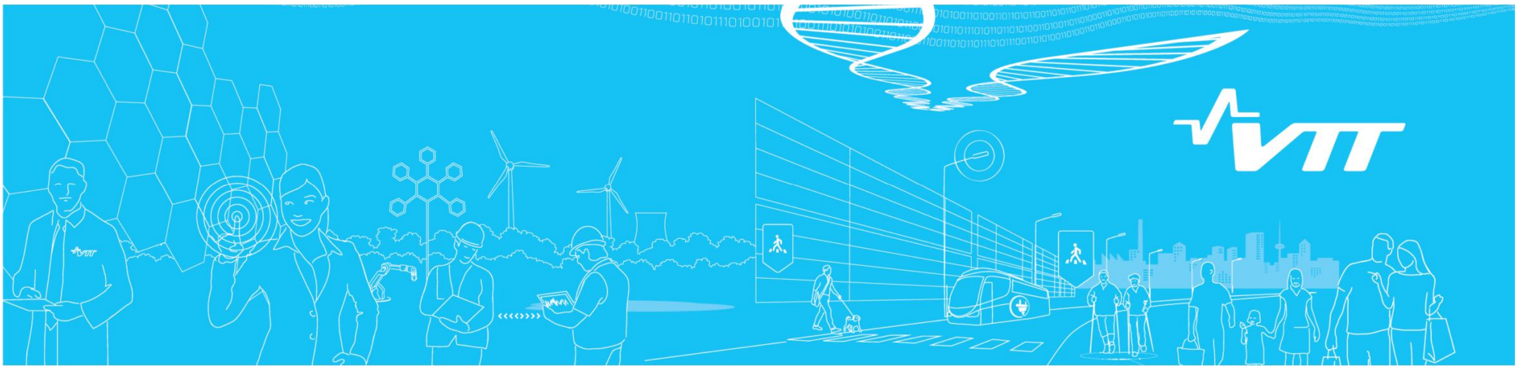

RESEARCH REPORT

VTT-R-05819-15

Improvements to a level 3 PSA event tree model and case study

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Confidentiality: Public

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Summary

This report presents implemented and potential improvements to a level 3 PSA model and its analysis previously developed in the PRADA project. The model is an event tree model, where wind direction, wind speed, precipitation, success of evacuation and success of sheltering (if evacuation is unsuccessful) are the nodes. The case modelled was an alternative take on the Fukushima Daiichi nuclear accident: what radiological consequences would the accident have had if the population in nearby big cities had been in place and not dislocated due to the tsunami. The radiological consequences were found to be small even under rather conservative assumptions.

The most important change to the event tree model introduced in this report is that wind speed is now drawn from a Weibull distribution in a Monte Carlo simulation. Also evacuation modelling was improved slightly.

In the uncertainty analysis, the most important change concerns the handling of source term uncertainties. Population dose is composed from doses caused by each radionuclide, and thus the amounts of radionuclides in the release can be made random variables and subjected to Monte Carlo simulation. An uncertainty distribution was attached also to wind speed parameters and evacuation success probability in the uncertainty analysis.

The radiological consequences to the general population were minor also in this study. This gives support to the hypothesis that the very small (according to UNSCEAR) radiological consequences to the general population in the Fukushima Daiichi nuclear accident were not a matter of good luck but rather something to be expected concerning the case.

Confidentiality	Public

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Preface

This report was written as a part of PRAMEA project, which is a part of the Finnish Nuclear Power Plant Safety Research programme 2015-2018 SAFIR2018. The report is also a part of Nordic cooperation within the “Addressing off-site consequence criteria using level 3 PSA” project which has received funding from NKS and NPSAG. The authors wish to thank Dr. Mikko Ilvonen for advice.

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Authors

Contents

1. Introduction

Level 3 probabilistic safety analyses (PSA) are a compromise between modelling and analysis accuracy on the one hand, and computational demands on the other hand. In (Karanta et al. 2015), a lightweight approach to level 3 PSA was presented. It consists of a PSA event tree model for weather and countermeasure variables, and utilizes a level 3 code named ARANO in calculating the population doses for each outcome. The model used is simple in many respects: weather is modelled as essentially static (no change in wind direction or speed), evacuation success is expressed as a single probability figure based on a very simple model, and sheltering success is also expressed as a single probability. An uncertainty analysis was conducted, but it did not incorporate uncertainty in the source term, and the uncertainty distributions of model variables were determined by judgment of the report authors.

