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Application of a genetic algorithm to minimize agricultural nitrogen deposition in nature reserves

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Abstract

The quality of Dutch nature reserves is threatened by high nitrogen input, a problem which to a large extent is caused by agricultural activities. The Dutch government intends to solve this by designating some areas where the emission level is allowed to increase and other areas where the emission level will have to decrease. Theoretically, this problem can be seen as a reallocation of emission sources.

In earlier research, the optimal spatial distribution of agricultural ammonia emissions to minimize atmospheric nitrogen deposition in nature reserves was determined. Linear programming (LP) has been applied because of the approximately linear atmospheric transport relations between emission and deposition locations. A more thorough analysis necessitates the addition of other nitrogen contributions important for the quality of nature, such as by groundwater and surface water transport. These processes can no longer be considered linear, so the application of non-linear optimization methods is necessary. Several non-linear programming methods can solve large-scale problems, but are not capable of dealing with non-smoothness and qualitative relations, especially when the number of variables and/or relations is large. In this study, the potential of genetic algorithms (GA) is evaluated, by comparing the GA results for the linear atmospheric emission–deposition process with results of LP. Kappa statistics and regression analysis were used to test the similarity of the spatial emission and

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deposition distributions on the GA and LP output maps. GA was shown to perform well, producing similar results to LP. Calculations in this article also showed that almost identical minimal deposition patterns may be achieved with somewhat different emission patterns. This is a potentially interesting feature for policy-makers, who may evaluate alternative emission distributions on a small scale, each with their specific socio-economic impacts, while still achieving optimal results for nature quality.

Keywords: Spatial optimization; Genetic algorithms; Agricultural nitrogen emission; Critical load; Kappa statistics; Map comparison

1. Introduction

Many plant species and ecosystems are dependent on soils and solutions with low levels of available nitrogen. As a result of human activities the amount of nitrogen available to Earth's ecosystems has more than doubled globally over the past century, causing many plant and animal species to become completely or locally extinct (Vitousek et al., 1997). One of the major threats is the atmospheric input of nitrogen (Galloway et al., 1995). Lakes and streams in geologically sensitive regions of Scandinavia, western Europe, Canada and the USA were affected by an increase in acidic and acidifying compounds in atmospheric deposition. Characteristic *Sphagnum* species in bogs in Denmark and the Netherlands were replaced by more nitrophilous species (Bobbink et al., 1998).

Mean atmospheric deposition of nitrogen in the Netherlands consists mainly of ammonia (ca. 70%), of which 80% originates in Dutch intensive agricultural activities (RIVM, 2002). For nature areas, this contribution can be even higher because these are often located close to agricultural areas.

Dutch policy aims at reduction of nitrogen deposition in nature areas to halt the deterioration of ecosystems. Besides measures to reduce total nitrogen emission, reallocation of emissions (in terms of intensification or expansion) can be used to reduce nitrogen deposition in nearby nature areas. In previous studies, we have used optimization techniques study the potential of reallocation of emissions (Van Dam et al., 2001; Heuberger et al., 1997; Heuberger and Aben, 2002). These techniques were applied in determining the optimal spatial distribution of agricultural emission sources with minimal atmospheric nitrogen deposition in nature areas, given a fixed level of total agricultural atmospheric nitrogen emission in the Netherlands.

The background for this approach lies in the way emission and deposition data are obtained at the Netherlands Environmental Assessment Agency (MNP). The NH_3 emission data are obtained from the Dutch Agricultural Economical Institute (LEI). These data are based on (actual counts of) numbers of animals, location and type of farms, cultivated area, production capacities, etc. After dedicated calculations, using additional information from various other institutes, LEI produces NH_3 emission data on a 500×500 m. grid.

At MNP these data are input for the operational priority substances model (OPS; Van Jaarsveld, 2004). This model simulates the atmospheric process sequence of emission, dispersion, transport, chemical conversion and finally deposition, resulting in NH_3 concentration and NH_4 deposition data on grid level.

Nature areas within the study area are all classified to a specific nature type, with a specific critical load value, based on its vulnerability to atmospheric N-deposition (Reynolds and Skeffington, 1999). The critical load for a nature grid cell is then determined by the lowest critical load of occurring nature types.

Combining the NH_4 deposition data with other N-deposition data (due to traffic, industrial and foreign sources, background concentrations, etc.), this procedure thus results in an evaluation of critical load exceedance in nature areas.

The OPS model basically performs three operations: (1) calculate the deposition in a single gridcel D, that results from an emission in a single gridcel E; (2) perform this operation for each gridcel E in the grid; (3) sum the resulting depositions in each gridcel D of the grid. The first step has the property – under fixed meteorological conditions, emission height and heat content – that it is multiplicative, i.e., multiplication of the emission in gridcel E with a factor K, will result in a multiplication of the deposition in gridcel D with the same factor K. One can conclude that the cell-to-cell emission–deposition relations as calculated by the OPS-model are essentially linear.

