Filling the gaps: using count survey data to predict bird density distribution patterns and estimate population sizes

Henk Sierdsema & E. Emiel van Loon

Birds play an increasingly prominent role in politics, nature conservation and nature management. As a consequence, up-to-date and reliable spatial estimates of bird distributions over large areas are in high demand. The requested bird distribution maps are however not easily obtained. Intensive fieldwork over a spatially dense observation network requires a large effort by hundreds or thousands of volunteers, and is only feasible once in every few decades. Therefore, to create distribution and abundance maps at shorter time intervals of years or even months, monitoring data has to be used. However, monitoring data typically come from a spatially less dense observation network. In order to produce reliable distribution maps with these data, additional biological knowledge and relatively complex statistical procedures have to be used. This study explains the several steps and issues involved via a case study where distribution maps of the Common Buzzard are constructed for The Netherlands.

Key words: spatial modelling, regression kriging, Common Buzzard, *Buteo buteo*, monitoring data.

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Birds play an increasing role in politics, nature conservation and nature management. Many species are of conservation concern and protected through national and international laws and agreements. Therefore, the consequence of projects like the construction of roads or buildings on bird distribution and abundance must be assessed. In addition, issues like climate-change, pollution and the increasing disturbance by traffic have to be addressed to estimate their consequences on bird populations. Estimates of population sizes form an important tool in national and international or regional policies. The selection of, for example, Red List Species, Habitat directive species or 'target species' is for a major part based on population estimates. With the increasing influence of these lists in society, reliable and reproducible estimates are becoming increasingly necessary.

In the aviation world a special relationship exists between people and birds. Planes can disturb birds, but more importantly, birds often collide with planes. Sometimes it causes a plane to crash, resulting in loss of human life (Thorpe 2003), but most often bird collisions just cause damage, leading to huge costs for repair and time-consuming inspections (Barras & Wright 2002; Dolbeer *et al.* 2000). In order to prevent collisions with birds, hazardous situations involving big birds or large numbers of birds should be avoided (Dolbeer & Eschenfelder 2003). Therefore, we would like to know when and where these kinds of situations can be expected.

Nationwide mapping of bird distribution or abundance are not easy to obtain. They require intensive fieldwork of hundreds or thousands of volunteers and can only be carried out every few decades. Only a small number of rare or aggregated species can be monitored on a national scale every year, let alone every month. For other species, we therefore have to rely on information obtained at a small sample of moni-

toring sites. Since these sites obviously cover only a fraction of the area of interest, a method is needed to fill in the gaps between the sites if we want to create distribution maps or estimate population sizes from these observations.

In this paper we present a method that can be used to create distribution maps from sample data. Results will be presented for one species with moderate conservation concern and large impact on flight safety, the Common Buzzard *Buteo buteo*. This widespread species is of moderate conservation concern because of its vulnerability to pesticides like DDT and local persecution. It is also one of the bird species that pose a great hazard to aviation and has been involved in hundreds of reported bird strikes in Europe (Dekker *et al.* 2003). The numbers of breeding and wintering Buzzards in The Netherlands have increased considerably in the last 20 years. At the beginning of the 21st century the number of wintering Buzzards is about twice as high as in the mid-eighties (Sierdsema *et al.* 1995; Boele *et al.* 2005) (Figure 1). There are however no nationwide maps available of the distribution in the winter period since the completion of the year-round atlas project in 1983 (SOVON 1987). There is for the reasons mentioned previously a need for recent detailed maps of the distribution and abundance of Buzzards in The Netherlands. The aim of this paper is to show how spatial statistics can be applied to create detailed maps of distribution and abundance from monitoring data of wintering Buzzards.

Materials and methods

Spatial statistics

A large number of techniques can be used to determine the expected number of birds at unsampled locations, each having its specific advantages and disadvantages. In our study, we use a combination of regression and a statistical interpolation.

It is generally acknowledged that the most suitable techniques for the non-spatial statistical modelling of abundance data are General Linear Models (GLM's), General Additive Models (GAM's) and Artificial Neural Networks (ANN's) (Guisan & Zimmermann 2000). The selection of the proper statistical distribution and the inclusion of the key factors or 'forcings' that influence the distribution and abundance of birds are often critical in being able to detect existing relationships.

