Optimizing the spatial pattern of networks for monitoring radioactive releases


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Abstract

This study presents a method to optimize the sampling design of environmental monitoring networks in a multi-objective setting. We optimize the permanent network of radiation monitoring stations in the Netherlands and parts of Germany as an example. The optimization method proposed combines minimization of prediction error under routine conditions with maximizing calamity detection capability in emergency cases. To calculate calamity detection capability, an atmospheric dispersion model was used to simulate potentially harmful radioactive releases. For each candidate monitoring network, we determined if the releases were detected within one, two and three hours. Four types of accidents were simulated: small and large nuclear power plant accidents, deliberate radioactive releases using explosive devices, and accidents involving the transport of radioactive materials. Spatial simulated annealing (SSA) was used to search for the optimal monitoring design. SSA was implemented by iteratively moving stations around and accepting all designs that improved a weighted sum of average spatial prediction error and calamity detection capability. Designs that worsened the multi-objective criterion were accepted with a certain probability, which decreased to zero as iterations proceeded. Results were promising and the method should prove useful for assessing the efficacy of environmental monitoring networks designed to monitor both routine and emergency conditions in other applications as well.

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1. Introduction

Environmental monitoring networks are typically designed to detect variables of interest to human or ecosystem health. Not only must these networks detect gradual changes in these variables, and background patterns, but they must also detect extreme values in case of an emergency. Several types of monitoring networks take these dual purposes into account, including air, water, radiation, and climate monitoring networks. The network design problem is clearly of great importance both for public health reasons and because costs associated with establishing and maintaining monitoring stations are typically very high (Chang et al., 2007). Both sampling pattern and data quality can have an effect on analysis and inference (Müller, 1998). It is therefore not surprising that the search for optimal sampling patterns has employed several approaches using a variety of pre-defined criteria and solution methodologies (Cressie et al., 1990; Müller, 1998; Loaiciga et al., 1992; de Gruijter et al., 2006).

In order to optimize a sampling network, one must first select an appropriate criterion with which to quantify the suitability of a given design. Also referred to as the objective function, the criterion must encompass the sometimes conflicting objectives of a monitoring network. One of the most common criteria employed uses a geostatistical measure of spatial prediction error to optimize a network for predicting variables at unmeasured locations (Cressie et al., 1990; Loaiciga et al., 1992). In the geostatistical literature, best linear unbiased prediction is found by kriging, and the criterion to be minimized is referred to as the average prediction error variance (Zhu and Stein, 2006). Recently, Brus and Heuvelink (2007) showed that, in the context of a linear model with trend components, minimizing the mean kriging variance simultaneously optimizes estimation of trend parameters.

The approaches described above rely on a known, pre-specified model for underlying spatial variation (i.e. a known covariance function or variogram), which is assumed constant across the...
The overall study goal was to optimize the design of a fixed radiation monitoring network for the dual purposes of mapping background radiation levels and detecting radiation levels above a critical threshold in emergency settings. To do so, number of stations was held constant, but the location of stations was allowed to vary. The specific objectives were to:

- design a dual purpose or multi-objective criterion that considers routine spatial prediction and emergency detection (i.e. detection capability);
- create a function to estimate network detection capability given simulated releases of radiation plumes tracked through time;
- account for monitoring network constraints or risk factors (e.g. the locations of nuclear power plants and population density).

2. Methods, simulations and algorithms

2.1. Study area and radiation monitoring networks

Radiation monitoring networks are designed to measure gamma dose rates (GDRs) emitted by both natural and human-induced radionuclide releases. The National Institute for Public Health and the Environment (RIVM) operates the Dutch National Radioactivity Monitoring network (Twenhöfel et al., 2005). In Germany, the Federal Office for Radiation Protection (BfS) is the agency responsible for the German network. Monitoring stations are more or less uniformly spread across the two countries, with increased densities near nuclear power plants and along country borders (Fig. 1). However, there is a need to coordinate the sampling design amongst these and other countries because radioactive releases can cross political boundaries.

