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Research Paper

Mapping recreation as an ecosystem service: Considering scale, interregional differences and the influence of physical attributes

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ABSTRACT

Methods to map nature-based recreation are increasingly used, especially in ecosystem services research and practice. Researchers that map nature-based recreation beyond local scales, however, have relied much on physical attributes, e.g. land cover and topography. In such instances the recreational potential of land is modeled based on expert judgement and not on public preferences. Participatory mapping data is based on public preferences and as such can be used to improve proxy-based methods to map the recreational potential of land. In this paper, we use data from an online mapping survey (the Hotspotmonitor/Greenmapper) to spatially analyze the recreational potential of land. We employed point pattern analyses to 1) investigate which physical attributes contribute to the recreational potential of land, at both a regional and a national scale, and 2) how preferences for such attributes differ between respondents from distinct geographical regions. We find that interregional differences, whereas prominent at the regional scale, are small at national scale, suggesting there is a shared understanding of what places are 'hotspots' for recreation within the Netherlands. These hotspots, however, are difficult to map using physical attributes alone. Discussing these discrepancies, our paper provides insights that contribute to a better understanding and mapping of the recreational potential of land.

1. Introduction

Nature-based recreation and tourism have become important activities in many contemporary societies, offering people who increasingly live in heavily urbanized landscapes the opportunity to relieve stress, enjoy nature and spend time with others (Davis, Daams, van Hinsberg, & Sijtsma, 2016). As such, there is a need for spatially explicit knowledge that helps identify the recreational potential of land, specifically for open and green space.

Maps provide such knowledge and are commonly used, particularly in ecosystem services (ES) research and practice (Burkhard & Crossman, 2013; Crossman et al., 2013; Maes et al., 2012). The widespread attention for ES mapping has lead to a diverse array of approaches that use different indicators to spatially represent the recreational potential of land (Casado-Arzuaga, Onaindia, Madariaga, & Verburg, 2014; Penã, Casado-Arzuaga, & Onaindia, 2015; Weyland & Laterra, 2014). Given the emphasis on the natural environment as a 'provider' of environmental benefits in the ES framework, maps to spatially represent the recreational potential of land have often been based on physical attributes. Reviewing methods for mapping ES, Martínez-Harms and Balvanera (2012) showed that recreation is commonly mapped on the basis of land cover and distance to roads. Paracchini et al. (2014) proposed a framework for mapping the recreational potential of land in the EU on the basis of proximity to coast, protection status and degree of naturalness. In the Netherlands, too, the widely used AVANAR model maps recreational potential based on land cover, path density and openness of the landscape (De Vries, Hoogerwerf, & De Regt, 2004). In such mechanistic models it is the researcher who decides which physical attributes can be considered to yield the highest recreational potential. This is problematic because such expert-based efforts may not resonate with the experiences and perceptions of the wider public.

Recognizing the need to include people's values in ES maps, a growing group of ES scholars uses participatory mapping (PPGIS) to study the spatial distribution of recreational experiences. ES researchers use PPGIS to engage a wide range of societal actors to identify ES that 'originate in place-based, local knowledge instead of proxy data from

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literature of process modelling' (Brown & Fagerholm, 2015, p. 119). These efforts are based on collaborative mapping in communities, where emphasis is put on participation as a way to improve legitimacy and empowerment in local spatial decision making processes (Dunn, 2007; McCall & Minang, 2005; Ramirez-Gomez, Brown, Verweij, & Boot, 2016) or on household surveys, where the emphasis lies on the production of high quality spatial data that can be compared to or integrated with other types of spatial data (see De Valck et al., 2016; Nahuelhal, Carmona, Lozada, Jaramillo, & Aguyao, 2013; Plieninger, Dijks, Oteros-Rozas, & Bieling, 2013; van Riper, Kyle, Sutton, Barnes, & Sherrouse, 2012).

In this study we focus on the use of PPGIS efforts that are based on survey data with the aim of producing quantitative spatial outcomes of nature-based recreation. As maps created with the use of PPGIS data directly reflect the perceptions of the public, they are considered to more accurately capture which land holds most potential for nature-based recreation. Yet, the mainstreaming of PPGIS as a way to map nature-based recreation across spatial scales is hampered by several methodological limitations. Firstly, the nature of PPGIS studies is largely descriptive. As such they often do not provide insights into the factors that contribute to the recreational potential of land that would help us better understand why people like certain places for recreation and not others (Brown & Fagerholm, 2015). Secondly, PPGIS is predominantly focused on values or experiences of single recreational sites or type of habitat, hampering comparisons across sites or the spatial representation of such values at larger policy relevant scales (Ibid). Finally, as with most survey-based methodologies, to collect data through PPGIS is both labor and resource intensive.

In light of the above, researchers will likely remain dependent on proxies to represent recreational opportunities beyond local scales (Maes et al., 2012). Knowledge from PPGIS studies can however be used to improve and inform such models. For instance, Eigenbrod et al. (2010) empirically investigated the performance of proxies for mapping ES, including nature-based recreation, by comparing proxy-based maps with maps based on survey data. Their study provides a solid first step in assessing the performance of proxy-based maps at national scale. However, to further scrutinize and improve proxy-based maps, it is also necessary to investigate the context in which such maps perform well or not. What is the influence of physical attributes on recreational potential at different spatial scales, from regional to national? What challenges do interregional differences bring for proxy-based maps?

It is these questions that we aim to tackle in this study. We bring novel insights to the literature on mapping nature-based recreation by looking into interregional differences and the influence of physical attributes at both the regional and the national scale. We employ point pattern analyses to examine the extent to which different physical attributes explain the spatial variability in the recreational potential of land and explore differences between respondents from six distinct geographical regions.

2. Theoretical background

Before elaborating on the methods we used to map the recreational potential of land, it is necessary to explain how we conceptualize recreational potential. To do so, we draw from the field of leisure sciences, wherein scholars have studied recreation by looking at who participates in (what type of) recreational activities and where they do so (see Hall & Page, 2014). Indeed, according to Pigram (as cited in Hall & Page, 2014), the decision for partaking in outdoor recreation at a particular site is the product of the propensity for particular recreational activities and the opportunities for doing so (Fig. 1), factors which are often conceptualized as 'demand and supply', 'origin and destination attributes' or 'push and pull factors' (e.g. Kim, Lee, & Klenosky, 2003; Klenosky, 2002). Push factors are related to the wants and needs of the individual or household, e.g. the desire to go hiking, and pull factors are the characteristics of the destination that may

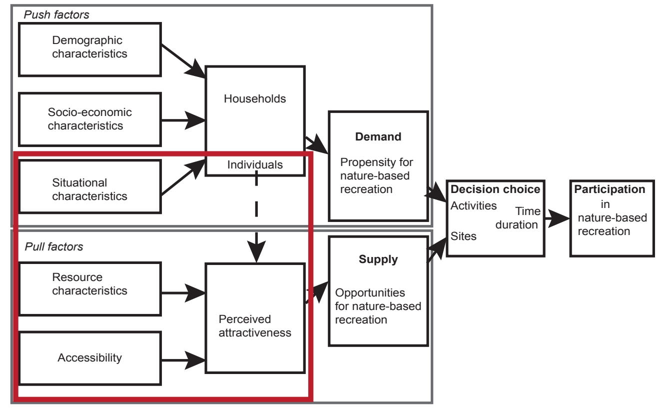

Fig. 1. The decision process in outdoor recreation, adjusted from Pigram 1983. The red box indicates the scope of this paper. We added the dotted arrow to the original framework by Pigram, to indicate that we look into the influence of geographical context (situational characteristics) on perceived attractiveness, as we compare perceptions of residents from six distinct geographical regions. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

contribute to this particular wish, e.g. proximity or type of landscape.

The distinction between demand and supply of nature-based recreation is also commonly made in the field of ES research, albeit somewhat differently. Supply is referred to as the 'potential' or 'capacity' of land to provide recreational services, and demand is conceptualized as its actual use or benefit (see Burkhard, Kroll, Nedkov, & Müller, 2012), marking a dichotomy between the physical environment (supply) and its users (demand). The recreational potential of land is thereby thought to be a function of biophysical characteristics and only its actual use is explicitly linked to human perception.