In statistics, observed data area usually treated as having a deterministic component and a noise (or error) term:

$$y_i = \mu + e_i$$

where μ is the expected (or mean) value of y_i and e_i is the random error term or residual. In practice, a large part of e_i is not random but is a reflection of model imperfections, scale and sampling issues. We do treat it as random however because we cannot explain or understand its variation. Different observations i are assumed to be independent. This implies that there is no structure in the error with respect to i. In practice though, observations that are taken close together in space or time are more alike than distant observations and this leads to spatial or temporal dependence between observed data. When the goal is spatial interpolation, information is typically required on a high spatial resolution and therefore spatial dependence within the data is likely to occur. In this case, spatial dependence can be exploited to let an observation be more informative about its direct surrounding than distant observations. Spatial statistics (Cressie 1991) is the field of statistics that
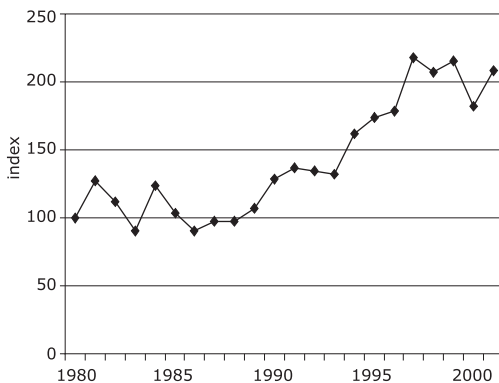

Figure 1. Index of wintering Common Buzzards in The Netherlands (1980=100). Since the mid-eighties the numbers have doubled.
Índex dels aligots comuns hivernants a Holanda (1980=100). Des de mitjans dels anys vuitanta el nombre d'aligots s'ha duplicat.

explicitly addresses spatial locations of observations and that tries to use spatial structure in order to get optimal, location specific predictions or interpolated values (Pebesma *et al.* 2000).

Spatial interpolation describes the spatial structure in the data without the use of other explanatory variables. Examples of the methods used for spatial interpolation are *inversed distance weighting* (IDW), moving window-methods (Osborne *et al.* 2001) and *kriging* (Cressie 1991; Pebesma & Bio 2002). The name *kriging* refers to a widely used method for interpolating and smoothing spatial data. Given a set of observations y_i, $i = 1, ..., n$, at spatial locations s_i, the kriging predictor for the underlying spatial surface, $\hat{Z}(s)$, takes the form:

$$\hat{Z}(s) = \sum_{i=1}^{n} w_i(s) y_i$$

where the *kriging weights* w_i are derived from the estimated mean and covariance structure of the data. Therefore an equation, the (semi)variogram, is fitted to describe the spatial correlation in the data. Kriging was originally developed for the mining industry to infer the spatial distribution of valuable minerals based on distant samples. It has since the 1980s been widely applied in the natural sciences (notably soil science, oceanography and meteorology). Spatial interpolation of observations implies that we estimate unobserved, unknown quantities from observed data. For this we need methods that allow us to assess the accuracy of the estimate by providing a measure of estimation error. Kriging can provide such an uncertainty estimate.

There is some overlap between (non-spatial) regression models and spatial interpolation (kriging) methods.

In regression models, spatial trend data like e.g. x- and y-coordinates can be added as variables, while spatial interpolation models can be extended with landscape data. The two methods can also be combined loosely by a method known as *regression kriging*. This method models the relation between independent variables and bird densities with regression, while the spatial structure in the errors of the regression is modelled by kriging (Hengl *et al.* 2004; Pebesma *et al.* 2000). The general form of regression kriging can be described with

$$\hat{Z}(s_i) = \sum_{k=0}^{m} \beta_k V_k(s_i) + \sum_{i-1}^{n} w_i \varepsilon(s_i)$$

where

$$\sum_{k=0}^{m} \beta_k V_k(s_i)$$

describes the regression part with variables V_k and β_k regression parameters for these variables and

$$\sum_{i-1}^{n} w_i \varepsilon(s_i)$$

describes the spatial interpolation of the errors ε of the regression model. The regression coefficients are estimated from the observations using weighted least squares. The kriging weights w_i are derived from the variogram of the residuals. The corresponding kriging variance incorporates the uncertainty about the estimation of the regression coefficients. If the regression model is linear with Gaussian errors, the terms kriging with external drift or universal kriging is used instead of regression kriging (Hengl *et al.* 2004; Leopold *et al.* 2006).

Materials

Bird data
In The Netherlands a large number of monitoring schemes monitor almost all the bird species that occur at various periods of the year. Data are collected on sample sites with natural boundaries or on sample points. Monitoring of Dutch bird populations forms part of a governmental monitoring scheme that includes other organisms. These projects aim to detect changes in the natural environment, both in terrestrial and aquatic habitats. Coordination of fieldwork and data processing is mainly carried out by non-governmental organisations like SOVON Dutch Centre for Field Ornithology, in collaboration with Statistics Netherlands. About 3000 volunteers and a small group of professional ornithologists carry out fieldwork for bird monitoring schemes.

One of these monitoring projects is the Point Transect Count. Since 1978, monitoring of mainly terrestrial wintering birds has been carried out annually along about 400 transects with 20 observation points each. Over 1000 transects have been monitored since the start of the project. Observers are requested to count all

species at each point during exactly 5 minutes (Sierdsema *et al.* 1995). Initially, counts were made in November, December, February and August, but after an evaluation of the results in 1997, it was chosen to continue only the count in the 2nd half of December. Since 1978, more than 20 000 points have been counted. From over 16 000 points the exact location is known and digitised. For the year 2000, over 8000 data points were available.