The case was a study in alternative history: what if the Fukushima Daiichi nuclear power plant accident, with its source term, had happened without the earthquake and tsunami? In this case, the population of the Fukushima prefecture would have been in their homes and workplaces, whereas in reality, the population of large areas within the prefecture either had died in the tsunami, or had already been evacuated because of it. The motivation of this piece of alternative history was to shed light on the following question: was the near absence of radiological consequences in the area – according to UNSCEAR report (UNSCEAR 2013), no radiological deaths or cancers due to the accident have occurred nor will be expected within the next 85 years – due to the fact that large areas were already depopulated, plain good luck, or were the insignificant radiological consequences something to be expected, given the weather conditions in that part of Japan, the fact that Fukushima Daiichi is on the Pacific coast and thus approximately 50 % of wind directions result in negligible dose to the general population, and the effectiveness with which the Japanese officials carried out the evacuation of the area.

The results of that study indicated that at the distances of 27…64 km no acute health effects were expected because individual doses remained below 1 Sv. They also indicated that late health effects, measured by the number of expected cancer deaths, were minor. This supports the hypothesis that insignificant radiological consequences outside the evacuation planning zone are to be expected rather than being good luck.

This report considers improvements to the model and analyses of that report. Uncertainty analysis, which did not take uncertainty related to the source term into account in the original report, is improved upon in this regard. Dynamic models for weather, evacuation and sheltering are considered.

2. Event tree model

The consequences of the accident are analysed using an event tree model that utilises deterministic dispersion calculations. The event tree structure is quite similar to the event tree in the previous study (Karanta et al. 2015). The main difference is that wind speed is not divided into branches, but it is sampled from a distribution on each simulation round (see Section 4.1). In this way the complete wind speed distribution and its effect on the population doses can be included in the model. The event tree can be found in Appendix A.

The probabilistic analysis was performed using VTT's FinPSA Level 2 software (Mätäsniemi et al. 2015), while the previous study was performed using SPSA. Both tools work almost identically. The CETL (containment event tree language), a programming language integrated to FinPSA Level 2, was utilized in the implementation of the improvements; all the code samples in this report are written with it. The supporting deterministic computations were performed mainly with ARANO software (Savolainen and Vuori 1977).

3. Uncertainty analyses

The main improvements of the uncertainty analysis, when compared to (Karanta et al. 2015), were the incorporation of uncertainty in the source term in the uncertainty analysis, and the changes brought about by the improved handling of wind speed.

Most of the uncertainty distributions presented in (Karanta et al. 2015) were used in this analysis too, excluding wind speed related distributions. The following improvements were made:

- In the previous study, the number of cancer deaths was calculated from the population dose by multiplying it by 0.05. In the new model, instead of being constant, the factor was assumed to follow uniform distribution between 0.03 and 0.07.
- Wind speed uncertainties were handled as presented in Section 4.1.
- The uncertainties of the source term were handled as presented in this section.
- Uncertainty distribution was assigned for evacuation time as presented in Section 5.

3.1 Uncertainty analysis of source term

Usually, the uncertainty related to the source term is an output of level 2 PSA analyses. In our case, such analyses were not available, and the uncertainty in the source term had to be assessed by other means.

Several estimates for the source term uncertainty in the Fukushima Daiichi accident exist, all of them related to the estimation of the source term.

The UNSCEAR report takes its source term from (Terada et al. 2012), This paper does not contain a proper uncertainty analysis, but on p. 145 it says ”the mean differences in logarithm of measurements and calculations [..] and the standard deviations of the differences [..] are also shown in Figure 4”. That figure contains the standard deviations of a “refined model”, where surface deposition measurements have been taken into account, and they are 0.93 (I-131) ja 0.91 (Cs-137) (unit: Bq/m^2). However, these uncertainty estimates do not take measurement uncertainty and uncertainty resulting from sampling into account; furthermore, it is unclear how these estimates could be transformed into ordinary uncertainty estimates. Therefore they were not used.

Reference (Stohl et al. 2011) presents another estimate, an uncertainty range expressed for Xe-133: 12.2-18.3 EBq. Presumably this is the 95 % confidence interval of the amount of Xe-133 in the release. The trustworthiness of this estimate is reduced because their baseline estimate (15.3 EBq) is more than double the estimates obtained by other researchers, and the baseline estimate for Cs-137 is more than four times that obtained by other researchers, as noted also by the UNSCEAR report (UNSCEAR 2014). Thus, this uncertainty estimate was not used either.