However, as also indicated by Pigram's framework, it is not merely the characteristics of natural land that directly capture its potential to become a place for recreation, but rather *how* such characteristics are perceived. Such perceptions remain implicit in most efforts that map the recreational potential of land based on biophysical indicators only, in which case the researcher defines what characteristics of land yield the highest potential for recreation. Implicitly or explicitly, the assessment of the recreational potential of land is always based on perceptions of what makes land suitable for recreation. In line with the framework presented in Fig. 1, in this study we take the perceived attractiveness of land as a direct measure for its recreational potential.

3. Methods

3.1. Survey data

In this study we made use of the HotSpot Monitor (HSM, www.hotspotmonitor.eu). The HSM is a Google Maps-based participatory mapping tool (see Bijker & Sijtsma, 2017; De Vries et al., 2013; Sijtsma et al., 2012a), where respondents are asked to pinpoint the place they find most attractive ('*aantrekkelijk*' in Dutch). In the online tool respondents were explained that they should think off attractiveness in a broad sense: they were to think about places that they considered, for whatever reason, meaningful ('*waardevol*' or '*belangrijk*' in Dutch). The prerequisite for placing a marker is that these locations had to have 'natural' qualities: with vegetation and/or water.

Several versions of the HSM exist (later versions at www.greenmapper.org), but in this study we make use of version 1.2., in which 3616 Dutch citizens from six regions participated. General findings of the survey are reported in De Vries et al. (2013). Whereas the results in De Vries et al. (2013) are mainly descriptive, in this study we specifically look into the effect of physical attributes on the perceived attractiveness of land by using point pattern analyses.

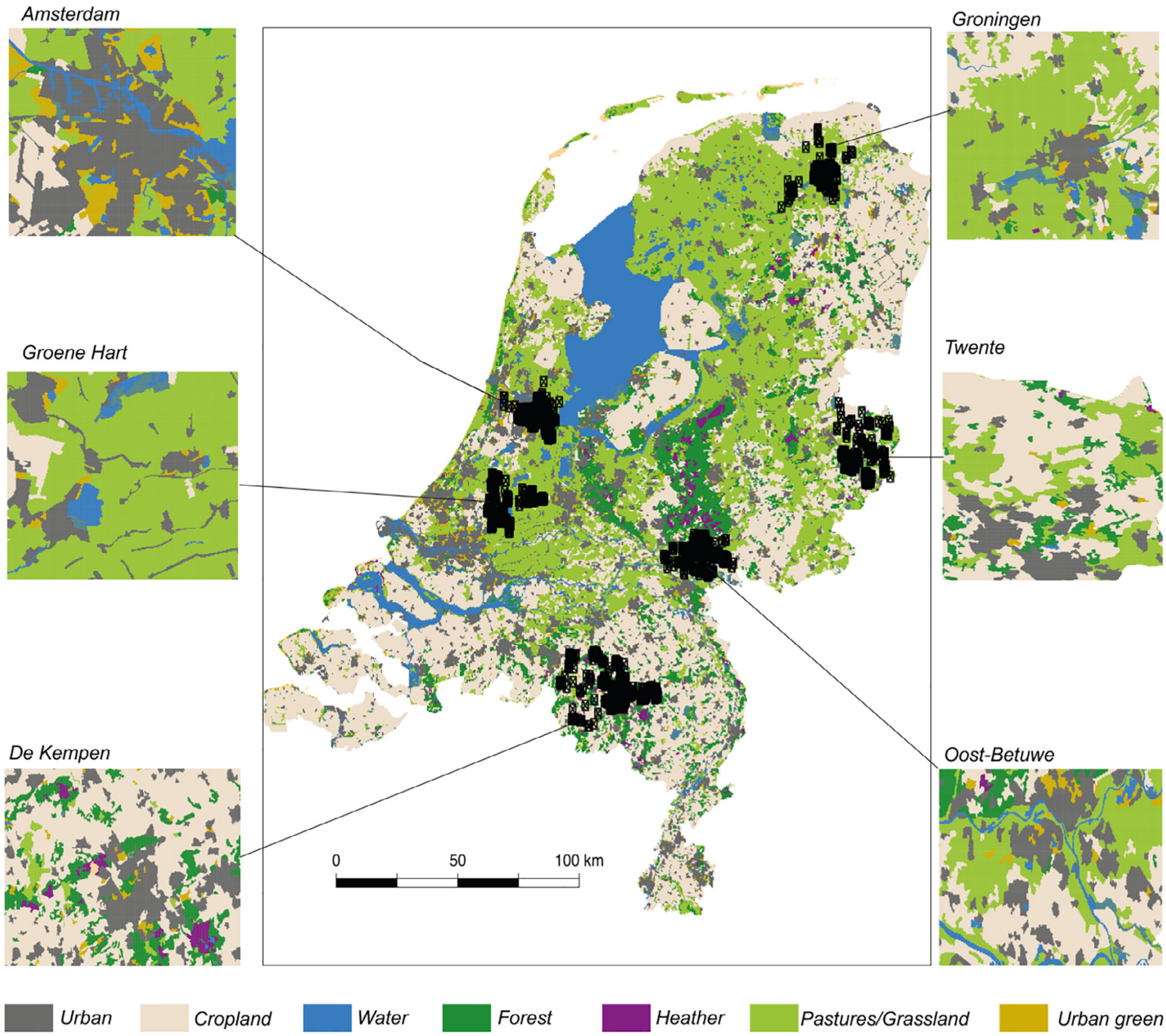

Fig. 2. Map of the Netherlands, indicating the location of surveyed respondents (black dots). Amsterdam (N = 564), de Kempen (N = 524), Oost-Betuwe (N = 572), Groningen (N = 562), Groene Hart (N = 586), Twente (n = 502).

For the HSM, six regions across the Netherlands were chosen which were thought to represent a wide variety in the character of the landscapes and the communities living in them (Fig. 2). A stratified random sampling approach was used to include a representative amount of residents living in small-sized, medium-sized and large-sized municipalities. The survey was conducted among the members of an Internet panel of a marketing research agency (GfK). In total 3616 respondents participated, corresponding to an overall response rate of 53 per cent. Respondents who marked locations outside of the Netherlands were removed, leading to a final sample of 3293 respondents.

The HSM 1.2 version data contain four observations per person: one marker put at local scale (within 2 km from home), one marker put at regional scale (within 20 km from home), and two markers put at national scale. Respondents were told that they were allowed to place markers at the same location multiple times, at different scales, if they wanted to. We chose to work only with markers put on a regional and national scale, so that we could compare results both within and across regions.

3.2. Spatial data

To make an appropriate selection of physical attributes (see Table 1) we conducted a literature review of mapping studies. We looked for articles (until December 2016) through web of knowledge using the search string (TS = (map* AND (recreat* AND ("ecosystem service" OR landscape)))). We coded the papers according to the type of attributes they included and based our own analysis on the attributes that were used most: land cover and land use, accessibility, topography, proximity to water and status of protection (for a detailed description of this analysis see supplementary material).

For the land cover covariates, we used Corine Land Cover data (2012, 100 m resolution). After checking for multicollinearity between several land cover categories, our final list of covariates included forest, wetlands, agricultural land, heathland and urban green.

We included the location of 'national landscapes' and 'national parks' as two separate variables, as these merit a different protection status in the Netherlands. National parks, as many other nature parks across the globe, are areas specifically designated for nature protection. The focus of these parks, therefore, is the natural heritage of a particular place. In contrast, national landscapes are considered to be landscapes of importance due to both the natural and cultural heritage these landscapes embody. As such national landscapes refer to wider regions, that, besides natural land, also include settlements and cropland.

To calculate an appropriate buffer distance for proximity to coast and water bodies, we analyzed the quantity of markers that were given

Table 1
Data used for covariates.