Under the mild assumption that the emission characteristics (source height, heat content) for agricultural NH_3-emissions are equal all over the Netherlands and assuming fixed meteorological conditions we can replace the OPS model calculations by calculation with a so-called source receptor matrix (SRM). Each (i,j)th entry of this matrix contains the deposition in grid cell i, resulting from a unit emission in grid cell j. For every potential emission raise or decline, but also for a change in the emission pattern, the resulting deposition or critical load exceedance can now be calculated with standard matrix–vector operations.

This property enables the formulation of an optimization problem – with the goal to minimize critical load exceedances – in terms of a linear programming problem (Luenberger, 1984). An additional requirement thereto is that so-called boundary conditions and the goal function (objective functions) are also formulated linearly.

For each grid cell a realistic lower and upper bound for emission was determined, based on maximal capacity and soil-bound emissions. The objective in the optimization is to find an alternative emission distribution which minimizes the sum of all exceedances of the critical loads, in order to improve the current situation of nitrogen surpluses in nature areas.

Of course one of the solutions to improve the situation of Dutch nature areas is to remove all agricultural activities close to nature. However, for economic purposes and ability to compare the former and optimized situation, the total emission level before and after the optimizations is kept constant.

Further, the deposition across province boundaries is not allowed to increase, to omit shifting the problem to neighbouring areas. Finally, for those nature cells where the deposition (in the 'base situation') already exceeds the critical load, the deposition is not allowed to increase ('do not make it worse').

Each of these constraints as well as the objective function could be formulated in a linear fashion, and hence the optimization can be converted into a linear programming formulation. This formulation has the merit that with standard software this type of optimization problems can be solved exactly within relatively short time, even if the number of variables (here the emissions per grid cell) and constraints is high (several thousands).

Calculations, using this setup and dedicated LP software, showed that such an optimized emission distribution would reduce the deposition in nature areas to more acceptable levels. Furthermore, additional calculations, where the total sum of emissions is lowered, showed that complete protection of nature areas would require a very substantial decrease of emission. In some areas the critical loads will always be exceeded due to other nitrogen sources. In this paper, we will only consider the first scenario, i.e., constant emission total.

A number of important factors were still not considered in the above-mentioned reallocation calculations. First, besides the atmospheric input of nitrogen, other processes, such as groundwater and surface water flow, also contribute to nitrogen input in nature areas. Second, Dutch policy aims at establishing about 150,000 ha of new nature reserves and 100,000 ha of restricted management zones in the next 20 years. Together with the existing nature reserves, these areas will form a network of high-quality nature areas called the National Ecological Network (EHS in Dutch). The new nature reserves will also be influenced by nitrogen emission sources. A third point of consideration is formed by the Bird and Habitat Directives of the European Community: Council Directive 79/409/EEC 1979 (EC Bird Directive) and the Council Directive 92/43/EEC 1992 (EC Habitat Directive). These directives oblige governments to protect all naturally occurring bird species and habitats of wild flora and fauna in the member states. To support the Dutch policy-makers, the reallocation calculations presented above will be extended to taking the above-mentioned additional factors into account. The resulting additional relations cannot be implemented using the LP method, because of their non-linearity, non-smoothness or possibly qualitative character. Therefore, other optimization methods are necessary. Several non-linear programming methods can solve medium- to large-scale problems, but are not capable of dealing with non-smoothness and qualitative relations, especially when the number of variables and/or relations is large (Cai et al., 2000). These methods often use the derivative of functions to find the optimal solution, however, derivatives of qualitative or irregular functions can hardly be formulated. In a comparative study of methods for large-scale environmental optimization problems, Mayer et al. (2001) conclude that so-called heuristic methods, e.g., GA and SA (simulated annealing), outperform more classical methods such as non-linear programming. See also Sarkar and Modak (2003), Van Dijk et al. (2002), Seppelt and Voinov (2002), Vink and Schot (2002), Brookes (2001) and Rauch and Harremoes (1999) for the application of heuristic methods to non-linear, qualitative and environmental optimization problems.

Here, we present the results delivered by a multivariate optimization of the spatial distribution of agricultural ammonia emission sources using a genetic algorithm (GA). The main objective was to find out if the GA produced similar solutions to

LP. If so, it would be worthwhile to apply GAs for investigating the multiple-goal problem, including the non-linear relations described above.