Reference (Winiarek et al. 2014) states that “total released quantity of caesium-137 in the interval 11.6 - 19.3 PBq with an estimated standard deviation range of 15-20 % depending on the method and the data sets”. This uncertainty estimate appears to be the most plausible available because their source term is well in line with those obtained by other researchers. Thus it was used. Uncertainty estimates for all radioisotopes were set to 17.5% from their baseline estimates corresponding to the caesium-137’s 15-20 % uncertainty range.

3.2 Propagation of source term uncertainty to population doses

In the uncertainty analysis, it was assumed that if a source term is scaled with a particular factor, the population dose can be scaled with the same factor. At least, the computation in ARANO software works this way. Therefore, it was possible to perform the uncertainty analysis by scaling baseline results in FinPSA instead of performing Monte Carlo analysis in ARANO.

The population doses were calculated for each radionuclide separately using the baseline release values from (Karanta et al. 2015). Fractions of different radionuclides of the total population dose were examined in order to calculate a scaling factor to be used in uncertainty analysis. For each radionuclide, an uncertainty distribution was created with the fraction as the mean value. On each simulation round, a weight of each radionuclide was drawn from the distribution, and the weights were summed up to obtain a scaling factor of the source term uncertainty.

It was found out that the fractions of different radionuclides of the total population dose depended slightly on wind speed and distance (while the doses changed significantly as can be seen from Section 4.1). In the case of no precipitation, it was mainly the fraction of xenon that changed according to wind speed and distance, while other fractions were approximately scaled according to the fraction of xenon. The baseline fractions that were used in the uncertainty analysis are presented in Table 1. The dependence to wind speed and distance was modelled quite roughly because the effect on the total results was assumed to be small. Table 2 presents the mean fraction of xenon in different cases. In the analysis, the fractions of other nuclides presented in Table 1 were scaled according to the fraction of xenon so that the sum of fractions was 100%.

Table 1: Mean fractions of different radionuclides of the total population dose when there is no precipitation.

Radionuclide	Fraction (%)
Te-132	11
I-131	51
I-132	0.5

I-133	1
Xe-133	6
Cs-134	11.5
Cs-136	1
Cs-137	18

Table 2: Mean fractions of xenon of the total population dose in different cases when there is no precipitation.

City	v ≤ 1	1 < v ≤ 4	4 < v ≤ 8	8 < v ≤ 16	v > 16
Minamisoma	8%	6%	4%	3%	3%
Iwaki	13%	8%	5%	4%	3%
Koriyama	22%	8%	5%	4%	3%
Kakuda	22%	8%	5%	4%	3%
Fukushima	26%	8%	5%	4%	3%

The fractions of I-132 and I-133 were so small that the iodine nuclides were grouped together for the uncertainty analysis. The correlation of radionuclides was handled simply by a correlation factor that was common for Te-132, iodine, Cs-134, Cs-136 and Cs-137. For the correlation factor, normal distribution was assumed with the mean of 0.5 and standard deviation of 17.5% of the mean.

In the case of precipitation, it was assumed that the entire population dose comes from xenon, meaning also that the dose is much smaller than without precipitation (for justification, see Section 4.4). This is not true with very high wind speeds, but the assumption was made to keep the model simple enough. Very high wind speeds are quite unlikely, and the only effect of the assumption is that the uncertainty distributions are slightly wider than they would be with more accurate modelling.

The scaling factors (st2 for Minamisoma and st for other cities) were calculated using the following code:

```
  $ source term uncertainty computation
  cor = rannorm(0.5, 0.0875) $ correlation factor
  i = rannorm(0.525, 0.0919)
  te = (1-cor)*rannorm(0.11, 0.0193)+i*0.11/0.525*cor
  xe = rannorm(0.06, 0.0105)
  cs134 = (1-cor)*rannorm(0.115, 0.0201)+i*0.115/0.525*cor
  cs136 = (1-cor)*rannorm(0.01, 0.00175)+i*0.01/0.525*cor
  cs137 = (1-cor)*rannorm(0.18, 0.0315)+i*0.18/0.525*cor
  st = te+i+xe+cs134+cs136+cs137 $ factor of source term
uncertainty
  st2 = te+i+xe+cs134+cs136+cs137
```

```
  if rain then
  begin
    $ when it rains, the whole population dose comes from
xenon
    st = xe/0.06
    st2 = xe/0.06
  end
  else
  begin
    $ factor of source term uncertainty changed according to
wind speed
    $ the fraction of xenon depends on wind speed
    $ st2 is for Minamisoma and st for other cities
    if wind_speed > 16 then
    begin
      st = (st-xe)*103/100+xe*0.5
      st2 = (st2-xe)*103/100+xe*0.5
    end
    else if wind_speed > 8 then
    begin
      st = (st-xe)*104/100+xe*4/6
      st2 = (st2-xe)*103/100+xe*0.5
    end
    else if wind_speed > 4 then
    begin
      st = (st-xe)*105/100+xe*5/6
      st2 = (st2-xe)*104/100+xe*4/6
    end
    else if wind_speed > 1 then
    begin
      st = (st-xe)*98/100+xe*8/6
    end
    else
    begin
      if samestr(dir, 'NWest') then
      begin
        st = (st-xe)*80/100+xe*26/6
      end
      else if samestr(dir, 'SWSouth') then
      begin
        st = (st-xe)*93/100+xe*13/6
      end
      else
      begin
        st = (st-xe)*84/100+xe*22/6
      end
      st2 = (st2-xe)*98/100+xe*8/6
    end
  end
```

