Comparison of Spatial Interpolation Methods based on Exposure Assessments of Air Pollutants: A Case Study on Nuclear Substances in Fukushima

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Keywords: Spatial Interpolation, Exposure Assessment, Air Pollutants, Nuclear Substance.

Abstract: In response to accidents and disasters involving the proliferation of pollutants to the environment, performing exposure assessments across a region of impact is important for evaluating health effects. Owing to the typical unavailability of the spatially continuous data of pollutant concentrations immediately after accidents, various spatial interpolation methods have been studied to assess exposures using limited available data. In this study, we compared representative spatial interpolation methods based on the estimation of the distributions of exposures through a case study of the Fukushima Daiichi nuclear disaster initiated by the Great East Japan earthquake and subsequent tsunamis. The nearest neighbour method, inverse distance weighted method, and ordinary kriging method were compared in the context of exposure assessments. Even though estimated air dose rates were slightly different depending on the method used, different interpolation methods produced significantly equivalent estimates of the distribution of cumulative exposure over one year.

1 INTRODUCTION

Accidents and disasters involving the proliferation of pollutants to the environment cause serious problems for human health. As a response to accidents, rapid and accurate exposure assessment is required for evaluating health effects. For this purpose, accurate spatially continuous data of pollutant concentrations across a region of impact are required. However, such data are typically not available immediately following accidents. In such cases, spatial interpolation is generally applied to estimate values at unsampled points from limited available data.

A motivating example is the proliferation of radioactive pollutants due to the accident at the Fukushima Daiichi Nuclear Power Plant (FDNPP) initiated primarily by the tsunami following the Tōhoku earthquake on 11 March, 2011. Extensive survey meter measurements, airborne monitoring, and vehicle-borne surveys have been conducted to grasp the state of the spatial distribution of pollutants (Fukushima Prefecture, 2011a; JAEA, 2013; MEXT, 2011a). In addition, exposure assessments have been attempted for each residential area based on these spatial data (Ishikawa, 2014; Takahashi et al., 2014). On the other hand, the point measurements of air dose rates were conducted immediately after the accident across the region of impact, and data were publicly reported (TEPCO, 2011; MEXT, 2011b; Fukushima Prefecture, 2011b). In a representative exposure assessment conducted by National Institute of Radiological Sciences (NIRS), the monitoring data scattered on maps were converted to spatially continuous data using the natural neighbour method (Akahane et al., 2013). The estimation of the spatial distribution of dose rate based on this data has been attempted (Ishikawa et al., 2015). However, the problem with this approach is that the estimate of the distribution varies depending on the interpolation method used.

Various spatial interpolation methods have been proposed to obtain spatially continuous data from limited available information in an appropriate manner (Lam, N. S. N. 1983; Li and Heap, 2008, 2014; Webster and Oliver, 2007). Additionally,

Otani, T., Takahashi, K., Takeuchi, A. and Asami, M.
Comparison of Spatial Interpolation Methods based on Exposure Assessments of Air Pollutants: A Case Study on Nuclear Substances in Fukushima.
DOI: 10.5220/0007523604150421
In *Proceedings of the 12th International Joint Conference on Biomedical Engineering Systems and Technologies (BIOSTEC 2019)*, pages 415-421
ISBN: 978-989-758-353-7

extensive comparative studies have been conducted (Li and Heap, 2011). In the context of the evaluation of human health, the effect of interpolation methods on the accuracy of the estimation of exposures should also be evaluated. Even though several comparative studies exist (for example, Wong et al., 2004), comparisons based on the influence of interpolation methods on exposure assessment have not been conducted in detail compared to the evaluation of predicted concentration levels.

In this study, we examine how the estimation of the distribution of exposure in a region changes based on the method of spatial interpolation through a case study of the accident at the FDNPP.

2 MATERIALS AND METHODS

In this study, we estimated the distributions of cumulative exposure by ^{134}Cs and ^{137}Cs for each municipality in Fukushima Prefecture for each age category. Our procedure consisted of the following two steps: convert monitoring data to spatially continuous data using interpolation methods and estimate the distribution of exposure using the continuous data based on an external exposure model.