2. Methods

2.1. Test case

The multivariate optimization of the spatial distribution of agricultural ammonia emission sources in the Dutch province of Noord-Brabant has been used as a test case. The optimization goal was to minimize the effects of atmospheric nitrogen deposition in nature areas. This optimization problem was solved using linear programming, as reported by Van Dam et al. (2001), Heuberger et al. (1997) and Heuberger and Aben (2002). Noord-Brabant comprises approximately 5000 km^2, of which some 60% (3000 km^2) is used for agricultural purposes. Although it comprises only 12% of the land surface of the Netherlands, it contains 20% of the Dutch cattle farms and contains a number of areas with intensive bio-industry. Forests and nature reserves in the province occupy a total of 1300 km^2.

The research area was converted into a covering grid of 5875 cells of 1×1 km. A cell is considered to be a nature cell if more than 25% of the cell actually contains nature, so for this research area the number of nature cells came to 1475. Agricultural activity was assumed possible in the calculations for 3997 cells. All remaining cells were classified as urban area.

Nature cells all have a specific critical load value for N deposition, depending on the most vulnerable type of ecosystem present (Reynolds and Skeffington, 1999). Deposition values exceeding the critical load are assumed to cause damage to the most vulnerable nature types within the specific grid cell.

Minimum and maximum values for ammonia emissions were determined in cells with agricultural activities. Linear ammonia emission–deposition relations were assumed between cells on the basis of atmospheric properties like temperature, wind speed, sun intensity and precipitation, as well as on surface characteristics and the chemical composition of the atmosphere (Van Jaarsveld et al., 2000). Cell-to-cell relations were calculated by the so-called 'operational priority substances' (OPS) model (Van Jaarsveld, 2004; Van Jaarsveld and de Leeuw, 1993; Van Jaarsveld, 1995).

In this study, only agricultural ammonia emission sources were considered for reallocation. All other atmospheric nitrogen inputs to nature areas were assumed to be fixed to the 1999 situation. In the calculations, a number of constraints have to be satisfied. The first constraint is that the total sum of emission in the research area must remain unchanged. The rationale behind this is to determine how much the current situation in nature areas can be improved and optimized by re-allocation of emission sources only. Measures to lower total emission were also considered in Van Dam et al. (2001), but were not considered in this comparative methodological study. A second constraint is used to satisfy the minimum (lower bounds) and maximum (upper bounds) emissions for each cell. The third constraint is that the initial exceedance of the critical loads within nature cells (i.e., the 1999 situation) was not allowed to increase; this is to make sure that the current situation would not deteriorate in these cells. A fourth constraint – the deposition in other provinces is not allowed to increase either – prevents the algorithm from moving the problem to neighbouring areas outside the province. This last constraint was implemented so that the deposition would not increase for each 5×5 km in the neighbouring provinces.

It should be noted that complete protection of nature from nitrogen deposition in the research area is impossible. If all agriculture were to be removed from the province of Noord-Brabant, critical loads for nitrogen would still be exceeded in several nature areas due to deposition from other sources. It is therefore impossible to find a solution under which all nature cells would be protected. For this reason, the objective function of this optimization problem was set to minimize the sum of exceedances of the critical loads in all nature cells.

2.2. Linear programming

Because of the linearity of the emission deposition relations and the fact that all constraints and relations could be captured in a linear formulation, the optimization problem could be solved using linear programming (Van Dam et al., 2001; Heuberger et al., 1997; Heuberger and Aben, 2002). In linear programming the maximum or minimum values of a linear expression, subject to a number of linearly formulated constraints, has to be found. This minimal or maximal value is called the 'optimal value'. A collection of variables, resulting in the optimal value, constitutes an optimal solution.

2.3. Genetic algorithms

A genetic algorithm is a search technique originally developed by Holland (1975). Genetic algorithms have been widely used to solve either single and multi-objective optimization problems (Sarkar and Modak, 2003; Dijk et al., 2002; Rauch and Harremoes, 1999). Recently, GAs have been applied to spatial optimization problems (e.g., Aerts, 2002; Vink and Schot, 2002; Matthews, 2001). The emission–deposition problem described here is also a spatial optimization problem.