Accidents like the radioactive release at Three Mile Island in Pennsylvania (1979) and the Chernobyl nuclear power plant (NPP) accident in the Ukraine (1986) serve to amplify public fears related to the risks of radiation accidents (Steinhauser, 2003). It is therefore important to take a number of risk factors into consideration, such as the locations of nuclear power plants (NPPs, Fig. 1), the road network used in the transport of radioactive materials, and population density (Fig. 2). Here, we consider only the position of the radiation sensors and not the number of sensors.

2.2. Atmospheric dispersion model simulations

The NPK-PUFF model (Verwer et al., 1990) is an atmospheric dispersion model that simulates emissions or plumes from a radioactive source over different time intervals (e.g. minutes, hours). This model is part of a GIS-based decision support system used by the RIVM. We used NPK-PUFF (v.4.0.6) to simulate the release of radioactive plumes in the study area with different magnitudes and varying weather conditions (Fig. 3, Table 1). Four types of accidents were simulated: (1) small and (2) large nuclear power plant accidents selected from a range of reference nuclear release scenarios; (3) deliberate radiation emissions (RED); (4) accidents involving the transport of radioactive materials (SPILL, Table 1). Radioactive releases were simulated throughout the area of interest, given a modifiable probability distribution for the release locations based on maps of: NPP locations (Fig. 1), densely populated urban centers (for RED type accidents), or transportation networks (for SPILLS, Table 2, Fig. 2a and c).

NPK-PUFF trajectories can be simulated using meteorological forecasts such as those produced by the High Resolution Limited Area Model for weather prediction (HIRLAM), (Eleveld et al., 2007). In this study, meteorological conditions during simulations were treated as stochastic and sampled from representative hourly weather data for the area collected from a weather station at De Bilt, NL, during the year 2005 (Table 3, Fig. 4). Sampling weather conditions from the observed multivariate distribution of conditions automatically preserves the statistical dependencies (i.e. correlations) between the variables (e.g. wind speed/direction). However, it is hardly realistic to assume that weather conditions at De Bilt were representative of conditions over the entire spatial domain. This simplification was necessary given data availability and time constraints. Future developments may include more realistic weather conditions and high resolution atmospheric dispersion models (see Discussion).

Radioactive plumes were tracked over time, and plumes were delineated as areas with gamma dose rates (GDR) above critical thresholds, which were based on the projected amount of air and depositional radiation at ground level. The threshold was set high enough to trigger emergency response procedures under normal circumstances ($=4100$ nSv/h). Five thousand accidents of each type were simulated and their evolution through time was monitored at three time steps. Each of the four accident types described were combined into a single map with 20,000 plume accidents tracked over three time steps.

2.3. Dual purpose optimization criterion

2.3.1. Kriging prediction error variance

The objective function combined two criteria to be optimized: average kriging prediction error variance and network detection capability. In this section we detail how interpolation was performed by regression kriging and we describe calculation of the first criterion.

Kriging variance was calculated by spatial interpolation of (mean) annual GDRs with known predictor variables using...
regression kriging. Regression kriging (RK, Odeh et al., 1995) is a hybrid spatial modelling technique (Zhang et al., 2005a) that combines regression with spatial interpolation of regression residuals (Hengl et al., 2007). RK has been shown to result in better predictions than either approach alone (Zhang et al., 2005a), and the model is mathematically equivalent to universal kriging with external drifts (Hengl et al., 2007).

Spatial correlation in the residuals is modelled by an autocovariance function or variogram that is inferred from the residual spatial structure in the observed point data. This hybrid model relies on the geostatistical assumption of stationarity, which implies that spatial correlation depends only on the distance between points and not on their location (Isaak and Srivastava, 1989). A detailed treatment of the methodology and

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**Fig. 1.** Current network of gamma dose rate monitoring stations (points, n=592) in Netherlands (west) and German states of Niedersachsen (northeast) and Nordrhein-Westfalen (south). See inset map of Europe for point of reference. Locations of two major cities (stars) and nuclear power plants (triangles) are depicted. ©EuroGraphics for administrative boundaries.