For each city and weather condition, the total baseline population dose was scaled by the scaling factor (st or st2) on each simulation round. The distributions of the scaling factor for Iwaki with and without precipitation are presented in Figures 1 and 2. The distribution is slightly wider in the case of precipitation: the 5th percentile was 0.71 and the 95th percentile was 1.29.

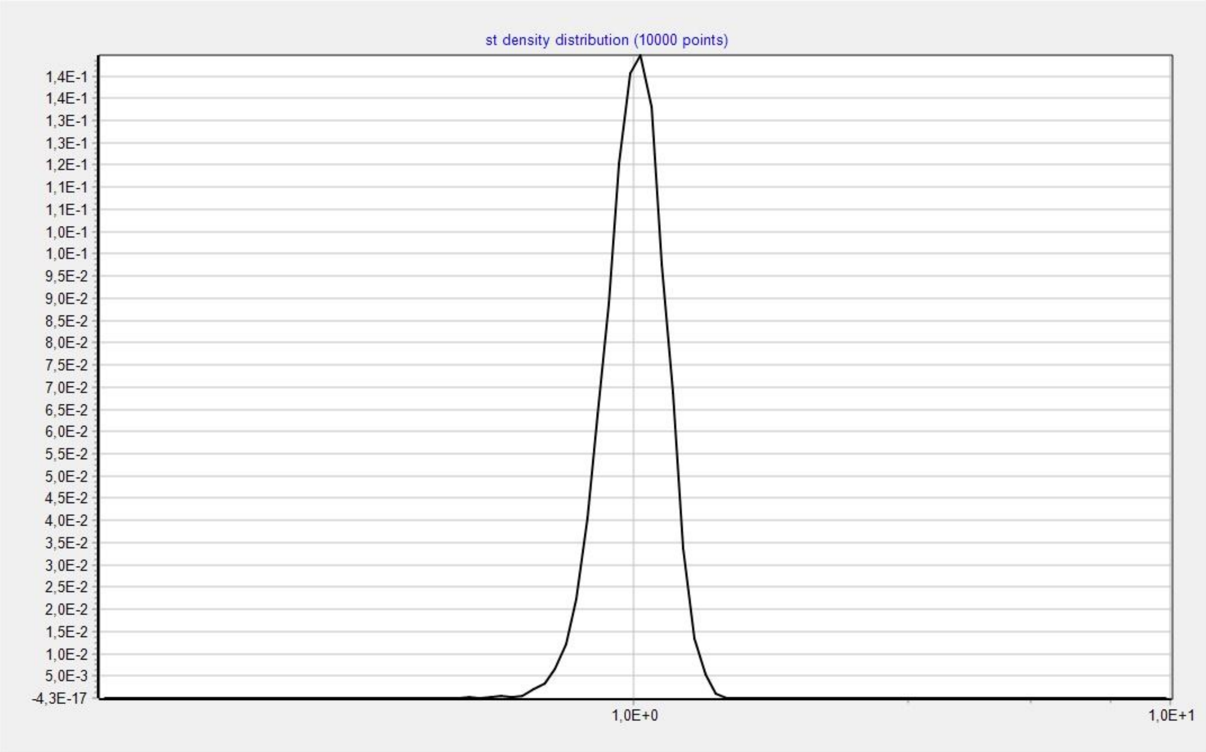

Figure 1: The uncertainty distribution of the scaling factor for Iwaki with no precipitation.