Genetic algorithms are based on the principles of Darwin's evolution theory. They search for an optimal solution by simulating processes of evolutionary development of a population of candidate solutions. Feasible candidate solutions are represented as individuals in a population. The values of parameters in an individual solution are considered to be genes, which can be inherited by mating. A fitness function is used to evaluate the suitability of the individuals. The fitness function takes a single individual as input and returns a quantitative measure of the 'goodness' of the solution represented by that individual. The method used in our study is usually initiated by choosing (often at random) an initial population, referred to as generation G_0. From a generation G_t a new generation G_{t+1} is created, by mimicking the evolution process. The most important operations within this procedure are given below (Holland, 1975):

- Selection (who survives) of individuals is based on the fitness of the individuals with respect to an objective function. Individuals with high fitness values (representing better solutions to the problem) will have a higher probability of surviving and entering the mating population, while low-valued individuals will have a high risk of being removed from the population. In this way individuals with the best genes or characteristics will have better chances of survival and mating.
- Cross-over (mixing genetic characteristics) is done by mating and exchanging or recombining characteristics or genes in the offspring.
- Mutation (random genetic changes) occur with a certain chance, often dependent on stagnating objective values. A mutation is a change in some randomly chosen genes. Mutation is – among others – useful to keep a population from converging to a local optimum too fast.

After cross-over and mutation have taken place, individuals will be selected for the next mating population. This process of selection, cross-over and mutation is repeated until a potential optimal solution is found. A potential optimal solution is defined here as the best individual in the population when the objective value stagnates and the algorithm is not producing better offspring.

Cross-over between two potential solutions, A and B, is implemented by creating a new solution candidate that inherits the values of parent A in a pre-specified set of grid cells and values of parent B in the remaining cells. Mutation is implemented here by exchanging the values of some randomly chosen grid cells within one parent.

Genetic algorithms are generally considered to be powerful tools for the solution of unconstrained optimization problems. However, many real life problems are subject to a large number of constraints, which is also the case in the emission reallocation problem. The emission–deposition problem is subject to four constraints (see Section 2.1). Contrary to LP, some constraints cannot easily be implemented into the GA approach. Beasly (2002) discusses four different strategies to deal with constraints:

- Representation, assuring that generated candidate solutions automatically satisfy the constraints.
- Use of a repair operator, taking care of constraint violations 'afterwards', for instance, by rescaling or projection.
- Distinguishing between fitness and unfitness, using two measures for each individual. The fitness value is used to evaluate the objectives, and the unfitness value represents the degree to which constraints have been violated.
- Use of a penalty function, 'punishing' constraint violations by adding a penalty to the fitness value.

The first strategy, representation, is, in fact, the most straightforward constraint-handler. The algorithm should be formulated so that the candidate solutions always satisfy the given constraints. Unfortunately, this is often a very difficult or even impossible venue.

Using a repair operator is often useful in cases where the first strategy cannot be applied. If, for example, a variable exceeds a certain maximum value, it can be converted to just that value. When using fitness and unfitness values, every potential solution will obtain a fitness and an unfitness value, the first value depending on how objectives are fulfilled and the second on to what extent constraints are violated. Individuals with high unfitness values will stay temporarily with the population, so the new offspring can inherit their potential valuable characteristics. Their unfitness value, however, will cause them to be replaced by 'better' individuals according to a decision rule. The last strategy discussed by Beasly is the use of a penalty function. This penalty is based on the extent to which the constraints are satisfied. The penalty is integrated into the fitness value, so individuals performing well will have a higher fitness and thus more chance of survival.

Tests using fitness or unfitness values showed this tactic either did not work out well for this problem or resulted in very long computation times.

Although the use of penalties is often dissuaded in the literature, penalties were used for two constraints in this study. In this particular case, penalties proved to be an acceptable method. The other constraints (such as total sum and lower and upper bounds for emission) were automatically satisfied. The total sum was satisfied by exchanging equal quantities of emission between two cells. These quantities were randomly chosen between zero and the minimal difference between the current levels of the exchanging cells and their lower or upper bounds. This makes the emission automatically satisfy the upper and lower bounds.

The fitness value is often composed of more than one criterion. Especially, in multi-objective studies it will be composed of different objectives, each having a certain weight value. Constraints that cannot be satisfied automatically and will be penalized, as described above, force the evolution in another direction, while raising the fitness value. In this study, two constraint penalties and the criterion in the objective function have to be minimized, often resulting in conflicting goals. The goals receive weight values according to their importance and the algorithm acts, in fact, like a multi-objective optimization problem.

Tests have been done using a regular GA; however, a radical simplified version of a genetic algorithm with a population size of 1, using only mutation and no crossover, was seen to produce similar results (similar K_{fuzzy} values), (see Section 2.4). This algorithm can be classified as a Stochastic Search Algorithm (SSA) (Patel et al., 1988) or an evolutionary strategy (Negnevitsky, 2002). Here, it is referred to as a simple GA. Both GAs performed well; results were only slightly different, although they differed greatly in execution time. After initial fine-tuning (i.e., trying different weight values in the criterion function, penalty factors, etc.), the simple GA attained the same exceedances for the critical loads in about the same execution time as or even faster than with LP, while the regular GA needed over 30 h. Results presented here are based on the simple GA runs.