**Fig. 2.** Study area characteristics and environmental predictor variables used in regression kriging.
application of regression kriging can be found in Hengl et al. (2007).

The RK interpolation error variance at an unsampled location, \( s_0 \), is given by the following equation in matrix notation:

\[
\sigma^2(s_0) = (C_0 + C_1) - C_0 \cdot C^{-1} \cdot c_0 + 
+ (q_0 - q^T \cdot C^{-1} \cdot c_0)^T \cdot (q^T \cdot C^{-1} \cdot q_0) - (q_0 - q^T \cdot C^{-1} \cdot c_0)
\]

where \( C_0 \) and \( C_1 \) are the nugget and partial sill variation, respectively; \( c_0 \) is the vector of covariances between the residuals at the observation and prediction locations, here calculated on a fine grid (1 km²); \( T \) indicates matrix transposition; \( C \) is the \( n \times n \) variance-covariance matrix of the \( n \) residuals; \( q_0 \) is the vector of \( k + 1 \) predictors; and \( q^T \) is the transposed, \( n \times (k+1) \) matrix of predictors at the observation locations. \( C \) and \( c_0 \) are derived from the variogram of residual error. It is important to note that the data values themselves are not used in the calculation of the RK interpolation error variance. This attractive property allows one to estimate the kriging prediction error variance prior to collecting the data, and it is this property that is used in the optimization procedure after (Brus and Heuvelink, 2007).

\[
\text{Fig. 3. Example radioactive plumes (} > 100 \text{ mSv/h GDR) simulated using an atmospheric dispersion model (NPK-PUFF) at hour one (bold grey), hour two (solid), and hour three (dotted) for (a) small NPP type accident, (b) large NPP type accident, (c) deliberate radioactive release (human-caused), and (d) emission of radioactivity due to a transport accident. Note that release characteristics of these example accidents are presented in Table 1, (a) through (d).}
\]

\[
\text{Fig. 4. Windrose diagrams for hourly meteorological data collected at De Bilt, NL in 2005, given atmospheric heights as shown. Pedals indicate proportion of time wind originates from a given direction. Grayscale bands represent wind-speed increments in 5 m/s.}
\]

| Table 2 | Start location probabilities by accident type. |
| --- | --- | --- | --- |
| Land use | Probability | Accident type |
| High density urban (> 6000 pe/km²) | 0.70 | RED |
| Medium density urban (3001–6000 pe/km²) | 0.28 | RED |
| Low density urban (501–3000 pe/km²) | 0.03 | RED |
| Largely unpopulated (1–500 pe/km²) | 0.0000001 | RED |
| Highway | 0.65 | SPILL |
| Major road | 0.15 | SPILL |
| Railway | 0.10 | SPILL |
| Airport | 0.08 | SPILL |
| Seaway | 0.02 | SPILL |
| Land | 0.00001 | SPILL |

Note that all nuclear power plants were modelled with equal probability of an accident.

| Table 3 | Summary statistics for various weather variables. |
| --- | --- | --- | --- |
| Statistic | P | HM | Obukv |
| Min. | 0.0 | 150.0 | –9964.2 |
| Max. | 3.2 | 251.0 | 9951.6 |
| Mean | 0.1 | 391.9 | 33.5 |
| S.D. | 0.2 | 383.4 | 1107.8 |