2.1 Monitoring Data

Figure 1 shows a map of Fukushima Prefecture with monitoring data. The data consist of 113 air dose rates measured on 22 March, 2011 and published online (TEPCO, 2011; MEXT, 2011b; Fukushima Prefecture, 2011b).

2.2 Interpolation Methods

The following three representative interpolation methods were compared in this study: the (i) nearest neighbour (NN) method, (ii) inverse distance weighted (IDW) method, and (iii) ordinary kriging (OK) method (Lam, N. S. N. 1983; Li and Heap, 2008, 2014, Webster and Oliver, 2007). Note that we applied logarithm transformation to the monitoring data before interpolation because the distribution of dose rates was skewed.

2.2.1 Nearest Neighbour Method

The NN method predicts the dose rate at an unsampled point based on the value of the nearest sample by drawing perpendicular bisectors between sampled points, forming Voronoi polygons (Li and Heap, 2008; Webster and Oliver, 2007). Let $\hat{z}(x)$ be the estimated air dose rate at unsampled points x. The estimates by the NN method are the values at the nearest single sampled data points, x_i, that is,

$$\hat{z}(x) = z(x_i). \tag{1}$$

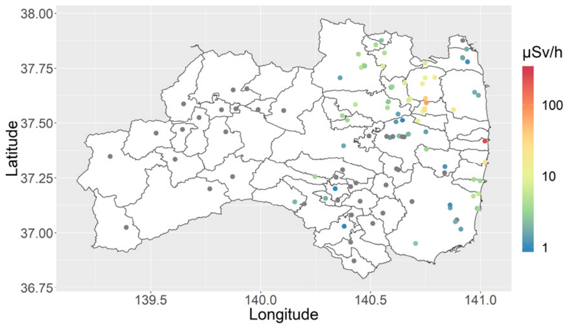


Figure 1: Air dose rates measured on March 22, 2011. Note that points with rates of <1 µSv/h are coloured in grey.

2.2.2 Inverse Distance Weighted Method

The IDW method estimates the values at unsampled points using a linear combination of the values at sampled points weighted by an inverse function of the distance from the point of interest to the sampled points. The estimated value is

$$\hat{z}(x) = \sum_{i=1}^{n} \lambda_i z(x_i). \tag{2}$$

Here, the weight, λ_i, is determined assuming that the sampled points closer to an unsampled point in terms of their values are more similar to it compared to those further away. The weights can be expressed as

$$\lambda_i = \frac{1/d_i^p}{\sum_{i=1}^{n} 1/d_i^p} \tag{3}$$

where d_i^p is the distance between x_0 and x_i, p is a power parameter, and n represents the number of sampled points used for estimation. In this study, we set $p = 2$ and $n = 5$.

2.2.3 Ordinary Kriging Method

Similar to the IDW method, the OK method estimates the dose rates at unsampled points by a weighted averaging of neighbouring samples. The correlations among neighbouring values are modelled as a function of the distance between the points, which is described by a variogram (Webster and Oliver, 2007).

An empirical variogram can be computed from sampled data using the following expression:

$$\gamma(h) = \frac{1}{2M(h)} \sum_{i=1}^{M(h)} \{z(x_i) - z(x_i + h)\}^2 \tag{4}$$

where $\gamma(h)$ is the estimated semivariogram at separation distance h, of which there are $M(h)$ pairs. The weight, λ_i, is determined such that the variance of estimated values is minimised. The method consists of the following two steps: fitting a function to the empirical variogram such that semivariograms can be computed at all separation distances and computing λ_i such that estimation variance is minimised. In this study, we used the spherical specification as the fitting function.

2.3 Estimation of Cumulative Exposure

We estimated the distribution of cumulative exposure one year after the accident for each municipality in Fukushima Prefecture based on the Monte Carlo sampling method by referring to existing studies (Takahashi et al., 2014).