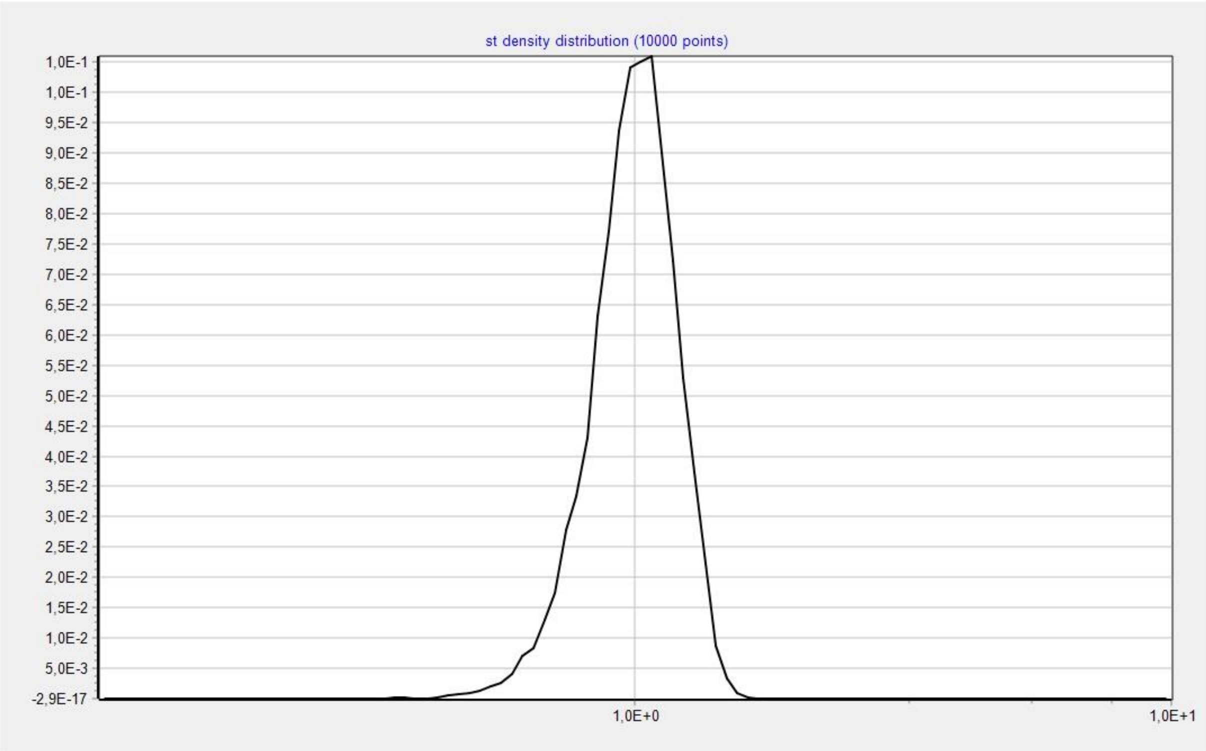

Figure 2: The uncertainty distribution of the scaling factor for Iwaki with precipitation.

4. Effects of weather dynamics

Improvements were made to the model concerning weather factors. Furthermore, computational experiments were conducted to determine what phenomena in weather dynamics have considerable effect on individual and population doses. This chapter describes these improvements and experiments, and provides some discussion on the effect of weather dynamics.

4.1 Accounting wind speed in the model

In the previous model (Karanta et al. 2015), wind speed was modelled very simply in the event tree: there were three branches, for 0 km/h, 8 km/h, and 16 km/h wind speeds. The probabilities of these three wind speed classes were estimated from a lognormal distribution.

The handling of wind speed was modified considerably. It was not handled as branches in the event tree. Instead, a wind speed was sampled from a distribution on each simulation round and the corresponding population doses were calculated as functions of the wind speed.

Population doses were calculated using various wind speeds, from 0.5 m/s to 40 m/s, in ARANO. The result was a vector of population doses for each city in both rain and no rain conditions. 40 m/s is the wind speed of a typhoon, and therefore no population doses for higher wind speeds were needed. Population dose curves as functions of wind speed are presented in Figures 3 and 4.