Acronyms described in Table 1.
Two environmental variables were used to model from the European Radiological Data Exchange Platform of radionuclides in the soil (i.e., $^{232}\text{Th}$, $^{235}\text{U}$, $^{238}\text{U}$, and $^{40}\text{K}$), which annual dose and consists of radiation from the natural decay chain $^{238}\text{U}$ (Melles et al., 2008). Terrestrial radiation accounts for the other 50% of the domestic radiation, which varies predictably with altitude above sea level (Wissman et al., 2007) and accounts for roughly 50% of the annual dose; the cosmic component is known to vary significantly with a few key environmental predictors (i.e., elevation and soil type, Melles et al., 2008; Blaauboer and Smetsers, 1996). The cosmic, airborne, and terrestrial radiation. The cosmic component varies predictably with altitude above sea level (Wissman et al., 2007) and accounts for roughly 50% of the annual dose; the cosmic component is primarily related to the amount of naturally occurring Radon ($^{222}\text{Rn}$, $^{220}\text{Rn}$), and their short-lived progeny, which are exhaled from the soil and transported through the air via aerosols. The airborne component accounts for a small percentage of the annual radiation dose; but shortly after precipitation events, the dose rate can increase by a maximum of up to 100 nSv/h for a few hours, as $^{222}\text{Rn}$ and its progeny are washed out of the air and deposited onto the ground (Smetsers and Blaauboer, 1997; Hiemstra et al., 2009). Given the short-lived nature of this increase in radiation, mean annual precipitation does not correlate strongly with mean annual GDRs (Melles et al., 2008). Terrestrial radiation accounts for the other 50% of the annual dose and consists of radiation from the natural decay chain of radionuclides in the soil (i.e., $^{232}\text{Th}$, $^{235}\text{U}$, $^{238}\text{U}$, and $^{40}\text{K}$), which can be modelled as a function of soil type (Smetsers and Blaauboer, 1997; Melles et al., 2008; Hiemstra et al., 2009).

Monitoring network locations and GDR data were acquired from the European Radiological Data Exchange Platform (EURDEP). Two environmental variables were used to model the trend component in RK: elevation and soil type (Fig. 2b and d) as in (Melles et al., 2008). Elevation data were based on the USGS Global 30 arcsec digital elevation data (U. S. Geological Survey, 1996). Soil effects were modelled using six soil classes as categorical predictors after Blaauboer and Smeters (1996), using data from the European Soil Database (European Soil Database, 2003). Model parameters were initially estimated by ordinary least squares (OLS) and the remaining anisotropic (directional) spatial variation was fit with variogram models. These variograms have a linear and spherical component in all directions, but the spherical component is more dominant in one direction than the other (Fig. 5). RK was then performed using R (R Development Core Team, 2008), package gstat (Pebesma, 2004) by GLS. The square root of prediction error variance (Eq. (1)) was used in the objective function so that GDR prediction errors were in the same units and magnitude as the observations themselves.

### 2.3.2. Detection capability

In this section we describe calculation of the second criterion, calamity detection capability. Detection capability was defined as the average cost of failing to detect a plume by a minimum of two detectors within 3 h of a release. The cost of a plume was a function of its depositional area, the hour at which it was detected, and the number of sensors that detected it. Cost was further weighted by population density because it is even more critical that radioactive plumes be detected if they are situated in highly populated places. To account for this additional design constraint, highly populated areas were associated with higher costs if the network failed to detect a release (Table 4). Lastly, if a plume followed a trajectory that carried the radioactivity entirely outside the study area, the detection cost was set to zero. These weights, probabilities, and time steps can easily be varied and should be set by expert judgement.

According to the definition above, the cost of failing to detect a developing plume satisfies:

$$C = \frac{1}{3N} \sum_{i=1}^{N} \sum_{j=1}^{3} w_{LUT(i,j)} w_{p(i)} A_{ij}$$

where $N$ is the total number of plumes, $A_{ij}$ is the deposition area of plume $i$ at time $t$, $w_{LUT(i,j)}$ is the look-up table (LUT) value corresponding to the state of plume $i$ at time $t$, and $w_{p(i)}$ is the population density at the centroid of plume $i$ at time $t$. Times $t_1$, $t_2$, and $t_3$ were chosen as 1, 2, and 3 h, respectively. Thus, if an accident is undetected in hour one, it will be twice as ‘costly’ as a similar accident detected by a single sensor in hour one, according to the LUT. Similarly, if an accident is undetected in hour one, but detected by two sensors in hours two and three, then the contribution of that accident to the average cost will depend only on the conditions of the plume at hour one because plumes that are detected by two or more sensors are given a weight of zero in the LUT. Times and weights can easily be changed according to user requirements.

### Table 4

Weights to increase detection capability in densely populated areas.