During fieldwork no distinction is made between sedentary and flying birds. There is also no limit set to the distance within which birds are counted nor are distance bands used. This is a minor problem in the establishment of trends, but a major difficulty in the establishment of densities. Therefore in 2001 part of the observers was asked to count bird numbers within and over a 200 meter band and to distinguish between sedentary birds and birds flying over. This made it possible to estimate the percentage of Buzzards within a 200-meter radius from the survey point (56%) and Buzzards flying over (2%). Even within the 200-meter radius, not all existing Buzzards will be observed during the 5-minute survey. The observed numbers are therefore a relative measure of abundance. However, since the Buzzard is a large bird and easily observed in winter time, we assumed that the number of observed Buzzards within this 200-meter radius is a reliable reflection of the absolute number of birds.

To illustrate the various methods to create distribution maps from count survey data, one species, the Common Buzzard, was selected (see also Section 1). Original counts of each year for the month of December were used. The final predictions of the number of birds per square kilometre were calculated by multiplying the predicted number per point with 7.96 (1 km^2 divided by the area of a circle with 200 m radius). Results of the models for the counts in December 2000 are described in detail in this paper.

Landscape data
Based on literature a number of variables were selected that are known to influence the distribution of Buzzards and for which maps with complete coverage for the Netherlands exist. A total of 20 variables were tested: two times 8 land-use variables derived from the 1:10 000

topographical map of the Netherlands (Topografische Dienst, Emmen), openness of the landscape (Alterra), physical geographical regions (or bioregions) and snow and ice cover (table 1). For the land-use variables both the area in a circle of 0-200 m and 200-1000 m around each point was used. For large-scale spatial trends, like an increase in densities from the west to the east of the country, the x- and y-coordinates were used.

Statistical analyses

Statistical modelling
A regression model (General Additive Model, 'GAM') was built for each separate year of the number of Buzzards per sample point in the December-count. The Poisson-distribution, with a log link, was selected in the modelling procedure for the following reasons: (1) the number of Buzzards per point is always positive (2) many points contain zeros (3) variance increases with increasing abundance. The dispersion parameter, describing over- or under-dispersion of the counts, was estimated from the residual deviance. Variables were selected by fitting all possible regression models and evaluated according to the Cp-criterion of Mellows for goodness of fit with the RSEARCH -command within GENSTAT 7 (Rothamsted-Experimental-Station 2003). Most variables were added as linear predictors. Openness of the landscape was added as a 3rd-degree smoothing spline, the coordinates as a 4th degree smoothing spline. As an indication of the variance explained by the regression model, the percentage of explained mean deviance was used. The deviance depends on the number of positive observations and is not a direct measure of fit, nevertheless it can be used to compare models of different complexity applied to the same data (Pebesma *et al.* 2000). The best fitting model predictions and standard errors were calculated at a 1 km^2 resolution for The Netherlands. These predictions were mapped with the Geographical Information System Arc-GIS (ESRI).

Spatial interpolation
Ordinary kriging was chosen to perform spatial interpolation. It was carried out with the software GSTAT (Pebesma and Wesseling 1998)
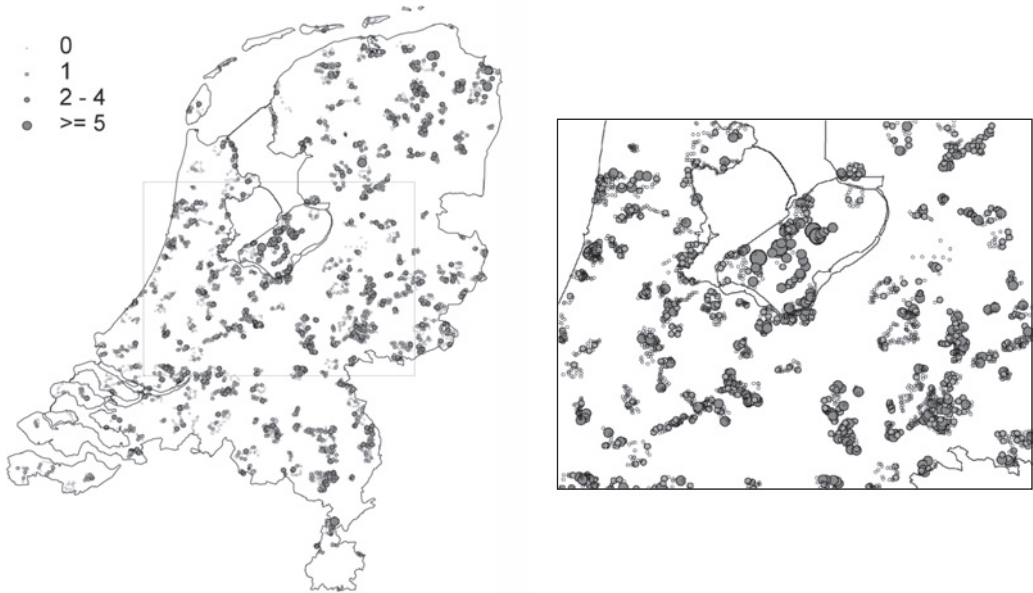
Figure 2. Number of observed Common Buzzards per sample point in December 2000 with detail for the central Netherlands
Nombre d'aligots comuns observats per unitat de mostratge al desembre del 2000 amb detall pel centre d'Holanda.