The 'Genetic Algorithm Toolbox for Use with Matlab' (Chipperfield et al., 1994) was used in the first experiments. Because of the specific characteristics of the problem, we coded up our own version in Matlab 6.5 (The Mathworks Inc., 2002).

2.4. Comparison of maps

The LP and GA optimization results were compared by analyzing: (a) the spatial distribution of optimized emissions and (b) the spatial distribution of resulting exceedances of the critical N-loads in nature cells.

Kappa statistics (Sousa et al., 2002) and regression analyses were used to quantify the resemblance of LP and GA output maps for (a) and (b). Hagen (2003, 2002) developed a method combining the Kappa Statistic tool with the Fuzzy Set theory. The so-called K_{fuzzy} provides information about the magnitude, nature and spatial distribution of similarity between two maps (where $K = 1$ represents perfect similarity and $K = 0$ no similarity). The main advantage of this method is the use of both the spatial component and the similarity between different categories. Where classical Kappa indices are restricted to cell-by-cell comparisons, the K_{fuzzy} takes into account both fuzziness of location and fuzziness of category. In practice, a K_{fuzzy} of 1 is not likely to occur in large optimization problems using GA. To validate the results of the K_{fuzzy} between GA and LP, the K values were also compared to a 'random distribution', satisfying only the constraints (see Section 2.1).

The regression analysis results in a straight line, $y = ax + b$, where a represents the regression coefficient and b the intercept. Near similarity is indicated by values of b near zero and a close to 1. Regression analysis was performed to compare the results from LP with GA optimizations, both on the original data derived from the optimization, as on a larger spatial scale (2×2 and 5×5 km). The latter analysis was performed to evaluate the spatial patterns on an aggregated level. This aggregation was motivated by the fact that the GA does not search in the edges of the search space like LP (Dauer and Liu, 1990). Therefore, in a cell-by-cell comparison, dissimilarities are expected when the LP solution is close to the lower and upper bounds. The dissimilarities will be smoothed by comparison on an aggregated level.

3. Results

Because different GA runs do not produce one unique solution, five different GA runs were used for calculating the map similarity. The visualized solution in Fig. 2 represents one of the runs.

In Fig. 1, the effect of optimization on the level of exceedances in critical nitrogen deposition in nature cells is made apparent. Before optimization (i.e., the actual situation in 1999) the critical loads are exceeded in 94% of the existing nature cells, while after optimization this is reduced to 82% (both for LP and GA). Furthermore, in the actual situation in 1999 the exceedance of critical loads is larger than 250 mol/ha/year in 71% of all nature cells; this is reduced to only 27% after optimization (both for LP and GA).

The corresponding emission patterns after optimization are only slightly different, as can be seen from Fig. 2, which shows the results of the optimal allocation of agricultural emission according to LP (a) and GA (b).

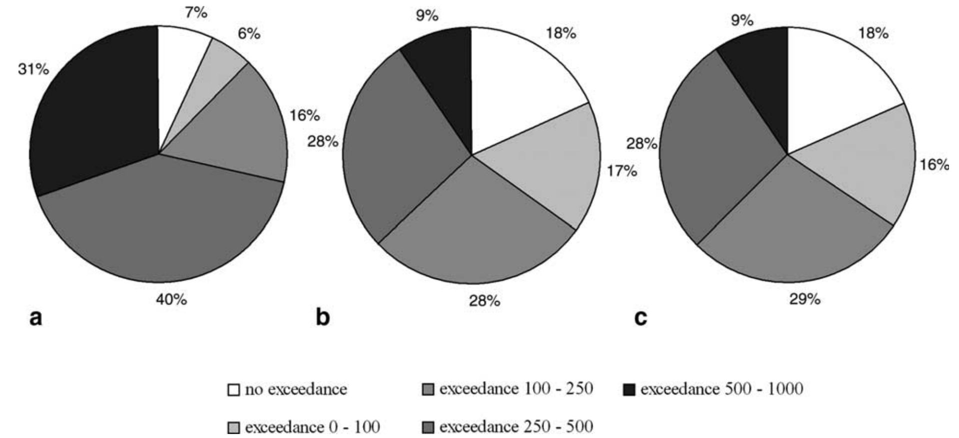

Fig. 1. Exceedance (mol/ha/year) of critical loads in nature cells for the situation before optimization (a) and after optimization (b and c) with GA and LP, respectively. The higher percentages of cells in lower classes after optimization indicate a decrease in exceedances. Absolute values for exceedance were used as a criterion, but relative exceedances are also possible.