2.3.1 External Exposure Model

In this model, cumulative exposure is estimated considering only the attenuation due to the physical half-life of radioactive caesium to be variable with time. Let L be the municipality of interest and x be the point in L at which the predicted air dose rate, $\hat{z}_T(x)$, at time T is available. The cumulative exposure one year after the accident is estimated by summing the cumulative exposure due to radionuclide i as

$$\begin{aligned} &\mathrm{E}_{\mathrm{ext}}^{(i)}(x, Y) \\ &= C^{(i)}(x) \cdot \Phi_i \cdot \tau(Y) \\ &+ C^{(i)}(x) \cdot \Phi_i \cdot \big(1 - \tau(Y)\big) \sum_j b_j \cdot B_j \end{aligned} \tag{5}$$

where Φ_i is the dose-rate conversion factor of radionuclide i, τ is the outdoor staying time ratio for age category Y, B_j is the proportion of building type j in Fukushima Prefecture, and b_j is the shielding factor for each type of building. In addition, $C^{(i)}$ is the cumulative exposure due to radionuclide i, and it is expressed as

$$C^{(i)}(x) = \int_0^1 C_0^{(i)}(x) \cdot e^{-\lambda_i t} dt. \tag{6}$$

As the purpose of this study is to estimate the cumulative exposure one year after the accident, the integration interval is from 0 to 1.

Here, we assumed that $z_T(x)$ can be determined only by the deposition amounts of ^{134}Cs and ^{137}Cs at time T. The initial deposition amount for each radionuclide can be obtained as

$$C_0^{(134)}(x) = \frac{\hat{z}_T(x)}{R\Phi_{134} e^{-\lambda_{134} T} + \Phi_{137} e^{-\lambda_{137} T}} \tag{7}$$

$$C_0^{(137)}(x) = \frac{\hat{z}_T(x)}{\Phi_{134} e^{-\lambda_{134} T} + R^{-1}\Phi_{137} e^{-\lambda_{137} T}} \tag{8}$$

where Φ_{134} and Φ_{137} are the dose-rate conversion factors of ^{134}Cs and ^{137}Cs, respectively, and R is the activity ratio of $^{134}Cs/^{137}Cs$ at $t = 0$.

In this model, the outdoor staying time ratio, τ, is derived from a log-normal distribution so that the 5th percentile and the 50th percentile of outdoor staying time for each age category are matched with those of USEPA (2011). Random numbers were generated corresponding to each point x in L and multiplied by the cumulative exposure at each point.

2.3.2 Parameters of the Model

We determined the parameters of the model by referring to existing studies and technical documents (IAEA, 2000; Merz, 2013; Statistics Bureau 2008; USEPA, 2011). The parameters are shown in Tables 1 and 2. The dose-rate conversion factors and decay constants of ^{134}Cs and ^{137}Cs and shielding factors were based on a technical document (IAEA, 2000).

Table 1: Parameters used in this study.

Description	Value
Activity ratio of $^{134}Cs/^{137}Cs$ at t = 0	1
Dose-rate conversion factor of ^{134}Cs [(mSv/h)/(kBq/m^2)]	5.4E-06
Dose-rate conversion factor of ^{137}Cs [(mSv/h)/(kBq/m^2)]	2.1E-06
Decay constant of ^{134}Cs	0.346
Decay constant of ^{137}Cs	0.0231
Proportion of wooden building	0.37
Proportion of non-wooden building	0.63
Shielding factor of wooden building	0.4
Shielding factor of non-wooden building	0.2

Table 2: Distribution of outdoor staying time (hours/day) for each age category (USEPA, 2011).

Age category	5th percentile	50th percentile
0–1	0.05	0.70
1–6	0.08	2.10
7–15	0.01	3.00
16–	0.02	4.30

In addition, the activity ratio at $t = 0$ was based on an existing study (Merz, 2013). As the proportions of wooden and non-wooden buildings are different depending on the region in Japan, we used the published ratios of Fukushima Prefecture (Statistics Bureau 2008).

In addition, points x were selected from a basic square grid with a size of approximately 1 km^2 (Statistics Bureau 2018). T was 0.027, which corresponds to the date of monitoring, i.e. March 22, 2011.