Variable	Description
Land cover	
Forests	Broad-leaved forest, Coniferous forest, Mixed forest
Wetland	Inland marshes, Peat bogs classes
Agricultural land	Cropland, Non-irrigated arable land, fruit trees and berry plantations, complex cultivation patterns, land principally occupied by agriculture with significant areas of natural vegetation
Heathland	Moors and heathland
Urban Green	Green urban areas, Sport and leisure facilities
Protected area status	
National parks	Areas designated as national park
National landscapes	Areas designated as national landscape
Proximity to water	
Proximity to inland water	500 m buffer around waterbodies
Proximity to coast	500 m (regional data) or 2 km (national data) buffer around coastline
Topography	
Elevation	DEM Netherlands (AHN)
Distance to respondents	
Regional scale distance	Kernel density of surveyed respondents
National scale distance	Distance to closest point in the point pattern
Accessibility	
Distance to roads	Based on Open Street Map (tags: "highway = motorway" and "highway = trunk")
Distance to trainstations	Based on Open Street Map (tag: "railway = station")
Urbanization	Degree of urbanization for each municipality according to the classification of Statistics Netherlands (CBS).

the characteristic 'water' by the respondents, with 500 m distance intervals from water bodies and the coast. For the national data-set, a buffer of 500 m around water bodies and a buffer of 2000 m from the coast seemed most suitable, whereas for the regional scale data a buffer of 500 m around water bodies and coastline was found to be sufficient.

It is likely that the closer a place is to the respondent's home, the more familiar it is and thus the more likely that it is marked as attractive, compared to similar places located further away. Indeed, several studies have shown distance decay effects, including De Vries et al. (2013) based on the same data at national scale. To account for this effect we included a variable that captured the distance of respondents homes to the marked locations. At the national scale we created a distance map on the basis of the point pattern consisting of the geographical locations of the respondents homes. The value in each cell of this map (a raster with a cell size of 250 m) equals the distance from each cell to the nearest data point in the pattern consisting of geographical locations of respondents' homes.

At the regional scale we took a slightly different approach, as we assumed that at this smaller scale not only the distance to the point pattern at large would matter, but also the distribution of points within the pattern. Whereas at national scale respondents were allowed to put a marker at any location in the Netherlands, at regional scale the respondents were asked to put a marker within 20 km of their homes. As such, we calculated a kernel density function on the basis of respondents' homes, using a bandwidth of 20 km. At regional scale a cell in the distance map therefore represents the density (respondents per km^2) of surveyed respondents within a range of 20 km, using a Gaussian weight function to account for distance (i.e. giving points closer to the cell a higher weight). Both the regional and national distance map were calculated separately for each of the six regions.

Finally, we added three accessibility indicators for analysis at the national scale, to control for accessibility via public transport or by car. Assuming that people are most likely to travel to recreational sites by car or public transport, we calculated the distance to the nearest highway and distance to the nearest train station based on Open Street Map data. Furthermore, assuming that trains in highly urbanized areas run more often than trains in less urbanized areas, we added degree of urbanization as a variable. We only make use of these variables for the national scale analysis because we assume they are less relevant for access to recreational areas at regional scale. We expect no large differences in accessibility at the regional scale, as the density of local roads in the Netherlands is quite high and people may also use the bicycle for such distances.

3.3. Spatial analysis

We employed a point pattern analysis (PPA) using the SpatStat package in R (Baddeley & Turner, 2005). Given the nature of participatory mapped data, PPA is commonly implemented to show the spatial distribution of mapped values and detect clustering (see Beverly, Uto, Wilkes, & Bothwell, 2008; Brown & Weber, 2012). Our PPA followed three basic steps: we first estimated the intensity of points (i.e. number of points per unit area) to spatially describe areas of high perceived attractiveness, using kernel density estimates. Using a kernel density function, intensity is estimated by applying a function to each data point, which averages the location of that point with respect to the location of other points within a certain radius, i.e. bandwidth. Points that are nearby receive a higher weight than distant points, depending on the type of function; in this study we applied a Gaussian function. We applied a bandwidth of 1.5 km on the regional scale, to allow the identification of popular areas of relatively small size (such as urban parks). At national scale we applied a bandwidth of 15 km, to allow for the exploration of densities in wider regions rather than individual parks.

Secondly, to test the influence of the role of physical attributes on the spatial distribution of markers, we fitted a point process model to our data. Point process models are based on the assumption that point patterns are based on a particular kind of spatial point process. Most commonly the null hypothesis is that the spatial distribution of points is random, i.e. a homogenous Poisson point process. In this case points are distributed independently from each other, so that they do not cluster, and the intensity of points does not vary across space. This is also referred to as complete spatial randomness (CSR). CSR is, however, not a realistic point of departure for many spatial processes, as our a priori assumption quite often is that phenomena are not randomly distributed but tied to particular spaces (e.g. car accidents happen on roads). The rejection of CSR as a null hypothesis may therefore be of little meaning (Aldstadt, 2010). Models based on physical attributes are often based on the assumption that particular characteristics make certain landscapes more suitable for nature recreation-based activities than others. For this reason we fitted an inhomogenous Poisson point process model to our data, assuming the intensity of points varies according to the spatial distribution of the physical attributes. We specified the model so that the intensity of points is a loglinear function of the parameters. The parameters were estimated by means of maximum likelihood (see Baddeley & Turner, 2000).

Thirdly, after fitting the model we used it to generate simulated point patterns, against which we can test for spatial clustering in our reported data. We employed Ripley's K statistic, i.e. the K-function, to study whether points cluster even after accounting for the variation in covariates. By comparing K-values to particular benchmarked values, specified through a model for instance, it is possible to indicate whether clustering occurs: higher values will indicate clustering, while lower values will indicate dispersion. In our study we compare the estimated Ripley's K of the reported data against the estimated Ripley's K based on the point process model for each region. As such, using Monte Carlo simulations, we can use the K-function to assess the goodness of fit of our inhomogenous poisson process model. We generated 99 simulated point patterns from the models as simulation envelopes, so that the values of the simulated patterns can be taken as 0.01 significance bands. This allows us to infer whether, when we account for the spatial variability in land use and other variables, markers occur randomly throughout space, as typically assumed in studies mapping nature-based recreation on the basis of proxies, or not. For example, in simpler terms: Do all forests display equal intensities of markers or are some forests particularly popular and display a higher number of markers than we would expect based on the distribution of the physical attributes alone?

For ease of interpretation we standardized the K-function into the L-function. The L function is calculated as follows:

$$L(r) = \frac{\sqrt{K(r)}}{\pi} \tag{1}$$

This transformation of the K-function, makes it easier to discern differences between the estimated values of K at lower levels of distance *r*. Given that we would expect clustering to occur at small distances (indicating the popularity of a local park for instance), we plotted the L function instead of the K function for our cluster analysis.

4. Results

4.1. Regional scale

4.1.1. Spatial distribution of hotspots

The kernel density estimates of the markers put at regional scale within the six different subsamples portray that in each area there are only a few locations that can be considered a 'hotspot' (i.e. by having a remarkably high density of markers, Fig. 3). In regions Groningen and the Groene Hart most markers are centered around one particular site in the region, in both cases around a lake. A much wider spread of markers was found in the other areas, where several places were found highly attractive, leading to lower intensity estimates at the hotspots.

4.1.2. Influence of physical attributes

The output of the point process models reveals a few common trends across regions (Table 2). Not surprisingly, the distance to respondents' places of residence is very important. As such, urban green is particularly important at regional scale, although the extent to which it is important differs across regions. In Twente, the intensity of markers is 15.6 times higher in urban green areas than in areas that are not classified as urban green. This difference in intensity between regions can in part be explained by the spatial variation of the physical attributes (Table 3). As the regions have very different characteristics, the responses include a diversity of landscapes which people are able to identify as most attractive.

To evaluate how the model compares to the reported point pattern and related kernel densities (Fig. 3), we simulated a point pattern based on the model outputs using the Metropolis-Hastings algorithm (on the basis of 10,000 iterations and the number of reported points as starting point).

At first sight the model seems to perform best in regions where one particular location was very popular: for instance in the Groene Hart, where many respondents indicate a nearby lake as locally most attractive. This may be because of the limited number of alternatives, allowing the model to locate the few places that portray particular characteristics (in this case water and close to respondents' place of residence). However, quite importantly, the model still underestimates just how popular these places are: the intensity on the basis of reported markers is higher than that based on the simulated markers.