The resulting deposition maps after optimization with LP and GA show almost no differences when observed with the naked eye (Fig. 2). The K_{fuzzy} for exceedance patterns of the critical loads in nature areas after optimization with LP and GA varies between 0.94 and 0.96 (compared to a K_{fuzzy} of 0.59 in a random situation, satisfying only the constraints). These values indicate almost complete similarity in the maps and thus in the exceedance patterns.

The K_{fuzzy} for the similarity of the emission patterns of the LP and GA solutions varies between 0.72 and 0.73 (compared to K_{fuzzy} of 0.27 in a random situation, satisfying only the constraints), indicating substantial similarity (Landis and Koch, 1977) between the LP and the GA allocation for emission patterns. The K_{fuzzy} values comparing emission patterns between pairs of GA-runs show lower similarities than the K_{fuzzy} values for comparisons between a single GA run and the LP solution. At the same time, the K_{fuzzy} values comparing deposition patterns show almost perfect similarity. This implies existence of a whole set of emission patterns close to the LP solution, resulting in the same deposition pattern.

Comparing the two maps, it is clear that high emissions are situated almost at the same locations. However, optimization performed with linear programming results in a relatively concentrated distribution of high emissions in the province compared to a smoother distribution derived from the GA optimization. Concentrated distribution by LP is caused by the fact that the optimal solution has values 'on the extremes', i.e., the edges, caused by the constraints. This results in a distribution of emission values situated in the lower or the upper bounds. Due to the aforementioned low sensitivity of local changes in the optimal emission patterns and the intrinsic random character of GA, the latter will result in a smoother emission pattern.

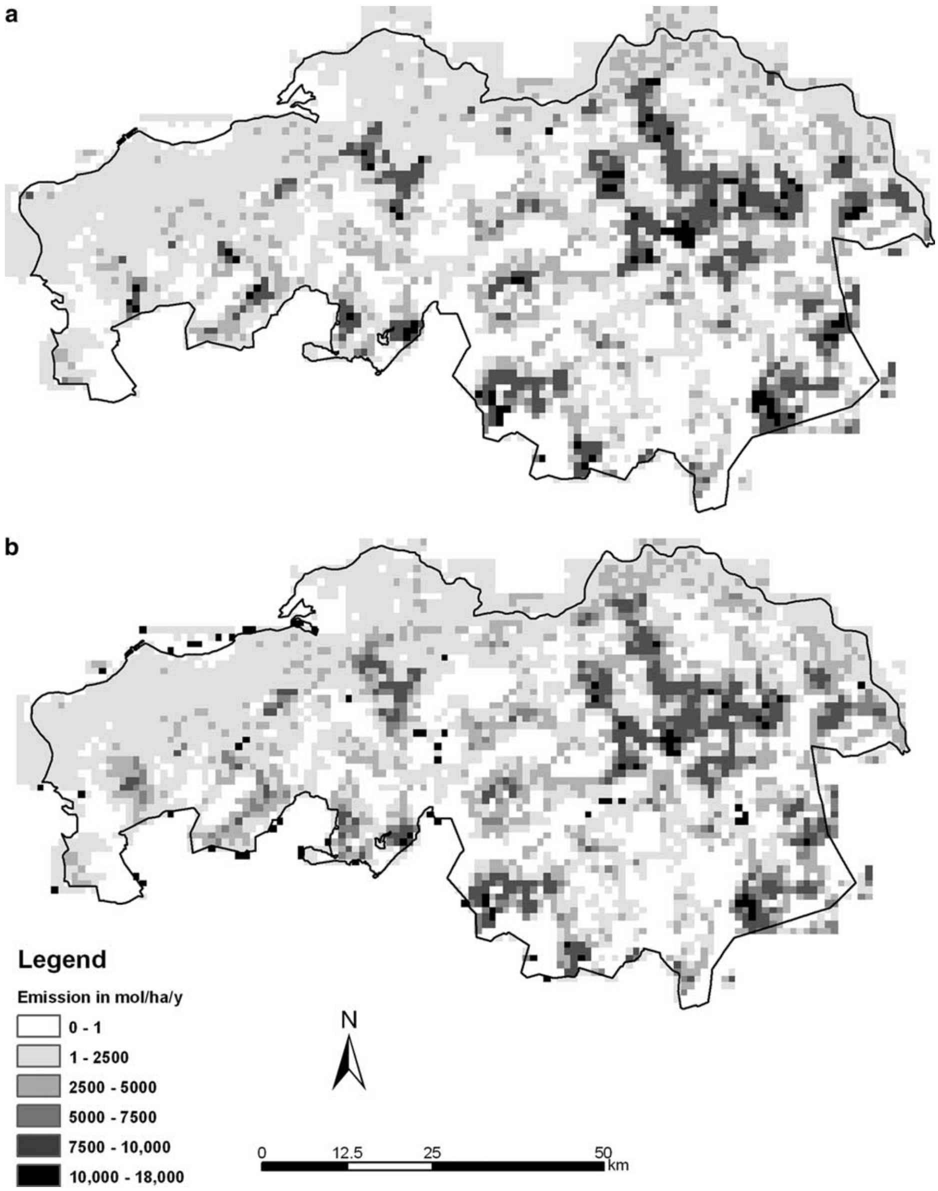

Fig. 2. Pattern of ammonia emission after optimization with LP (a) and GA (b).