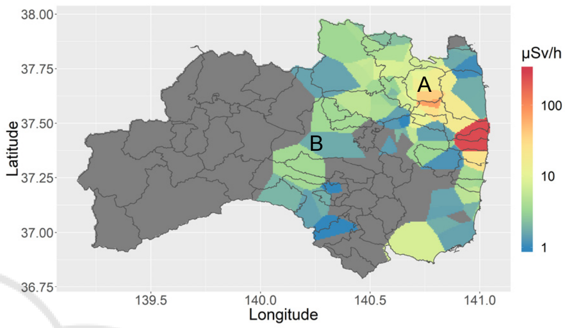
2.4 Comparison with Airborne Survey

We compared the estimated cumulative exposure with the estimates obtained from the results of the fourth airborne monitoring survey conducted from 22 October, 2011 to 5 November, 2011 (MEXT, 2011c) to assess the validity of our method. The survey data consisted of radioactive caesium deposition densities at the median points of quarter grid squares with a size of approximately 250 m^2 (Statistics Bureau 2018). Cumulative exposure was estimated based on the model described in Takahashi et al., 2014.

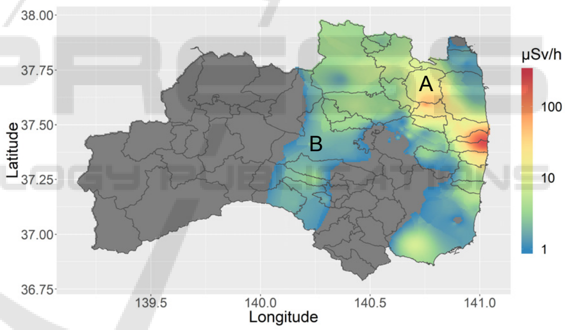
3 RESULTS

First, we obtained the spatially continuous data of air dose rates from the monitoring data shown in Figure 1 using the three interpolation methods. Figure 2 shows the spatial distributions of air dose rates in Fukushima Prefecture estimated by each method. Different estimations were produced depending on the method used, particularly in areas close to the FDNPP. Among these, the estimates by the NN method were higher than those by the other methods because only monitoring data with significant air dose rates obtained at the FDNPP (TEPCO, 2011) were available in this area and the NN directly used these data as predicted values.

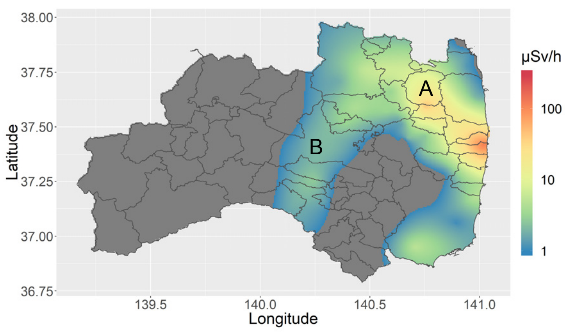
Based on these results, we estimated the distributions of cumulative exposure for each municipality in Fukushima Prefecture using the model described in section 2.3. Figures 3 and 4 show the histograms of the estimated cumulative exposure in municipalities with comparatively high doses (A) and low doses (B) for ages 1–6. Here, we also describe the estimates based on the data from the airborne monitoring survey (MEXT, 2011c; Takahashi et al., 2014). In contrast to the estimates of air dose rate (Figure 2), different interpolation methods did not produce significantly different estimations in most parts of Fukushima Prefecture.