<table>
<thead>
<tr>
<th>Population density (people/km²)</th>
<th>Weight ($w_p$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1–500</td>
<td>0.25</td>
</tr>
<tr>
<td>501–3000</td>
<td>0.33</td>
</tr>
<tr>
<td>3001–6000</td>
<td>0.5</td>
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<tr>
<td>&gt; 6000</td>
<td>1</td>
</tr>
</tbody>
</table>

The two criteria were combined into a single objective function as follows:

$$\min \left[ w_1 \cdot C_{r1} + w_2 \cdot C_{r2} \right]$$  \hspace{1cm} (3)

where $C_{r1}$ is the average kriging error criterion, $C_{r2}$ is the calamity detection capability criterion and $w_1$ and $w_2$ are the relative weights assigned to each criterion. The relative weights assigned depend on the objectives of the institute in charge of the network. For the purposes of this research, weights were assigned such that both criteria contributed more or less equally to the combined criterion.

2.4. Spatial simulated annealing

Spatial simulated annealing (Van Groeningen and Stein, 1998) is the spatial counterpart to simulated annealing (SSA, Kirkpatrick et al., 1983), and as such the algorithm uses slight perturbations of previous designs and a random search technique to solve spatial optimization problems. For the present study, the procedure began with the current monitoring network design. Optimization proceeded iteratively by randomly moving monitoring stations one by one, calculating the objective function, and accepting improved designs over a set number of SSA iterations. With SSA, worsening designs are accepted with a decreasing probability (generally set to $p \leq 20\%$) to avoid selection of local minima, and the ‘cooling schedule’ of SSA dictates the rate at which $p$ decreases to zero. We used the simplest and most commonly used cooling schedule, whereby $p$ was set to exponentially decrease as a function of number of iterations to ensure convergence (Heuvelink et al., 2006; Brus and Heuvelink, 2007).

In addition to the cooling schedule and the initial $p$, another important parameter in SSA is the stopping criterion. Here we chose to perform a fixed number of iterations, but it is also possible to stop SSA when there is no improvement in the criterion over a set number of iterations. Alternatively, one may choose to stop when $p$ declines to a final value set by the user (Heuvelink et al., 2006; Brus and Heuvelink, 2007). SSA is useful for problems that cannot be solved either analytically or by an exhaustive search, but the method is essentially heuristic because it is not possible to guarantee that the final sample pattern is a true optimum (Kirkpatrick et al., 1983). By repeating the annealing algorithm multiple times and checking if we arrive at a similar solution, we can be more confident that a near optimal solution has been attained (Brus and Heuvelink, 2007). We optimized the monitoring network over a total of $k=4000$ iterations, and we repeated the annealing algorithm three times to ensure solutions were similar. One of these solutions was optimized over a total of $k=8000$ iterations because it was apparent that the objective function was still decreasing after $k=4000$ iterations.

Analyses and simulations were performed using a set of functions written in the R language for statistical computing (R Development Core Team, 2008).

3. Results

The size and development of each accident was the result of weather conditions sampled at the start of each simulation—in addition to the parameterization of NPK-PUFF. Figs. 1 and 2a and c depict maps of power plant locations, urban centers, and transportation routes, respectively: each of these locations had an associated accident probability (Table 2). As there were a limited number of NPPs and high density urban areas in the region (population > 6000/km$^2$), the combined accident map (Fig. 6a) was dominated by radioactive releases originating in these areas and developing in all directions. Winds in the Netherlands typically come from the southwesterly direction and their magnitudes increase with atmospheric height (Fig. 4). It is difficult to detect an increase in the number of plumes originating from the predominant wind direction in Fig. 6a, but given that weather conditions were treated as stochastic, plumes from a southwesterly direction were more likely to occur. The goal here was to optimize the fixed monitoring network for all possible conditions throughout the year, so we aimed to simulate enough releases to cover all possible weather conditions.