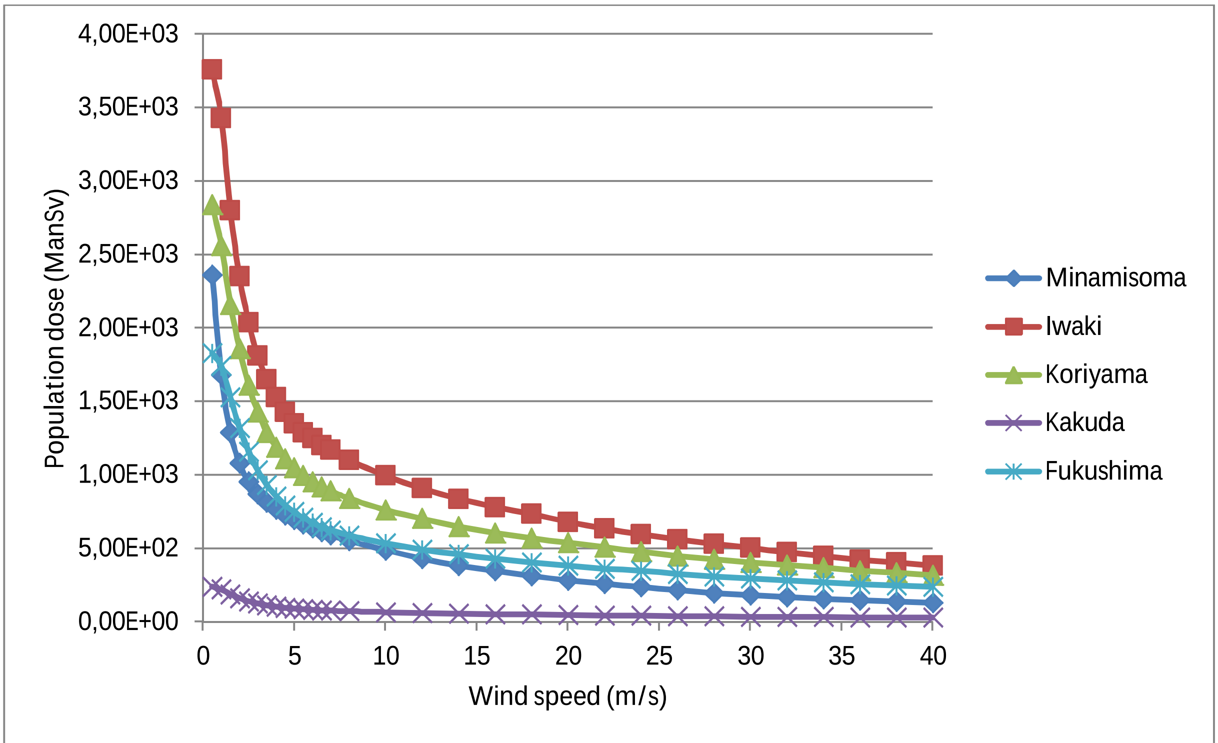

Figure 3: The population doses calculated in ARANO as functions of wind speed in the case of no rain.