(see also, www.gstat.org). First, for each year, a semivariogram was calculated that describes the spatial relationship in the observations (Cressie 1991). With this semivariogram numbers in kilometre-squares without counts were interpolated from squares with counts by means of ordinary kriging. Variances were also calculated per square kilometre and saved.

Regression kriging

Regression kriging was carried out in two steps. First a regression model (GAM) as described before was fit and predictions for all data-points were calculated. Then the difference between the counts and the predictions ('simple' or 'response' residuals) was calculated by subtracting the fitted values from the data.

These residuals were spatially interpolated with ordinary kriging, resulting in a 1 km² map with complete coverage for the Netherlands of the residuals. This method differs from the general method as described in the introduction: instead of solving one equation the process has been separated in two separate steps. We have chosen this method because the combination of GAMs and kriging is not possible yet in the

available software (GSTAT) and is very computationally intensive with other software.

Maps for the Buzzard densities were finally obtained by adding the estimated trend from the GAM to the predicted value of the residual. The predicted variance was approximated by adding the variance of the GAM to that from kriging (Odeh *et al.* 1995; Pebesma *et al.* 2000).

Estimate of population size

A national or regional estimate of the population size was obtained by summing the predicted numbers per km² from the interpolated map as predicted by the regression kriging.

Results

Statistical model: regression

Significant predictors (variables) included in the regression model for Common Buzzard counts in December 2000 are summarized in Table 1. This model explains 14.8% of the variation in Buzzard numbers per point. The selected predictors for the other years are in most cases the

Table 1. Regression model (GAM) of wintering Common Buzzards in 2000 (FGR: Physical geographical region; Ice & Snow: coverage of ice and snow; X & Y: X- and Y- coordinates; other variables: amount of land use types within 200m and 200-1000 from sample point).
Model de regressió (GAM) dels aligots comuns hivernants l'any 2000 (FGR: Regió fisiogràfica); gel i neu: cobriment de gel i neu; (X,Y): coordenades x,y. D'altres variables: quantitat de l'ús del territori dins dels 200 m i de 200-1000 m del punt de mostratge).

Variable	Estimate	s.e.	t-value	p-value
FGR	298.74	19.92	23.50	< 0.001
Ice	11.33	5.66	6.68	0.001
Snow	8.62	4.31	5.08	0.006
X	0.0000070	0.00000081	8.62	< 0.001
Y	-0.0000032	0.00000085	-3.82	<.001
Arable-1000m	0.0026	0.00094	2.79	0.005
Grassland-1000m	0.0026	0.00095	2.73	0.006
Small waterbody-200 m	-0.086	0.030	-2.88	0.004
Small waterbody-1000 m	-0.0039	0.0017	-2.24	0.025
Large waterbody-200 m	-0.094	0.047	-2.01	0.044
Built up −200 m	-0.16	0.030	-5.27	< 0.001
Built up −1000 m	-0.0080	0.0015	-5.27	< 0.001
Forest −200 m	-0.067	0.022	-3.11	0.002

same. The amount of explained deviance varied from 13% to 16% in the years 1978-2003. In all years physical geographical region (FGR) and spatial trend (x- and y-coordinates) were significant. In general, a positive relationship was found with the amount of arable land and grassland with comparable regression coefficients and a negative relationship with built-up area, open water and forest. In most models, either land use within a 200 m radius or a buffer of 200 to 1000 meters was included in the model. For small water bodies and built-up areas though, both distances were included. Ice, snow and openness of landscape had a significant influence in a limited number of years. In

2000, ice and snow had a significant negative influence (Table 1).

The residuals of the model of 2000 are shown in Figure 3. Figure 4 shows the results of the predicted number of Buzzards per Km^2.

Spatial interpolation: kriging

All semivariograms found were of the exponential form and are expressed as:

a Nug (0) + b Exp (c) .