Small and large NPP accidents covered a much larger area than modelled RED type accidents (Fig. 6a) due to the magnitude of nuclides released (Table 1). Transport spills are barely recognizable on Fig. 6a as a series of small dark speckles. Indeed, transportation type accidents had plumes above the critical threshold in only approximately 10% of NPK-PUFF simulations. The majority of RED type accidents originated in the densely populated cities of Amsterdam, Rotterdam, Den Haag, Köln, Düsseldorf, and Essen.

An optimized network design is shown in Fig. 6b. The majority of network stations were highly clustered around nuclear power plans and densely populated urban centers in the optimized design pattern. In comparison with the current monitoring network (Fig. 1), more sensors were moved into the Netherlands; there were less stations concentrated at the border between the Netherlands and Germany; and there were fewer evenly dispersed stations in the optimized network pattern.

**Fig. 6.** Optimized sampling pattern given simulated accident scenarios and start locations. (a) Map of simulated radioactive emissions (plumes) showing only a 10% subset of accidents of each type. (b) Final sampling pattern optimized for combined objective function.
Fig. 7. (a) Decrease and leveling off of objective function with increasing iterations for three repeats of SSA algorithm. (b) Trade-off between two optimization criteria for curves shown in (a). Asterisks represent simulation end-points (best designs).

As expected, the objective function improved during the three repeats of the simulated annealing algorithm (Fig. 7a). Although the objective function had begun to level off when SSA was terminated at 4000 iterations, it is apparent that more iterations were necessary to reach the minimum as evidenced by the lower value obtained with 8000 iterations. Fig. 7b shows how mean prediction error variance and detection capability changed as SSA progressed. Generally as detection capability improved, mean prediction error worsened. Given the costs associated with failing to detect a radioactive release in densely populated areas, network detection cost dominated the change in the objective function at the expense of mean prediction error. That is to say predictive accuracy for mapping annual background GDR levels decreased overall as stations became more clustered around NPPs and urban areas. However, this decrease was very slight (e.g., criterion 1 ranged between 8.21 and 8.29).

Overall, optimization was slow in terms of computational efficiency (12+ days for \( k = 4000 \) iterations on a windows operating system with a 3.01 GHz processor and 4.0 GB of RAM).

4. Discussion and conclusions

Radiation monitoring networks in the Netherlands and two neighboring German states were optimized using a combined variance-based and simulation approach. The objective function was a combination of two equally weighted criteria: regression kriging prediction error variance, which emphasized the importance of monitoring background levels of radiation under routine conditions, and detection capability, which emphasized the networks ability to detect an accident in the event of a nuclear emergency. An obvious advantage of the combined method we have presented in this paper is that fixed monitoring networks can be optimized for both routine prediction error and emergency cases.

We found few examples in the literature with strong similarities to the proposed method. Although simulation based approaches are well known and often used to generate multiple contaminant fields with a range of uncertainties (Loaiciga et al., 1992), the focus has generally been on optimizing designs to detect a single contaminant source (Meyer and Brill, 1988; Marryott et al., 1993; Reed and Minkster, 2004; Zhang et al., 2005). For example, Meyer et al. (1994) used Monte Carlo simulation of groundwater transport to characterize uncertainty in the source location of a single contaminant plume from a landfill site. These authors also used a multi-objective formulation of their objective function, and analogous to our study, simulated annealing was used to optimize the design of the groundwater monitoring network. Their objective function included: number of monitoring wells; probability of detecting a contaminant plume; and the area of contamination at the time of detection. Alternatively, variance-based approaches have focused on optimization under conditions of nonstationarity (Atkinson and Lloyd, 2007) or unknown variogram/covariance function (Zhu and Stein, 2006; Zimmerman, 2006). Our method uses an atmospheric dispersion model to generate multiple contaminant fields with numerous release locations and links simulation model results with multi-criteria optimization of a monitoring network.