Another reason for the slight dissimilarities in the LP and GA emission patterns lies in the difference between the objective functions for LP and GA. Local differences in the emission values can cause small differences in deposition patterns for the three components within the objective function, but may result in the same total objective function values.

Because of these local differences in emission, resulting in almost the same deposition patterns, a regression analysis was performed on the emission values, not only on a cell-to-cell level but also on an aggregated level. The similarity in spatial patterns can be tested this way. The regression analysis on a cell-to-cell level results in almost the same values as for K_{fuzzy} (R^2 of 0.74 and 1.0 for emission and exceedance (of critical loads) patterns, respectively). Here, intercepts are equal to 493 (95% confidence interval: (436, 551)) and 1.1 (95% confidence interval: (0.37, 1.89)) mol/ha/year and regression coefficients of 0.83 (95% confidence interval: (0.81, 0.84)) and 1.0 (95% confidence interval: (0.99713, 1.00002), respectively). The values for emission are easy to explain by the differences in the extremes; logically this will result in one line, with an intercept higher than zero and a regression coefficient smaller than 1. The values for deposition can be explained by a very small difference in the solution. The highly significant regression coefficient of 1.0 between the GA and LP solutions indicates the standard mean exceedance of 1.1 mol/ha/year of GA in the LP solution (for a total of 262 mol/ha/year).

After aggregation of the emission data to cells of 2×2 and 5×5 km, the similarity for the emissions improves considerably (Fig. 3). The R^2 values for the GA solution compared to the LP solutions were 0.92 and 0.98, respectively, while the random-solutions had R^2 values of 0.59 and 0.79, respectively. The intercepts on 5×5 km aggregation levels are still 453 mol/ha/year for the random distribution (with a regression coefficient of 0.67), while the GA-solution intercepts the y-axis at 68 mol/ha/year (with a regression coefficient of 0.95). Therefore, it can be concluded that differences between the LP and GA solutions occur only on small scale (1×1 km). On aggregated levels (2×2 and 5×5 km) the emission patterns for both methods are near to similar.

Various concepts and options have been investigated to improve the efficiency of the applied genetic algorithm. Constraint handling seemed to emerge as the most important issue in this problem. For the first constraint (total emission should be kept constant), representation and use of a repair operator were tested. The major problem with the latter is that it was too time-consuming, resulting in very long computation times. Representation, especially with respect to the first constraint, performed well. The second and third constraints (i.e., no deterioration of the initial situation, both inside and outside the region) were handled using penalty functions. Although the use of penalties is often dissuaded in the literature, they proved to be an appropriate method in this application. The major lesson learned here was that the weights used for these penalties should be kept variable throughout the execution of the algorithm so as to prevent premature stagnation; the penalty factors should be kept relatively small in the initial phase of the execution and be gradually increased during the optimization process.

In the simplified version of the algorithm, the total sum of emission in the current situation is first allocated randomly to the 3997 cells in which agricultural use is allowed. In the next steps random quantities of emission are exchanged between arbitrary grid cells. After every exchange the new candidate solution is evaluated using the objective function. If the result of this function, the fitness value, is lower than the