In this expression c is the range parameter, b the sill (the steepness of the curve) and a the
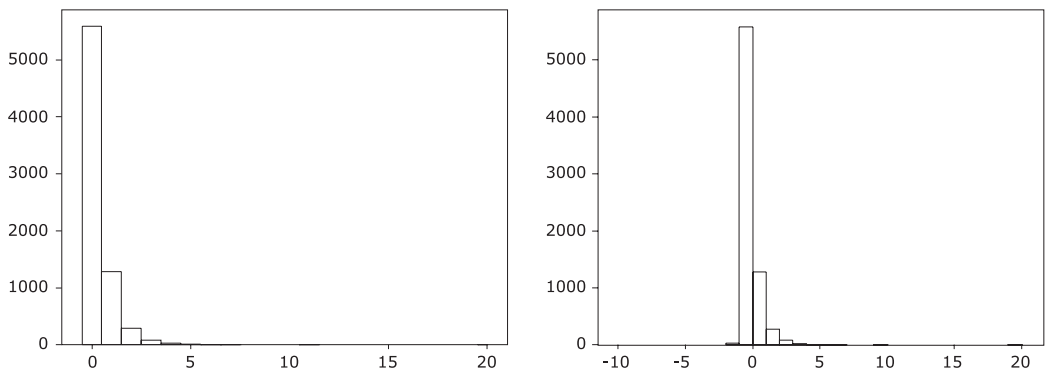

Figure 3. Counts of Common Buzzards (left) and residuals (right) of the regression model for 2000.
Comptatges d'Aligot Comú (esquerra) i els seus residus (dreta) del model de regressió per a l'any 2000.

size of the nugget ('short distance noise'). The expression for the year 2000 was:

$$0.2 \, \text{Nug}(0) + 0.25 \, \text{Exp} \, (800)$$

Figure 5 shows the result of the spatial interpolation of the counts with ordinary kriging and the variance of these interpolations. There are large regions with a relative high variance. These regions are mainly coinciding with regions with a low density in observation points (Figure 2). This implies that the reliability of the interpolated numbers is lower in areas with low observation density.

Regression kriging

The residuals of the regression model are spatially correlated. The semivariogram for the residuals of December 2000 was

$$0.211986 \, \text{Nug}(0) + 0.211462 \, \text{Exp}(944.318)$$

This spatial correlation is for example quite clear in the centre of the Netherlands (Figure 6). This region shows areas where adjacent points show over-prediction (blue) and under-prediction

(red) by the regression model. By spatially interpolating the residuals, distinct regions with higher or lower numbers of counted Buzzards than predicted by the regression model can be seen (Figure 7). Finally, the spatially interpolated residuals and the predicted distribution of the regression model were combined in one map. This results in the final prediction for December 2000 (Figure 8).

Comparison of the resulting map of the predictions of the regression model (Figure 4) and the spatially interpolated map shows a fair amount of concurrence (Figure 5). There are, however, a number of areas showing important differences between the two maps. In the map as produced by the combination of the two methods (Figure 8), results of the two approaches are combined. This results in a map with a large amount of detail, mainly due the output of the regression model, and regions with relatively high or low numbers that cannot be explained by the variables included in the regression model due to spatial interpolation of the residuals.

Estimate of population size

For the second half of December 2000 the population of wintering Buzzards in the Netherlands was estimated to be c. 45000 – 56000. This range reflects the range in the estimate of the number of Buzzards within a 200-radius from the counting point and does not reflect the variance in the models. This total number is about twice as high as the estimate for the beginning of the eighties as produced by the year-round atlas for the Netherlands (SOVON 1987) and in agreement with the general trend (Figure 1).

Trend mapping

The increase in the number of Common Buzzards in the Netherlands (Figure 9) is reflected in an overall increase of densities all over the Netherlands. Most regions that held reasonable numbers in the mid-eighties show a large increase in densities. Most striking is the increase in the southern part of the Netherlands where Buzzards were quite scarce in the mid-eighties. This increase in the southwest shows a time lag as compared to the northeastern parts of the country. In the western part of The Nether-
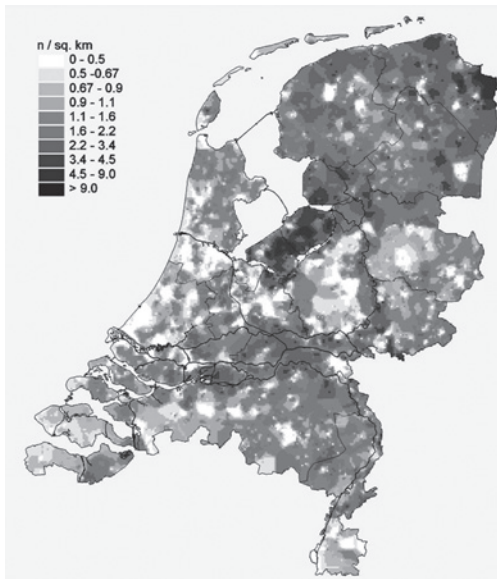