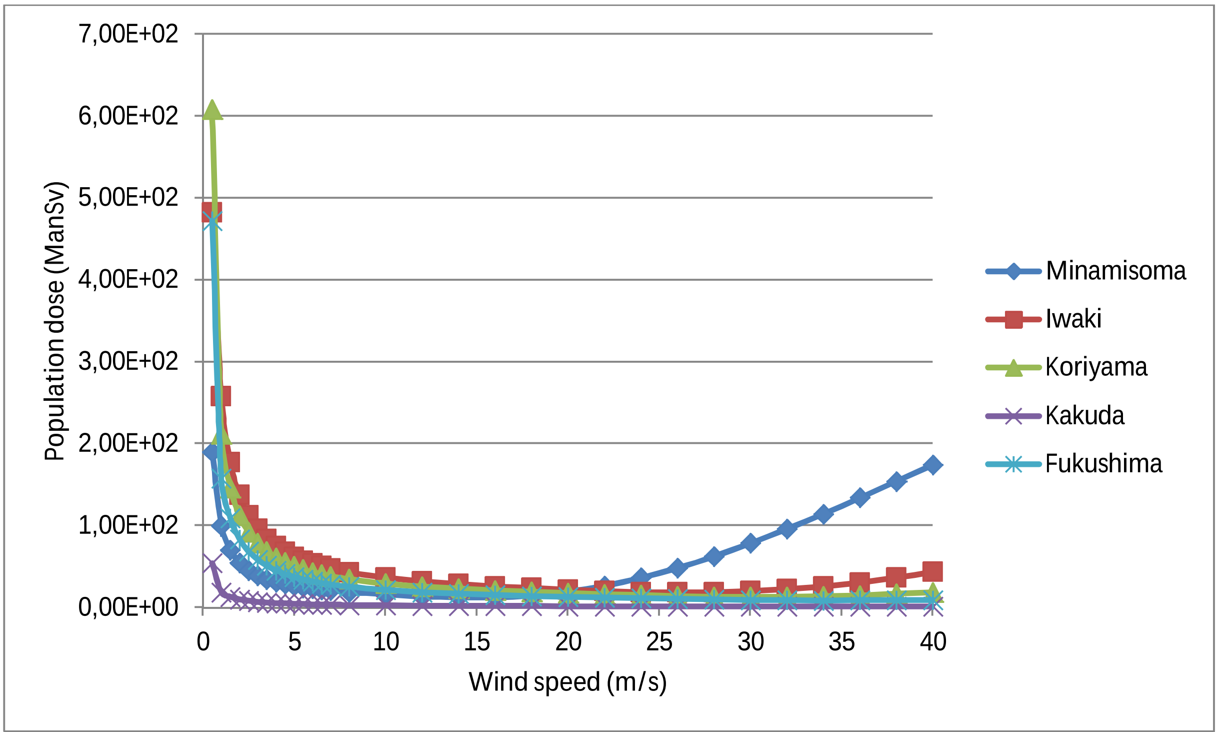

Figure 4: The population doses calculated in ARANO as functions of wind speed in the case of rain.

In Figure 4, dose is increased with increasing wind speed in the towns located at shorter distances from the release point. This is due to minor scavenging of the plume at high wind speeds: the rain does not have time to wash the aerosols down before the plume reaches the city and aerosols are washed down on it by the rain as ground deposit.

Wind speed was handled with Monte Carlo simulation. On each simulation round, the wind speed was drawn from a probability distribution, and the corresponding population doses were looked up from the wind speed / population dose vectors for each city in both rain and no rain conditions. The population doses were calculated from the elements of the vectors by linear interpolation. For wind speeds smaller than 0.5 m/s, the population doses of 0.5 m/s were used, and for wind speeds larger than 40 m/s, the population doses of 40 m/s were used. The simulation gave a probability distribution for population doses, from which e.g. mean population dose can be calculated.

The probability distribution used in simulation was the Weibull distribution. Although many probability distributions have been used for wind speeds (Carta et al. 2009), Weibull distribution remains the most popular, because daytime wind speed observations are generally consistent with it (night time wind speeds are positively skewed when compared with the Weibull distribution) (Monahan et al. 2011). The parameters of the Weibull distribution were estimated so that they fit the statistical information available from Onahama, a city in the Fukushima prefecture some 60 kilometers south of the Fukushima Daiichi site (the same weather statistics data was used in (Karanta et al. 2015)). The wind speed statistics are from the www site http://www.windfinder.com/windstatistics/onahama, and they are as follows: mean wind speed in March 8 knots, probability of wind speed exceeding or equalling 4 Beaufort 0.19. The wind speed distribution is presented in Figure 5.