(a) Nearest neighbour method

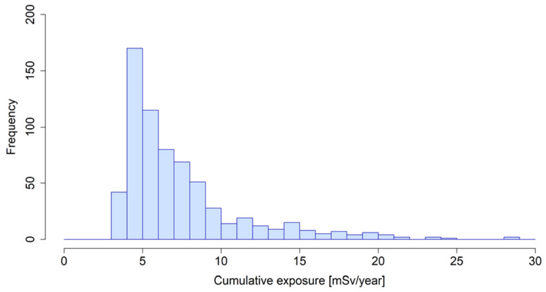


(b) Inverse distance weighted method

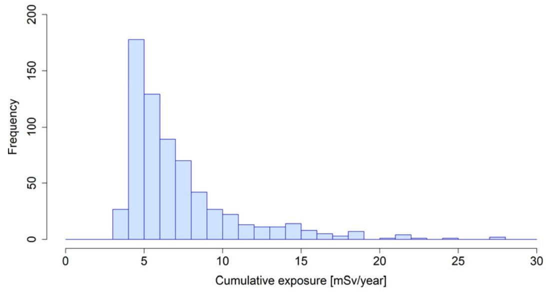


(c) Ordinary kriging method

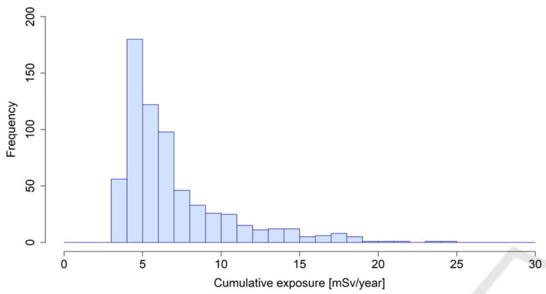
Figure 2: Estimated distributions of air dose rates in Fukushima Prefecture on 22 March, 2011. Note that areas with dose rates of <1 μSv/h are coloured in grey. A and B are municipalities with comparatively high doses and low doses, respectively.



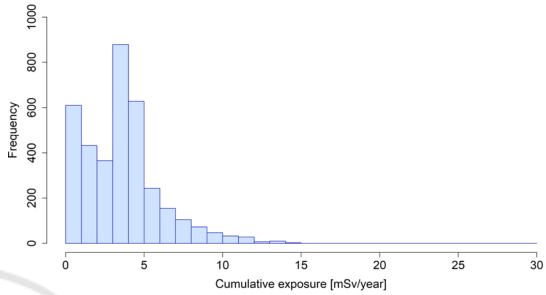
(a) Nearest neighbour method



(b) Inverse distance weighted method



(c) Ordinary kriging method



(d) Airborne monitoring

Figure 3: Histograms of the estimated grid-wise cumulative exposure in municipality A for ages 1–6.

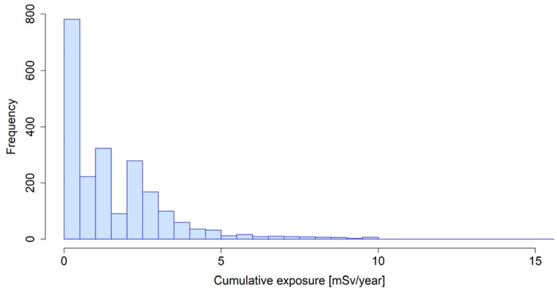
In contrast, our estimates were slightly different from the results of the airborne monitoring survey. For municipality A, even though the estimate from the survey suggested the existence of a low exposure of <3 mSv/year, our estimates could not express such a low exposure. For municipality B, our estimates suggested that almost all regions had low exposure while the distribution of airborne monitoring result indicated high exposure. However, the estimates of the mode were comparable in both municipalities. These results imply that the estimates of cumulative exposure for most regions in each municipality are almost the same regardless of the method used. Of the three interpolation methods, the mode of the OK method was the most similar to the airborne monitoring.

Owing to these results, the percentiles of our estimates were different from the results of the airborne monitoring survey. Table 3 shows 50th and 90th percentiles of the estimated cumulative exposure in municipalities A and B for each age category. There was an approximately twofold difference between these estimates and the results of this survey. The differences varied depending on the municipality, e.g. our estimates were higher than the existing estimates in municipality A and lower in municipality B.