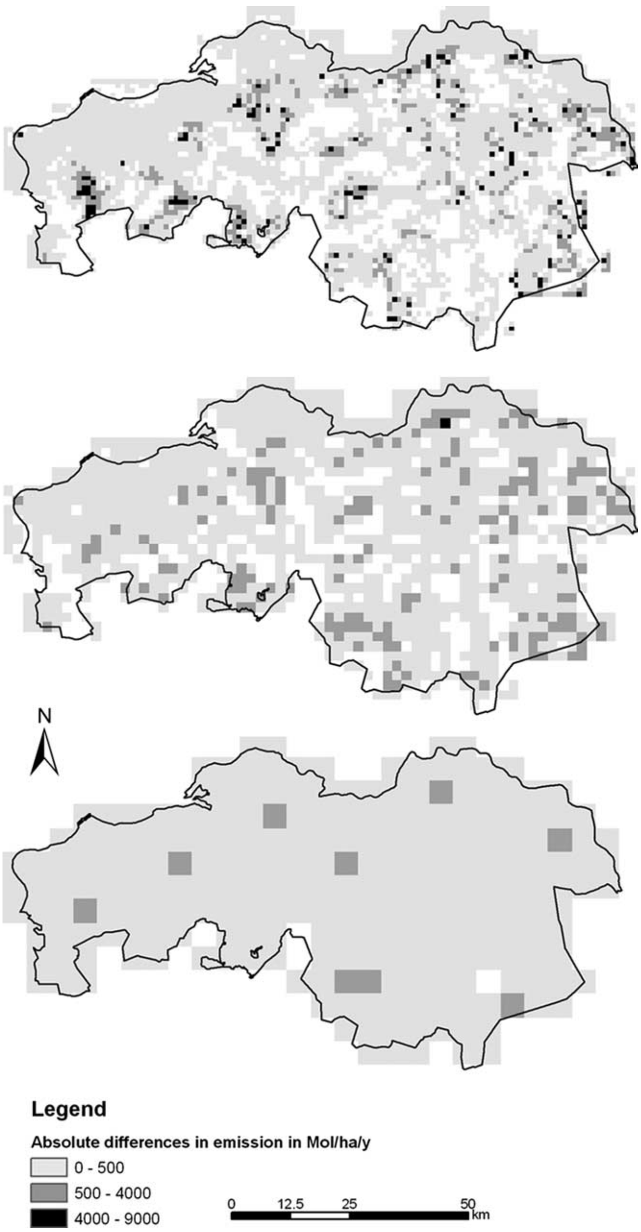

Fig. 3. Effect of resolution on absolute differences between LP- and GA-optimized ammonia emission patterns. Emission is not allowed in the white areas.

current best value, the new candidate solution will replace the old solution. It should be noted that this improvement is very likely due to the relatively simple and linear character of the underlying optimization problem. For more complicated problems, the simple GA may not be applicable and a more traditional GA may have to be applied.

4. Discussion

The comparison of LP and GA optimization for the emission–deposition problem in our case study showed K_{fuzzy} values of 0.73 for emission patterns and 0.95 for exceedance patterns. These values were judged to be sufficient for GA application for future multi-objective optimization of N input to nature areas. Therefore, the intention is to expand the optimization problem in the near future with more processes and more constraints or criteria, as mentioned in the introduction. The model can be a useful tool in future policy-making related to land-use problems. Our case study showed the potential of optimization methods for decreasing ammonia deposition in nature areas.

The calculations also showed that almost identical minimal deposition patterns can be achieved with somewhat different emission patterns. This is an interesting feature of GA application for policy-makers, who can evaluate alternative emission distributions on a small scale, each with their specific socio-economic impacts, while still achieving optimal results for nature. Another advantage of the method is that large numbers of scenarios with different constraint values and emission totals can be optimized in a relative short time.

For optimization problems where small changes in input values have a large impact on the output, an interesting step in future research could be to initiate a local optimization after the (aggregated) optimization of the complete research area. For the problem at hand this would lead to even better results for the similarity in emission patterns between LP and GA. Although differences still occur in emission patterns, the differences in the exceedance of the critical loads are negligible. As mentioned earlier, the problem at hand is relatively simple and linear. Differences in emission patterns between GA and LP occur mainly in the extremes, which can be expected due to the fact that LP solutions are generally located in the extremes.

As an overall conclusion GA can be stated as having proved its potential in optimizing a high dimensional, linear problem and the implication is that GAs might also perform well on non-linear problems. Of course it will be necessary to perform tests on this subject. This study showed that problems with a high number of variables can be tackled within the same computation time as LP needs. In general, the process of tuning is most time-consuming, and therefore the total procedure takes more time than LP; on the other hand, when non-linearities occur, LP is no longer suitable. GA does not impose any restrictions on the type of model and can be used in a variety of applications. GA can, in principle, tackle discontinuous, non-linear or stochastic problems.

In our experience the main disadvantage of GA is the time-consuming process of constraint-handling. This part of the fine-tuning process differs for every constraint and the necessary time is not predictable.

After optimization, the main criterion in the objective function, the actual minimization of the exceedances of the critical loads within nature areas, is still above the threshold for 82% of the area (before optimization exceedance occurred in 93% of the cells). However, the number of cells with an exceedance less than 250 mol/ha/year, increased from 29% to 63%. This is a very promising result if we also consider the fact that both national and international policies are causing future emission totals to decline and hence the number of 'clean' cells will increase rapidly. The results of this study are potentially interesting to policymakers, because even small changes in emission patterns can result in higher numbers of 'clean' nature areas in the near future. The proposed procedure results in multiple configurations to achieve this goal, allowing policymakers to take local limitations and considerations into account.

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