In contrast, areas such as Twente and de Kempen are characterized by a fragmented landscape, displaying several patches of forest and green. According to our reported data people develop a particular preference for only a few of these places, which cannot be explained by the indicators we included in our model. As such, the model does not perform very well when trying to locate the hotspots in these areas.

4.1.3. Clustering

Given the discrepancy between the modeled outcomes and the reported data, it is plausible to think that markers are indeed not distributed randomly across the different types of land cover, but center at particular areas. To test whether clustering occurs beyond the intensity that is estimated on the basis of the covariates we calculated Ripley's K (transformed into the L-function) for 99 simulated point patterns based on the model for each region (Fig. 4). Results largely confirm what

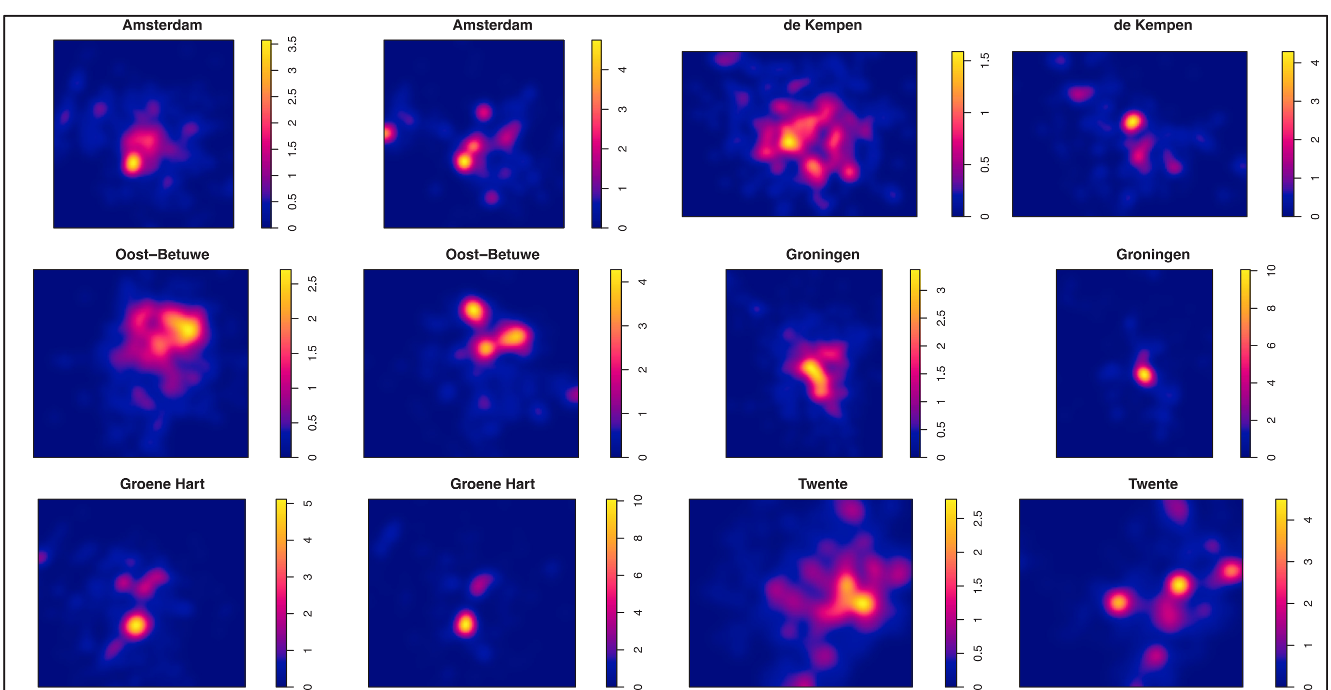

Fig. 3. Kernel density estimates based on simulated point patterns (left) and reported point patterns (right).

Table 2
Results from the point process models at regional scale.

	Amsterdam		De Kempen		Oost-Betuwe		Groningen		Groene Hart		Twente	
Variable	β	s.e.	β	s.e.	β	s.e.	β	s.e.	β	s.e.	β	s.e.
Intercept	-0^{***}	0.52	-0.001^{***}	0.44	-0^{***}	0.64	-0^{***}	0.66	-0^{***}	0.53	-0^{***}	0.57
Agriculture	-0.295^{***}	0.28	-0.445^{***}	0.14	1.107	0.14	-0.568^{***}	0.13	-0.408^{***}	0.20	−0.825	0.14
Elevation	1.126^{***}	0.01	-0.967^{***}	0.01	1.009^{***}	0.00	1.131^{***}	0.02	1.083^{***}	0.02	1.012^{**}	0.00
Intensity of respondents within 20 km	1.904^{***}	0.03	1.672^{***}	0.03	2.056^{***}	0.04	2.225^{***}	0.04	2.24^{***}	0.04	1.709^{***}	0.04
Forest	−0.745	0.22	2.895^{***}	0.12	2.517^{***}	0.17	3.645^{***}	0.16	−0.84	0.71	6.323^{****}	0.12
Heathland	−0.509	0.51	2.262^{***}	0.20	4.262^{***}	0.20	2.87^{**}	0.37	−0	656.02	2.556^{**}	0.32
Coastal region	42.959^{***}	0.23					8.278^{***}	0.34	246.2^{***}	0.35		
National landscape	1.586^{**}	0.18			−0.954	0.13	1.801^{***}	0.12	1.335	0.16	1.554^{***}	0.09
National park	1.107	0.29	3.644^{***}	0.33	2.941^{***}	0.12	1.496^{*}	0.19			−0	715.73
Urban green	2.326^{***}	0.14	2.269^{***}	0.21	4.259^{***}	0.19	4.147^{***}	0.14	1.724^{***}	0.16	15.676^{***}	0.20
Urban green size	1.247^{***}	0.02	1.316	0.35	1.917^{***}	0.16	1.66^{***}	0.13	1.072	0.16	2.981^{**}	0.37
Water	1.421^{***}	0.09	2.531^{***}	0.17	2.226^{***}	0.12	7.181^{***}	0.10	9.146^{***}	0.09	1.668^{*}	0.20
Wetland	−0.941	0.41	6.581^{***}	0.40	−0.914	0.51	-0.575^{*}	0.27	1.304	0.17	13.643^{***}	0.31

$^{***} < 0.001$ $^{**} < 0.01$ $^{*} < 0.05$. The coefficients can be interpreted as follows: for elevation in Amsterdam, a one unit change (meters) will lead to a 12.6% increase in intensity (points per (km^2)). For land cover variables coefficients should be interpreted with respect to the reference level: in de Kempen, the intensity in areas that were classified as forest was 2.895 higher than areas that were not classified as forest. For the variable reflecting the intensity of respondents a coefficient represents a 0.01 unit change as the values ranged from 0.1 to 0.2.

Table 3
Summary of covariates in the different regions.

	Amsterdam		De Kempen		Oost-Betuwe		Groningen		Groene Hart		Twente	
Variable	Units	%	Units	%	Units	%	Units	%	Units	%	Units	%
Agriculture (km^2)	394.65	16.14	1768.82	60.61	779.92	33.2	960.18	40.07	465.2	17.36	651.11	40.29
Elevation (mean (sd), meters)	−0.44(3.78)		19.48(8.26)		19.23(19.23)		2.81(4.17)		−1.02(2.96)		20.93(11.84)	
Forest (km^2)	142.84	5.84	508.54	17.42	437.27	18.62	93.22	3.89	49.54	1.85	153.24	9.48
Heathland (km^2)	32.13	1.31	76.55	2.62	89.89	3.83	15.93	0.66	24.44	0.91	23.29	1.44
Coast (km^2)	26.27	1.07	n.a.	n.a.	n.a.	n.a.	70.35	2.94	17.48	0.65	n.a.	n.a.
National Landscape (km^2)	368.78	15.08	n.a.	n.a.	953.95	40.61	257.37	10.74	1463.17	54.59	479.73	29.69
National park (km^2)	29.32	1.2	39.7	1.36	106.83	4.55	140.9	5.88	n.a.	n.a.	6.14	0.38
Urban green (km^2)	105.11	4.3	46.7	1.6	44.49	1.89	35.05	1.46	110.01	4.1	12.6	0.78
Urban green size (km^2)	0.13(0.84)		0.02(0.13)		0.02(0.19)		0.02(0.26)		0.1(0.72)		0.01(0.06)	
Water(km^2)	809.39	33.11	76.01	2.6	340.28	14.49	154.88	6.46	514.45	19.19	22.5	1.39
Wetland (km^2)	36.82	1.51	24.61	0.84	16.43	0.7	62.98	2.63	48.54	1.81	8.97	0.56

became apparent in the previous section: the model performs quite well in the case of the Groene Hart, where the L-function of the reported data is almost entirely within the simulation envelopes. A similar pattern is visible for the Oost-Betuwe data. In contrast, the reported L-function for the Twente data is entirely outside the envelopes, indicating significant clustering at all scales. For markers put by respondents from Amsterdam, de Kempen and Groningen there is significant clustering at small scales (up to about 4 km), but not at larger scales.