Figure 4. Number of Common Buzzards per sq. km. in 2000 as predicted by the regression model.
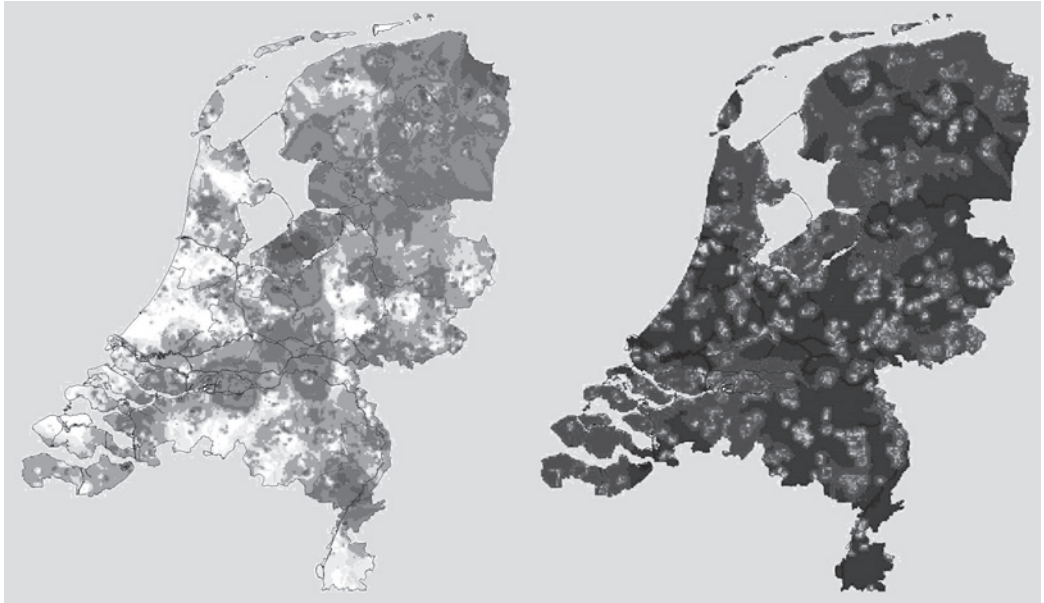*Nombre d'aligots comuns per quilòmetre quadrat l'any 2000 predit pel model de regressió.*

Figure 5. Ordinary kriging spatially interpolated map of counts of Common Buzzards in December 2000 (left) and kriging variance (right).Dark areas in the variance map denote areas with relatively high variance.
Mapa de punts de comptatge d'interpolació espacial "kriging" normal de l'Aligot Comú el 2000 (esquerra) i variança "kriging" (esquerra). Les àrees fosques en el mapa de variança denoten les àrees amb alta variança relativa.

lands, wintering Buzzards are still far from common, but also increasing.

Discussion

In this paper we show that monitoring data are a valuable source of information to create distribution maps. With the aid of spatial statistics these sample date can be interpolated to maps with full spatial coverage. These maps can easily compete with modern distribution maps of bird atlases, and can be produced with very short time intervals in comparison to distribution atlas projects. The drawback, however, is that these maps approximate real distributions and predictions. In areas with low sample densities (and often high variances) they should be used with care. Since the described method of monitoring wintering birds delivers relative measures of abundance, transformations are needed to estimate absolute abundances. In this paper, only an estimate has been used of the percentage of birds within a circle of 200 m. We assumed that this number is a reliable estimate of the abso-

lute numbers. This may be reasonable for a conspicuous bird like the Common Buzzard, but not for many other species. Since most of the current monitoring programmes produce relative
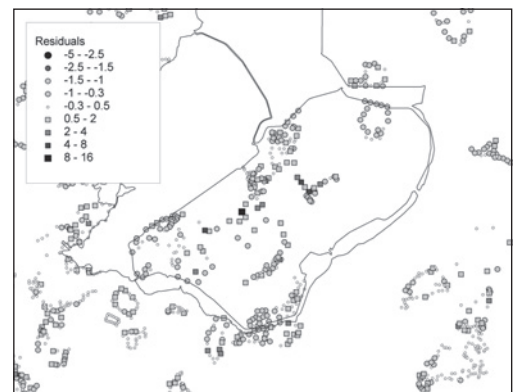

