delivered by mail to residents. The overall response was about 15%, with a range of 42 to 142 respondents per area. Respondents were asked to rate the area that was delineated on the provided map on several aspects, among others on its overall attractiveness.

To validate the model, average ratings were calculated for each of the 52 areas. Averages for overall attractiveness ranged from 7.5 to 9.2 on a 10-point scale. The overall average for the 52 areas was 8.4. This is considerably higher than that observed in the study that was used to calibrate the model ($M = 7.9$), signifying that the intended selection of high-quality areas was successful to at least some degree. Also the average predicted values for the attractiveness of all the countryside grid-cells were calculated, for each area separately. Predicted values were based on the regression equation from the calibration phase. The last step was the calculation of the correlation between the predicted attractiveness ratings and the actual average ratings. The correlation coefficient was $r = 0.69$, with an 'explained' variance of 47%. Note that the level of explained variance now is higher than in the calibration phase (36%), despite the fact that independent data were used.

6.6 CONCLUSIONS AND DISCUSSION

At the end of the calibration phase it appeared that only four of the six initially proposed indicators make a significant unique predictive contributions: Naturalness, Urbanity, Historical Distinctiveness and Skyline Disturbance.

A remarkable finding is that the explanatory power of the model (in a statistical sense) was higher in the validation phase than in the calibration phase. This outcome is even more surprising given the fact that in the validation study a restriction of the range may have occurred, due to the selection of high quality and/or attractive areas by experts. The result is likely to be due to the differences in the set-up of the empirical studies used in the two phases. Whereas in the calibrations study respondents were asked to rate the countryside surrounding their place of residence, in the validation study the area to be rated was delineated on a map. Consequently, ambiguity regarding the area being rated, and therefore individual differences in this respect, may have been smaller than in the calibration study. Furthermore, in the validation study the average rating per area was based on a much higher number of respondents than in the calibration study: at least 42 versus at least 3 (and usually not more). So, individual differences were averaged out to a larger degree in the validation study.

As for the desirability of averaging out individual differences, we make a distinction between differences in appreciation that are not related to the physical characteristics of the landscape, and those that are. The former (e.g. personal experiences with the landscape) are unlikely to be very informative with regard to landscape monitoring and spatial design. So, from an applied perspective it may not be that important to try and incorporate such differences into the model. That is not to say that such differences are also negligible in the social process evolving around spatial planning, but this is clearly beyond the scope of our model. Individual differences that are related to a different appreciation of the physical characteristics (see e.g. Dramstad and others, 2006) might be relevant, depending on their size. And although we do not deny the existence of individual differences in landscape preferences related to the landscape's physical appearance (see e.g. Van den Berg, 1999), we think in general they are small compared to the differences in appreciation caused by the physical differences between the Dutch landscapes themselves. In other words: we would like to argue that there is a substantial amount of agreement in landscape preferences between individuals (see also Herzog et al., 2000; Palmer and Hoffman, 2001), and it is precisely this agreement that allows for the predictive validity of the GLAM model.

At the same time we acknowledge that GLAM is not only crude in its spatial level, but also in the landscape (features) between which it distinguishes e.g. it mainly distinguishes between natural and agricultural areas, and between areas with significant (recent) human interference (in the form of visible artefacts) and those without. This can be seen within the Naturalness indicator, where no distinction is made between different types of nature area, such as forests, dunes, heath and wetlands. At the same time it is known from other studies that even different types of forest are appreciated differently. For example, in general people seem to prefer old mixed forests to young coniferous production forests (Ribe, 1989). To a large extent the crudeness of the model in this respect is due to a lack of sufficiently detailed data on the landscape. It is reasonable to argue that, with further refinement on the side of the physical appearance of the landscape, also refinement on the side of individual differences in preferences becomes more relevant. People are more likely to agree on the crude distinctions between landscapes than on the finer ones. For example, in the Netherlands young people seem to prefer more rugged nature areas than elderly people, which tend to prefer more easily accessible, park-like landscapes (Reneman et al., 1999). Also the work by Tveit and others (2006) on landscape character may prove to be useful, pointing out aspects that are not explicitly included in GLAM yet, such as stewardship and visual scale.

A related aspect is that, besides differences in aesthetic preferences, functional aspects (fitness for use/suitability) may also play a part in rating the attractiveness of the landscape (see e.g. Ribe, 1989; Buijs et al., 2006). In other words, the attractiveness may depend on whatever function the individual has in mind when considering the landscape. GLAM primarily focuses on the pleasure of experiencing the landscape when travelling through or spending time in the area. In as far as functions are involved, this coincides with the landscape as a leisure setting, especially for resource-based recreation. This is probably the dominant function the countryside has for most Dutch inhabitants. The other way around, the scenic beauty of a landscape may determine its suitability for certain types of development, e.g. touristic development, and so inform planning (Brown, 2006).

Although we have the desire to elaborate GLAM, the validation provided quite strong support for the model. Does this mean that the model is also suited for use in practical application? We think it is, although only at a regional level. For example, the model does not take the local composition or the design quality of the area into account. So, the model's predictive capabilities should only be applied at a higher spatial level. But even at the lower spatial level it is likely to be quite useful for monitoring purposes: it can give early signs that the landscape may be changing in a way that makes it less attractive. This might also be one way to evaluate the effectiveness of landscape policies.

Moreover, the model offers a very cost-efficient way to get a valid impression of how people (or, more specifically, inhabitants) on average appreciate the countryside surrounding their place of residence. Two other methods to get such an impression would be a survey among the inhabitants living in or near the area, or to solicit an expert judgement. The survey method would generate valid results, but is costly to perform for the whole of the Netherlands. The expert method, on the other hand, is less costly, but is also less likely to generate valid results. What experts consider high-quality, valuable and therefore attractive landscapes does not always coincide with the views of ordinary inhabitants (Herzog et al., 2000; Daniel, 2001). Replacing expert judgements by predictive models such as GLAM may contribute to what in the policy arena is called 'democratising landscape' (see e.g. Fairclough, 2002). This may also be considered a reminder that GLAM represents the opinions of Dutch people only.

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