4.2. National scale

4.2.1. Spatial distribution of 'hotspots'

The results from the markers at national scale (Fig. 5), reveal two important insights: markers are predominantly placed close to the residential places of the respondents, i.e. confirming a so-called 'distance decay' effect, and there are several sites in the Netherlands that have been marked by respondents from all the different regions. Indeed, the Veluwe, a large stretch of forest and heather in the central-eastern part of the country, is a favorite location for respondents from all regions. However, perhaps not surprisingly, it is most popular among residents from the region itself, as the intensity of points at the Veluwe is much larger in the Oost-Betuwe sample than it is in all the other samples.

Similarly the area of Limburg in the southern tip of the Netherlands, the country's hilliest area with a maximum elevation of 323 m, is favored by respondents from all regions. Again, however, Limburg is mostly appreciated by respondents living nearby as the intensity of markers is highest in the data from de Kempen than it is for the other data. Finally, the coastline also seems to be much appreciated, although respondents from different regions prefer different parts of the coastline.

4.2.2. Influence of physical attributes

In the previous section we showed that at regional scale there was a lot of variation in the importance of different physical attributes, depending on what types of land were locally present in the different regions. Akin to results from the kernel density estimates, however, at national scale we see some similarities for the modeled perceived attractiveness of places (see Table 4). For instance, agriculture has a similar negative effect across all regions whereas elevation has a similar positive effect. Again distance has a significant impact: for each km away from the respondents homes, the intensity drops between 1 and 3% for all regions.

There are, however, some differences. Although the coast is popular among respondents from all regions, as indicated by the kernel density estimates, according to the model the coast is particularly important for respondents from regions that do not live near the coast: Twente and Oost-Betuwe. What is also interesting is that water played a significant positive role for residents from all regions at regional scale, especially in the Groene Hart, but it plays less of a role at national scale.

Comparing the kernel density estimates for the simulated and reported point patterns, at first sight the model does seem to be able to, roughly, locate the areas of importance. The Veluwe, Limburg and the Dutch coast are clearly visible in the densities based on the simulated point patterns, and we also see a clear distance decay effect. However, as in the case of the regional data, the intensity of points is often largely underestimated. This could be because the spread of the points is much wider in the simulated point patterns than in the actual data, suggesting

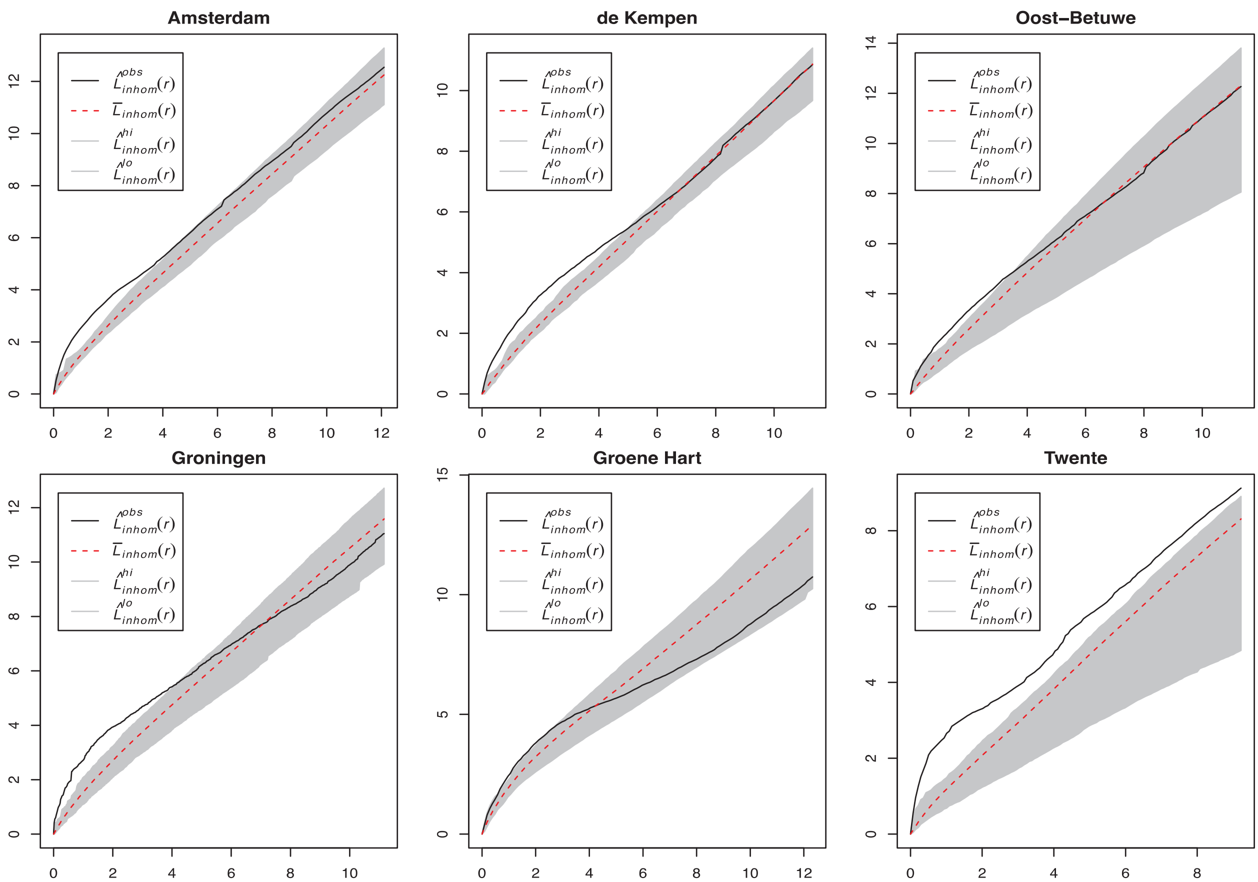

Fig. 4. Ripleys K, transformed into the L-function, for the reported data (black line) and the simulated point patterns. The red dotted line indicates the sample mean for the simulated point patterns. The grey envelopes can be interpreted as 0.01 significance bands and as such, any occurence of the L function outside these envelopes is an indication for significant clustering (above the envelope) or dispersion (below the envelope). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

that points are clustered around a few specific locations. Indeed, the values for Ripley's K show that points are clustered beyond what would be expected from the variation in covariates in all regions (Fig. 6).

4.2.3. Residuals

To gain better insight into where the model performs well, and where it does not, we plotted a kernel-smoothed version of the model residuals (Fig. 7). The plots display the differences between the non-parametric estimate of intensity, given by the kernel density of the reported data, and a smoothed version of the parametric estimate of intensity according to the fitted model.

Results from the plotted residuals reveal similar information as results from the simulated envelopes of Ripley's K. The model seems to perform relatively better in the case of the Groene Hart than in Oost-Betuwe. Although the range of residual values is larger for Groene Hart than that for any of the other models, indicating that the difference between reported and simulated intensity values is largest, these high values are very concentrated at a particular location (the coast). In large parts of the mapped area for markers from the Groene Hart, values of the residuals are zero (as indicated by the green color). Interestingly, the intensity of markers at the Veluwe is quite accurately predicted by the model, as it is only slightly underestimated in all models except for the Oost-Betuwe. In the case of Amsterdam and Groningen, the model underestimates the markers put in Limburg the most. In all regions the model underestimates the intensity of markers nearby the respondents' place of residence and the markers that were put at the coast. This is quite likely because respondents did not evenly distribute markers along the coast of the Netherlands, but at particular parts of the coastline, and not necessarily those parts that are closest to home.