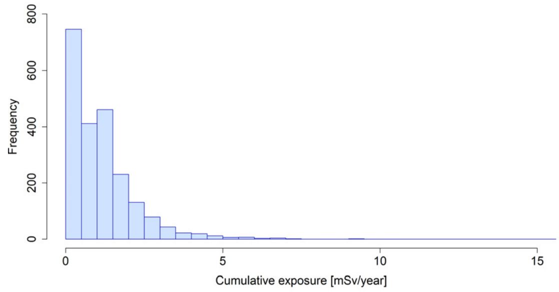
4 CONCLUSIONS

In this study, we compared three representative spatial interpolation methods in the context of the exposure assessments of air pollutants through a case study of the Fukushima Daiichi nuclear disaster. Even though estimated air dose rates were slightly different depending on the method used, different interpolation methods did not produce significantly different estimates of the distribution of cumulative exposure over one year. On the contrary, the estimates of exposure were different from the results of the airborne monitoring survey, even though they were of the same order of magnitude. As the method based on spatial interpolation estimates the air dose rate using only acquired data, such bias might be strong when measurement points are not dense. It is crucial to perform measurement densely, particularly in areas where the dose rate difference is large depending on location.

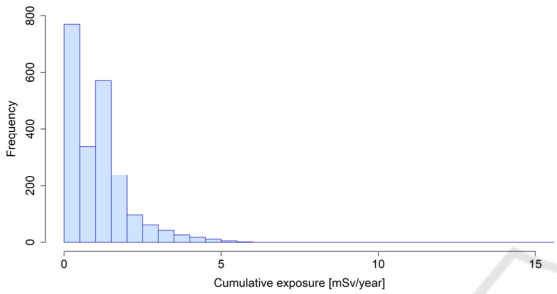
Even though we only considered estimating the grid-wise cumulative exposure for each municipality in this study, the estimated distribution can also be used to estimate the exposure population. More appropriate exposure assessment might be conducted using demographics.



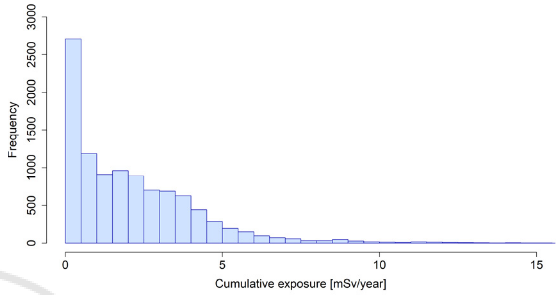
(a) Nearest neighbour method



(b) Inverse distance weighted method



(c) Ordinary kriging method



(d) Airborne monitoring

Figure 4: Histograms of the estimated grid-wise cumulative exposure in municipality B for ages 1–6.

Table 3: Estimated grid-wise cumulative exposure [mSv/year] in municipalities A and B.

Area	Age	Nearest Neighbour		Inverse Distance Weighted		Ordinary Kriging		Airborne Monitoring (Takahashi et al. 2014)	
		50^{th} percentile	95^{th} percentile	50^{th} percentile	95^{th} percentile	50^{th} percentile	95^{th} percentile	50^{th} percentile	95^{th} percentile
A	0–1	5.2	12.7	5.3	10.7	5.1	9.8	3.2	5.7
	1–6	6.2	15.6	6.1	15.5	5.7	14.6	3.4	8.0
	7–15	6.0	16.8	5.6	16.5	5.3	15.2	3.3	8.4
	16–	6.4	17.6	5.9	15.9	5.5	13.0	3.4	8.6
B	0–1	1.0	3.3	0.9	2.2	0.8	1.9	1.5	4.5
	1–6	1.1	4.5	0.9	3.1	0.9	2.8	1.7	5.9
	7–15	1.0	4.8	0.9	3.2	0.9	2.8	1.6	6.0
	16–	1.0	4.9	0.9	3.3	0.9	3.3	1.7	6.2

As demonstrated in this study, when spatial interpolation is performed from the measured data of pollutant concentration levels, the estimation result varies depending on the method used. While the evaluation of predicted concentration levels is naturally crucial, it is also necessary to consider the magnitude of change in exposure evaluation for selecting an interpolation method and interpreting results.

ACKNOWLEDGEMENTS

This work was supported by the Environment Research and Technology Development Fund (S-17) of the Ministry of the Environment, Japan.

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