The focus here was not on predicting unmeasured values if extremes were detected. Rather our approach emphasizes detection of emergency releases and associated costs if a network fails to detect spreading contaminant plumes originating from probabilistic start locations. Spatial prediction error was included in the objective function to account for routine GDR conditions, which are the prevailing monitored state. Once detected, other more advanced methods can be used to model the field of extremes and delineate the contaminant surface (e.g., Chang et al., 2007; Kazianka and Pilz, 2009). Zhu and Stein (2006) suggest that unless the nature of nonstationarity is known ahead of time, adaptive design schemes may be necessary to refine a monitoring network as more information becomes available (e.g., Datta et al., 2009). In the context of radiation monitoring, mobile monitoring devices are available to increase network density during an emergency. Heuvelink et al. (2009) show how these mobile monitoring devices can be optimized to better delineate the spreading contaminant as part of an emergency response strategy.

It is important to recognize that the final sample pattern shown in Fig. 6b is not unique. Given the same starting conditions, resulting spatial configurations can be fairly different, even if the final objective function values are equivalent (Zhu and Stein, 2006). In practice, network designers could experiment using our approach and arrive at an ensemble of sampling patterns that have the same or similar performance. Or, given that most network planners have other constraints to consider (i.e., economic costs, station placement restrictions, accessibility and space requirements), they could select a specific design that addresses objectives other than or additional to the ones considered here.

We are aware that the proposed approach also has limitations. The combined simulation and variance-based approach is very computationally intensive. In addition to the time involved in the SSA iterations, one needs to run the NPK-PUFF model (Verver...
to simulate 1000's of radiation releases. Interpolation of 592 points took almost 1.5 min of CPU time on our system, but calculating network detection capability required relatively little time to compute, depending on the number of accidents considered. Calculation of network detection capability used between 22 s and 3 min of CPU time to check for the detection of 15,000 and 60,000 plumes using 170 and 592 points, respectively. If a subset of stations was reserved to minimize prediction error alone, this could reduce computational time substantially because interpolation would not need to be performed at each SSA iteration. Computational time could then be reduced by more than 60%. Alternatively, interpolation can be sped up by encoding knowledge that at each iteration, only a single sample location is changed. So, only a single row and column in the \( n \times n \) kriging matrix need change. Heuvelink et al. (2009) suggest that this can be implemented using a block Gaussian elimination algorithm (Golub and Van Loan, 1996), which is also easily amenable to parallel computing. Thus computational time could be significantly reduced.

The NPK-PUFF model is perhaps one of the largest sources of uncertainty in the simulation-based approach. This model includes meteorological variables that have limited predictive abilities due to their inherent uncertainties. Atmospheric dispersion models must also account for numerous processes such as: relative diffusion given wind shear and turbulence; advection as a function of space and time; diurnal cycles of boundary layer height and stability; wet and dry deposition; and linear chemical transformations of radioactive decay (Verwer et al., 1990). Virtually any simulation model could be employed, however, and linked to the optimization approach we have described in a similar manner. Another limitation to our approach is that several other sources of uncertainty were unaccounted for. Uncertainty in variogram estimation was not taken into account and therefore routine spatial prediction error may be underestimated. Only a single nuclide was modelled using the NPK-PUFF model, which means that GDRs were also underestimated. We partially compensated for this underestimate by lowering the GDR critical threshold to 100 nSv/h from a more typical 200 nSv/h emergency alert threshold. The lower alert threshold was recently recommended in the framework of the Council of Baltic Sea States, but higher levels (i.e., up to 200 nSv/h or more) are typically used by GDR networks in most European countries. Lastly, as mentioned previously, it is a large oversimplification to assume that weather conditions at De Bilt are representative of all GDR release locations across the study area. A future improvement to the methodology could involve using more realistic weather conditions either sampled from weather stations in the vicinity of release locations or simulated using high resolution climate models.

Despite the drawbacks, our combined simulation and variance-based approach to fixed network design is appealing in its simplicity and flexibility. The method can be used to examine how an environmental monitoring network responds to a huge variety of release conditions. Other design constraints than the ones considered here can also be easily implemented. With careful interpretation of results, design constraints and trade-offs between criteria can be explicitly examined.

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References


IntamapInteractive. 2010. Procedures for automated interpolation - methods only to be used interactively, not included in intamap package, R package version 1.0–9, Utrecht, <http://CRAN.R-project.org/package=intamapInteractive>. (Accessed 22 July 2010).