5. Discussion

In the Netherlands discussions on how to best map recreational potential to inform nature conservation policies, have led to an evaluation of currently used models (see Farjon & van Hinsberg, 2015). Until recently the Netherlands Environmental Assessment Agency ('PBL') has relied much on GLAM (GIS-based Landscape Appreciation Model) and AVANAR (a model balancing demand and supply for recreational areas) to map the recreational potential of land. Recognizing the limitations of these models – the first focuses primarily on scenic beauty of landscapes and not on recreation landscape preferences in a wider sense, the latter is based on expert judgement and not on actual preferences – PBL is investigating new approaches to 'evaluate the perception, appreciation and recreational use of nature and landscape' (Ibid, p.2). Our paper provides several insights that are of relevance to both policy makers and researchers. We discuss these insights, and how they can contribute to the advancement of mapping the recreational potential of land, below.

5.1. The effect of physical attributes on recreational potential at regional and national scale

Studying the validity of proxy-based maps, Eigenbrod et al. (2010) conclude that 'proxies that are based on coarse or categorical input data (e.g. broad vegetation types) are likely to provide poor estimates of the actual distributions of ecosystem services' (p. 381). Our results add

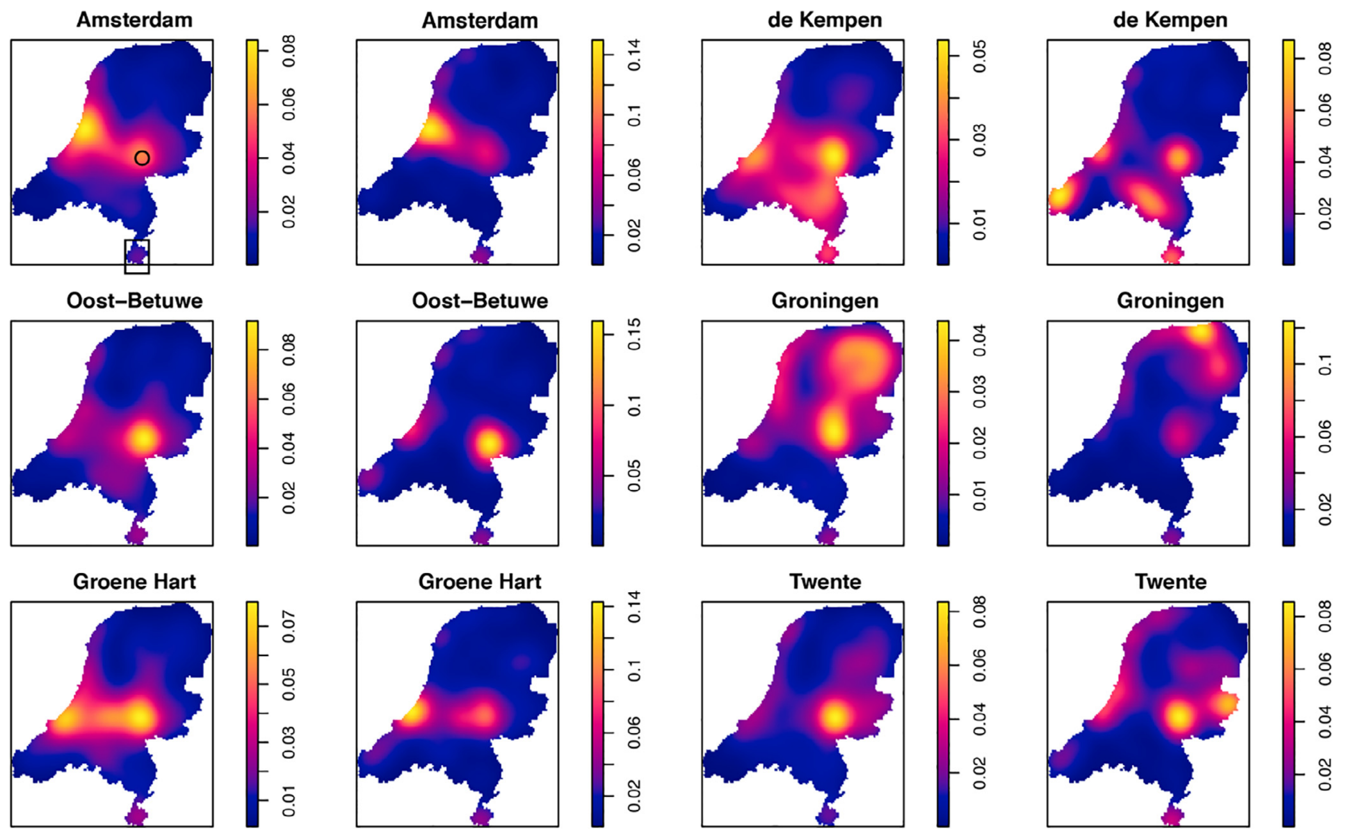

Fig. 5. Kernel density estimates based on simulated point patterns (left) and reported point patterns (right). In the density map, based on simulated point patterns, of Amsterdam we indicated the location of the Veluwe (black circle) and Limburg (black square), as we refer to these places in the text.

some nuance to this claim, as at regional scale the model was at a few instances able to capture the location of highly attractive areas. This seemed to be particularly the case for areas where the number of alternatives is limited: in the Groene Hart, where there is little forest, a few lakes close to respondents' homes and a small piece of coastline, it was perhaps not difficult to predict which locations would be favored. Similarly in Oost-Betuwe, close to Veluwe national park, the modeled point pattern did not deviate significantly from the reported point pattern.

Overall, however, our results confirm findings by Eigenbrod et al. (2010) as in most cases, both at regional and national scale, the reported point patterns showed clustering after accounting for the spatial variation in physical attributes. This indicates that points were not randomly distributed after accounting for land cover, suggesting that

Table 4
Results from the point process models at national scale.

	Amsterdam		De Kempen		Oost-Betuwe		Groningen		Groene Hart		Twente	
Variable	β	s.e.	β	s.e.	β	S.E.	β	S.E.	β	S.E.	β	s.e.
(Intercept)	−0.07***	0.14	−0.024***	0.14	−0.026***	0.14	−0.033***	0.11	−0.024***	0.14	−0.020***	0.13
Agriculture	−0.633***	0.09	−0.683***	0.09	−0.635***	0.09	−0.751**	0.10	−0.684***	0.09	−0.740**	0.10
Elevation (m)	1.029***	0.00	1.016***	0.00	1.018***	0.00	1.027***	0.02	1.017***	0.00	1.020***	0.00
Distance respondents (km)	−0.979***	0.00	−0.991***	0.00	−0.992***	0.00	−0.988***	0.00	−0.990***	0.00	−0.989***	0.00
Distance roads	1.092***	0.01	1.102	0.01	1.049***	0.01	1.017*	0.01	1.021*	0.01	1.032***	0.01
Distance train stations	−.940***	0.01	1.009	0.01	−0.965	0.01	−0.998	0.01	−0.995	0.01	1.002	0.01
Forest	1.349**	0.09	1.723***	0.09	1.144	0.10	1.887***	0.10	1.938***	0.09	1.936***	0.10
Heathland	1.375	0.17	2.661***	0.15	2.731***	0.13	2.384***	0.15	2.212***	0.15	2.486***	0.15
Coastal area	5.957**	0.11	12.575***	0.12	15.357***	0.12	14.310***	0.14	13.376***	0.09	22.659***	0.14
National landscape	−0.968	0.09	1.212*	0.09	1.353***	0.09	1.379***	0.09	1.927***	0.08	1.410***	0.09
National park	1.856***	0.14	2.796***	0.11	2.600***	0.10	2.408***	0.11	2.559***	0.10	2.762***	0.10
Urban green	1.474***	0.17	2.213***	0.16	2.332***	0.14	2.539***	0.16	2.340***	0.15	2.445***	0.17
Urban green size	1.253*	0.03	−0.880	0.10	1.053	0.07	1.083	0.08	1.146*	0.06	−0.737	0.18
Urbanization[1]												
Slightly urban	1.000		−0.881	0.09	−0.763**	0.10	−0.893	0.09	−0.942	0.09	1.030	0.10
Medium urban	1.148		−0.960	0.12	1.195	0.11	1.035	0.12	1.147	0.11	1.479***	0.11
Strongly urban	1.1068		1.425**	0.12	1.354*	0.12	−0.884	0.15	0.989	0.13	1.479**	0.13
Very strongly urban	1.826***		2.905***	0.15	2.672***	0.15	2.785***	0.17	2.957***	0.14	4.784***	0.16
Water	1.196	0.09	1.398***	0.09	1.391***	0.09	2.229***	0.10	−0.933	0.10	1.501***	0.11
Wetland	1.065	0.25	1.571	0.26	1.571*	0.21	1.674*	0.21	1.534	0.25	2.439***	0.20