Figure 6. Section of the central Netherlands showing the simple residuals per observation point (filled squares: more birds than predicted by the model, filled circles: fewer birds than predicted).
Secció del centre d'Holanda que mostra els residus per punt d'observació (quadrats plens: més aus que en els predits pel model; cercles plens: menys aus que en els predits pel model).
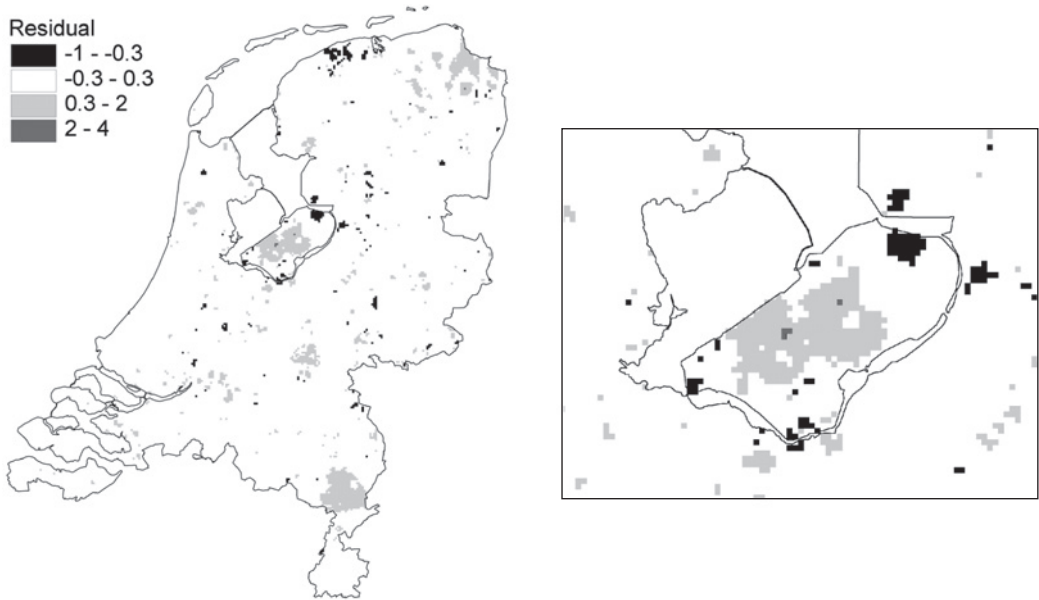
Figure 7. Spatially interpolated map of the simple residuals (n/km^2) of December 2000 for the Netherlands (left) and detail for the central Netherlands (right) (black: less birds observed than predicted, grey: more birds observed than predicted).
Mapa espacial interpolat de residus simples (n/km^2) de desembre 2000 per a Holanda (esquerra) i detall del centre d'Holanda (dreta) (negre: menys aus que en el predit pel model; gris: més aus que en el predit pel model).

numbers of abundance statistical procedures are required to upgrade these numbers to absolute ones. In northern America, there is an active debate on this topic and we will have to solve this problem before abundance maps for all or parts of Europe can be produced from monitoring data (Kery *et al.* 2005; Royle 2004). Another issue that has to be dealt with should be the reliability of the counts themselves. Since the counts are prone to error, the magnitude of these errors should be included in the variance of the final map. Pebesma *et al.* 2000 gives an example of the inclusion of errors of counts of see birds in a spatial interpolation.

In this paper, a relatively straightforward method is described to create interpolated maps from sample data. Although the Poisson distribution is suitable for the description of the bird data, other distributions may also be well suited. These are for example the negative binomial distribution or mixed models. These distributions require often more parameters (like the aggregation-factor k in the negative binomial distribution) that are not straightforward to ob-

tain and can lead to worse results if not estimated properly. In our study, the counts data were not transformed prior to regression kriging. It can however be advantageous to consider data transformations in some cases. The ordinary kriging technique as applied to the residuals assumes normality. While in this study there was no sign that this assumption was violated, it may be a problem in other situations. With other methods it is possible to relax the restrictions of ordinary kriging (Diggle *et al.* 1998). A problem with our regression kriging method is that no satisfactory variances can be calculated. We estimated the variance by simply adding up the variance of the regression part and the kriging part, but this probably leads to an overestimation of the error of the models. (Odeh *et al.* 1995; Pebesma *et al.* 2000). It is better to carry out the Poisson regression kriging in one simulation process instead of two separate ones. There are software tools available to perform this kind of modelling like WINBUGS (Link *et al.* 2002) and R-libraries like GeoR and GeoRglm (www.r-project.org). With the increase of the number

Figure 8. Final map of the distribution of Common Buzzards in December 2000 as a result of regression kriging.
Mapa final de la distribució de l'Aligot Comú el desembre de 2000 com a resultat de la regressió "kriging".

size of each point is small compared to the density and land use of the birds. On a vast majority of the points only 0, 1 or 2 Buzzards were seen. Due to the small size of the points many suitable points will just by chance have no Buzzards. The estimates for individual points may therefore be rather poor, but much better when looking at a larger scale (like blocks of one km^2). In general, R-squared and explained deviance should only be used to compare comparable models and not as a direct measure of model performance: rescaling of the values and changes of the slope can lead to large differences of R-squared. Despite the small percentage of explained deviance, most of the variables that entered the regression models are highly significant. This is mainly due to the large size of the dataset: over 6000-8000 points per year.