*** < 0.001 ** < 0.01 * < 0.05.
[1] Reference level is non-urban.

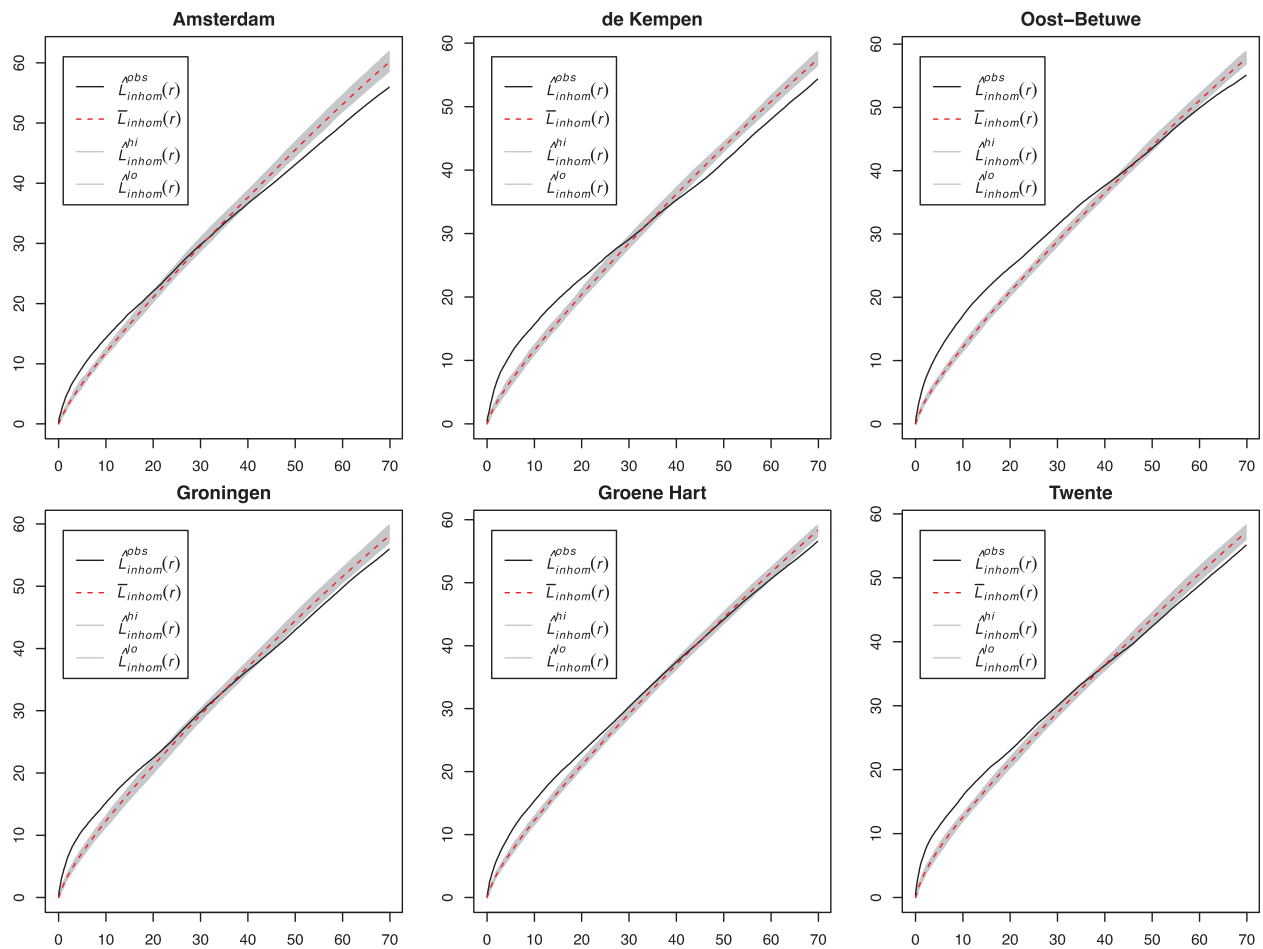

Fig. 6. Ripleys K for the national scale, transformed into the L-function, for the reported data (black line) and the simulated point patterns. The red dotted line indicates the sample mean for the simulated point patterns. The grey envelopes can be interpreted as 0.01 significance bands and as such, any occurence of the L function outside these envelopes is an indication for significant clustering (above the envelope) or dispersion (below the envelope). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

people develop preferences for specific areas. It must be noted, however, that our results do not account for the fact that some areas, for instance because these are privately owned, are not accessible to the public. As respondents are likely to pinpoint areas that are open to the public it may be that part of the clustering is due to differences in accessibility.

At national scale, another observation stands out. Urban green remains an important predictor of perceived attractiveness, even at national scale. This is an important notion since in many efforts to map the recreational potential of land at larger scales urban green is not taken into account (see Paracchini et al., 2014). Indeed, Daams, Sijtsma, and van der Vlist (2016) too showed that the value of attractive nature in or close to urban homes is high and likely to increase in the future. As a growing part of the population will live in cities, a focus on rural areas for recreation may not sufficiently capture the recreational trips urban residents are able and willing to make. Ignoring the potential positive effect of urban green on the supply of recreational opportunities may lead to a serious bias in ES maps. Therefore a more inclusive and integrated approach for planning recreation areas in urbanized societies seems warranted (Sijtsma et al., 2017).

5.2. Interregional differences at regional and national scale

Our results show both differences and communalities in the perceived attractiveness of land across respondents from different regions in the Netherlands. At regional scale, the coast, water and urban green are all important for the perceived attractiveness of land. We find particularly high values for the coast, in Amsterdam and the Groene Hart, where it is relatively scarce compared to other types of land. On the other hand water was particularly important in the Groene Hart, perhaps because of the lack of competing alternatives (e.g. larger stretches of forest as there are in Oost-Betuwe).These interregional differences indicate the difficulty of finding a unified model that would be able to accurately capture the availability of recreational opportunities for communities at regional scale. However, at national scale, we saw that many of the interregional differences disappeared: we found remarkably comparable estimates for many of the physical attributes. This may suggest that at national level respondents have similar values for what the nice places of the Netherlands are. This suggests on the one hand that values for the environment are not only shaped by individual experience but may also be mediated by cultural norms and social representations (Buijs, 2009; Mommaas et al., 2017). On the other hand, it clearly shows the importance of taking into account spatial scale when mapping recreational potential.

Although the coast was extremely popular among respondents from all regions, it seems it was particularly important for respondents from regions that are located further away from the Dutch coast. This may indicate that at larger scales people are attracted to places that are not part of their ’daily landscapes’ (compensating for what is present in their own living environment). This could explain why water did not seem to play any part for residents from the Groene Hart at national scale, while it was important at regional scale. This ’compensation

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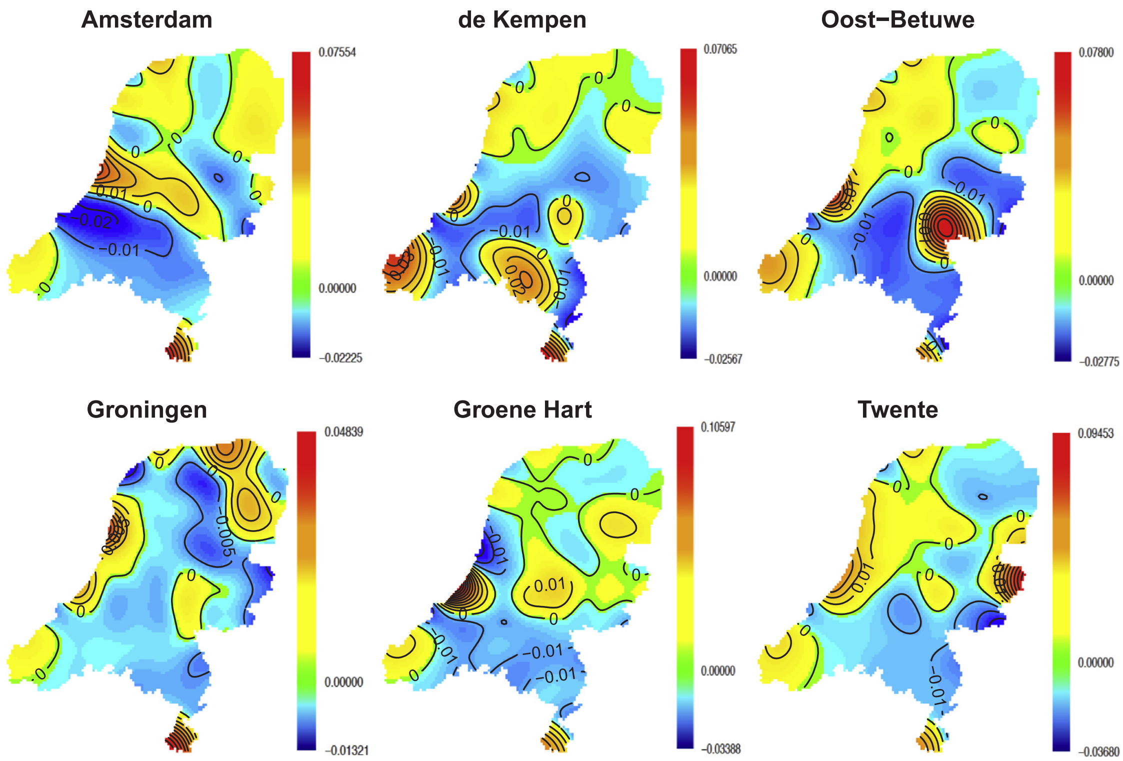

Fig. 7. Plotted smoothed residuals. A difference of zero indicates good model performance, positive values suggest that the model underestimates intensity and negative values suggest that the model overestimates intensity.

hypothesis' has received some attention in the context of urban green space and recreational behavior with mixed results: Maat and De Vries (2006) found no significant relationship between the use of larger parks and the amount of green space in the immediate neighborhood of urban residents, whereas Sijtsma, de Vries, van Hinsberg, and Diederiks (2012b) did find a correlation between holiday nights spent away from home and shortages of locally available green space. Such studies have predominantly focused on the availability of green space in urban living environments, and so further research into the compensation hypothesis in different contexts and at different spatial scales is necessary (Bijker & Sijtsma, 2017).

5.3. Advancing methods to map the recreational potential of land

It must be noted that the use of variables other than land cover to map recreation, for instance accessibility approximated by population density or road density and the presence of facilities such as hiking trails or accommodation, is becoming more common (Koppen, Sang, & Tveit, 2014; Remme, Schröter, & Hein, 2014; Schägner, Brander, Maes, & Hartje, 2013). Indeed, our results show that proximity to place of residence of respondents had a large influence on the intensity of markers at a given location. However, the exact specification of such a distance decay function is not straightforward, and so proximity to densely populated areas in itself may not adequately explain the recreational potential of land. People may be willing to travel further for some areas than others, which could explain why the model underestimated the intensity of markers at the far southern, hilly tip of the Netherlands, particularly for respondents living up north (Amsterdam and Groningen). At the same time, at national scale our model underestimated the intensity of markers that were put close to the respondents' place of residence. This indicates that the relationship between distance and nature-based recreation is complex and unlikely to be linear.

As the majority of the reported point patterns showed significant clustering, even after accounting for proximity to respondents and accessibility, a logical question is to ask by what such clustering can be explained. Drawing from the wider literature on tourism and recreation, it may be that more specific socio-economic attributes play an important role in the recreational potential of land. Indeed Deng, King, and Bauer (2002) summarize a much broader suite of indicators than commonly accounted for in studies mapping nature-based recreation. Such indicators are for instance the presence of historical buildings (e.g. Koppen et al., 2014), the presence of facilities, in terms of trails (e.g. Caspersen & Olafsson, 2010) or accommodation (e.g. Schröter, Barton, Remme, & Hein, 2014), and the presence of substitute areas (e.g. Schägner, Brander, Maes, Paracchini, & Hartje, 2016). The influence of such indicators will likely depend on the type of recreation people undertake. In our study we did not specify between different types of recreation, but rather focused on nature-based recreation in a broad sense.

Perhaps more importantly, however, not only the characteristics of the landscape itself matter, but the way in which these characteristics are framed and communicated. In forming destination choices people are motivated by 'destination images' (Prebensen, 2007), reflecting a mental construct of what potential destinations have to offer. As such 'marketing agencies at all levels (…) have a vested interest in building strong and positive images for their destinations' (Cai, 2002, p. 721). Governments and park managers may actively contribute to the attractiveness of a place by means of branding and communication. In the Netherlands for instance, the government recently launched a campaign to elect the most beautiful natural landscape of the country (see www.mooistenatuurgebied.nl). Similar to our findings the Veluwe and parts of the Dutch coast, specifically the Wadden islands and national park 'de Hollandse Duinen', were voted as winners. It may well be that the ensuing media-attention for these parks will motivate people to come and visit.

It is thus important to remember that recreation is not limited to on-site experience, but also includes a planning/anticipating phase, a traveling phase, and a recollection phase, which could be particularly important for planning the next experience (see Clawson & Knetsch, 1966). The spatial representation of the recreational potential of land can therefore not be seen apart from the decisions made by the people who visit (or plan to visit) it. An important avenue for future research is to investigate how decisions for recreational destinations are affected by the degree to which people find places attractive. In this paper we only took into account the upper end of the attractiveness scale, by asking respondents for the places they found most attractive. Looking into the 'full' attractiveness scale will help us identify how much time and travel costs people are willing to invest to visit a place they find very attractive in comparison to places they find less attractive.

Finally, an elaborate literature on place attachment (see Lewicka, 2011) has shown that people are likely to get attached to particular places and so will not always make a rational trade-off between places that provide similar facilities, as often assumed in economic models of recreation. Place attachment has cognitive, affective and behavioral components, meaning that people may prefer a particular place out of habit, because of emotional bonds and/or because it connects to their sense of self or social identity (see Scannell & Gifford, 2010). This multidimensionality makes place attachment a particularly difficult concept to capture in spatial terms (Brown & Raymond, 2007). Although scholars using PPGIS methods often point towards the importance of 'place-based' values, such studies lack the theoretical foundation that would help us better understand how place attachment influences the spatial distribution of recreational ES (Brown & Kyttä, 2014). Further research into how place attachment can be meaningfully incorporated into efforts mapping nature-based recreation is necessary.

6. Conclusion

Due to the paucity of data on recreational values, mechanistic models based on physical attributes are widely used to map nature-based recreation. Our results show the difficulty of coming towards a 'blueprint' (see Crossman et al., 2013) for mapping the recreational potential of land: differences in scale and taste make that there is unlikely to be a single map that can fully capture the complexity of nature-based recreation. Whereas some areas may be important resources for recreation at regional scale, reflecting use by nearby communities, others may be important on both a regional and national scale. Maps reflecting recreational opportunities have little meaning if it is not specified for *whom* these opportunities are meant. We therefore advocate that a plurality of mapping approaches remain, fitting the contextualized nature of the policies these maps are aimed to inform. Our paper provides insights that may further guide the development of more sophisticated mapping methods that will yield a better understanding of the recreational potential of land.

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Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at https://doi.org/10.1016/j.landurbplan.2018.03.011.

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