The combination of monitoring data and statistical interpolation statistics makes it possible to map trends: we can now see how the distribution and abundance changes over times with much shorter time intervals than is possible with nationwide bird atlas projects. Series of maps show that the increase in numbers may not be equal all over the country, but time-lagged in some areas. Although from the current models it might be concluded that the western part of the Netherlands is not, or is less, suitable for wintering Buzzards, the current distribution might reflect the historic distribution. If that is the case, a further increase in numbers in the west of the country may be expected.
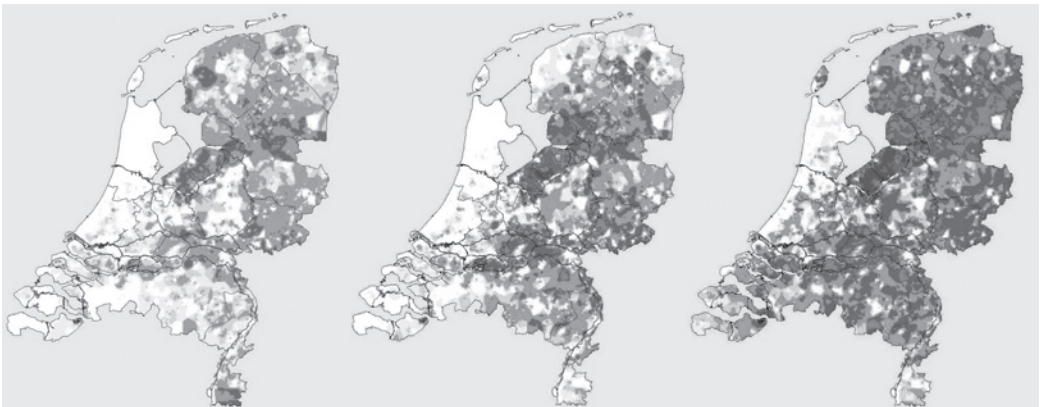
of data points, however, the calculation time increases exponentially and still forms a real problem with large datasets like that of the Buzzard-example in this paper.

The explained deviance of the models is rather low. This is no surprise since the sample

Figure 9. Predicted distribution of Common Buzzards in December 1985, 1990 en 1995. The increase in numbers was time-lagged in the southwest of the country as compared to the northeast.
Distribució predita de l'Aligot Comú el desembre de 1985, 1990 i 1995. L'increment d'individus va tenir un desfasament al sud-oest del país en comparació al nord-est.

This study has shown that spatial statistics are a valuable tool to extend the use of bird monitoring of wintering Buzzards in the Netherlands from trend calculations to detailed distribution maps. The methodology we outlined can easily be generalized to other types of monitoring data or other species. However, if we want to produce similar maps on a European scale, data from different monitoring projects have to be made comparable first. Further steps have to be taken to integrate as much of our biological knowledge about the bird behaviour and movement with deterministic or statistical models, after which a statistical interpolation can be performed. Parallel to this, research to establish both empirically and theoretically the uncertainty in the various spatial predictions is required in the future.

Acknowledgements

Resum

Omplint els buits: l'ús de dades de programes de seguiment per predir les pautes de distribució de densitat i estimes poblacionals

Els ocells juguen un paper cada vegada més important en la política, la conservació i la gestió de la natura. Com a conseqüència d'això, és necessària una estimació espacial actualitzada i fiable de les distribucions de les aus per a grans àrees. Els mapes de distribució requerits per a això no són fàcils d'obtenir. Un treball de camp intensiu sobre una xarxa espacial densa requereix un gran esforç de centenars o milers de voluntaris, i només és factible una vegada cada poques dècades. Per crear els mapes d'abundància i distribució a intervals més curts d'anys o fins i tot mesos, es necessiten dades de seguiment. No obstant això, les dades de seguiment tenen una estructura espacial poc densa. Amb la finalitat de produir mapes de distribució fiables amb aquestes dades, s'ha d'usar informació biològica addicional i procediments estadístics relativament complexos. En aquest article s'expliquen els diversos passos i qüestions necessaris que requereix un estudi on es construeixen uns mapes de distribució de l'Aligot Comú *Buteo buteo* per a tota Holanda.

Resumen

Rellenando los huecos: uso de datos de programas de seguimiento para predecir las pautas de distribución de densidad y estimas de tamaños de población

Las aves juegan un papel cada vez más prominente en la política, la conservación y la gestión de la naturaleza. Como consecuencia de ello, es necesaria una estimación espacial actualizada y fiable de las distribuciones de las aves para grandes áreas. Los mapas de distribución requeridos para ello no son fáciles de obtener. Un trabajo de campo intensivo sobre una red espacial densa requiere un gran esfuerzo de cientos o miles de voluntarios, y sólo es factible una vez cada pocas décadas. Para crear los mapas de abundancia y distribución a intervalos más cortos de años o incluso meses, se necesitan datos de seguimiento. Sin embargo, los datos de seguimiento tienen una estructura espacial poco densa. Con el fin de producir mapas de distribución fiables con estos datos, se debe usar información biológica adicional y procedimientos estadísticos relativamente complejos. En este trabajo se explican los diversos pasos y cuestiones necesarios que requiere un estudio donde se construyen unos mapas de distribución del Ratonero Común *Buteo buteo* para toda Holanda.

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