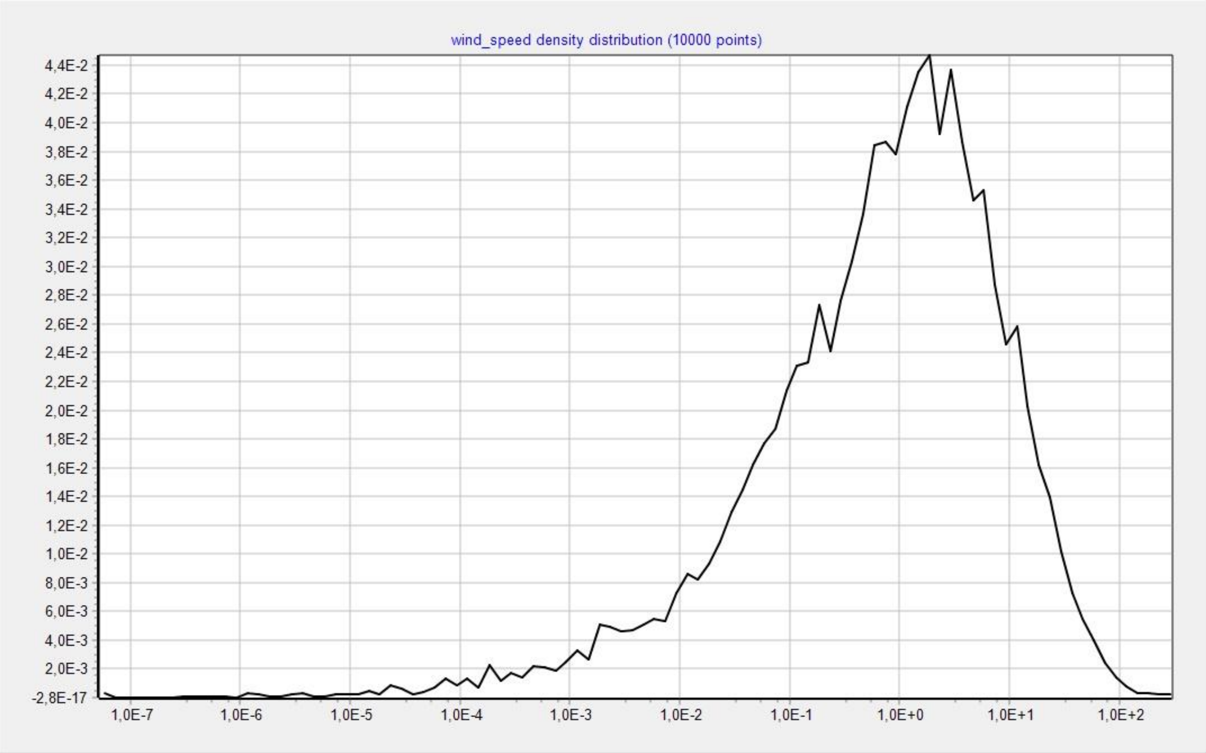

Figure 5: The distribution of wind speed (unit: m/s).

4.2 Effect of wind speed and direction changes

Wind speed change may either increase or decrease population dose when compared to the situation where wind speed is constant.

- The wind calms down while the release plume is over a population center. In this case, the population’s dose is expected to increase when compared to the constant wind speed situation.
- The wind speeds up when the plume is over a population center. In this case, the (local) population’s dose is expected to decrease when compared to the constant wind speed situation.
- The wind calms down before the release plume reaches the population. This prevents the population from being subjected to ionizing radiation from the release altogether.

Wind direction changes may also increase or decrease population dose:

- If the wind was initially blowing towards a sparsely populated or nonpopulated area (e.g. sea), and then turns toward a densely populated area, population dose will increase unless evacuation is carried out in time. This applies also to situations where the wind was initially blowing towards a densely populated area, and then turns towards another densely populated area (instead of continuing towards a sparsely populated area).
- If the wind was initially blowing towards a population center, and then turns towards a sparsely populated area, the dose will decrease. This applies both in situations where the radioactive plume had not yet reached the population center, and in situations where, without change in wind direction, the plume would have continued towards another population center.

Near a nuclear power plant, most directions do not contain a population center within short distance. This applies especially to NPP's located on a coast; in Fukushima Daiichi, for example, more than half of directions from the plant are either uninhabited (the Pacific ocean) or have relatively low population density close to the site. Furthermore, if a radioactive plume turns towards a population center after moving through a less populated area, it has moved longer than it would have if it had moved in one direction only, and thus has lost more of its radioisotopes on the way than a plume that has moved in one direction only. Thus, there is some justification in saying that having the plume move in one direction only (as in ARANO), one gets more conservative estimates for population doses.

Wind speed and direction changes could be incorporated in the model through combining wind speed and wind direction (direction is now handled as branches in the event tree) handling into a procedure that would calculate plume paths through Monte Carlo, and calculate doses if the path crosses a population center. This, however, would require weather data of the wind conditions near Fukushima Daiichi (from which wind speed statistics, including time correlations, could be estimated); such data was not available for this study. Furthermore, implementing this would require a major programming effort, which was beyond the resources of the project.

4.3 Effect of rain timing

Rainfall has quite a different effect on population dose depending on whether it occurs before the plume has reached a population center, or while the plume is above a population center. Before the plume reaches the general population, rainfall washes aerosols from the plume, and with the aerosols, the most harmful radioisotopes (Iodine and Cesium) get washed down to sparsely inhabited or uninhabited regions. While the plume is above a population center, rainfall washes aerosols to the ground there, and thus contributes to surface deposition.

Population dose as a function of start time of rain before the plume reaches the population center (Iwaki) is depicted in Figure 6. Rain intensity was assumed to be 5 mm/h, stability class C, and wind speed 4 m/s. As can be seen, even half an hour's rain reduces the population dose to less than 2 % of the original if the rain occurs before the population center.

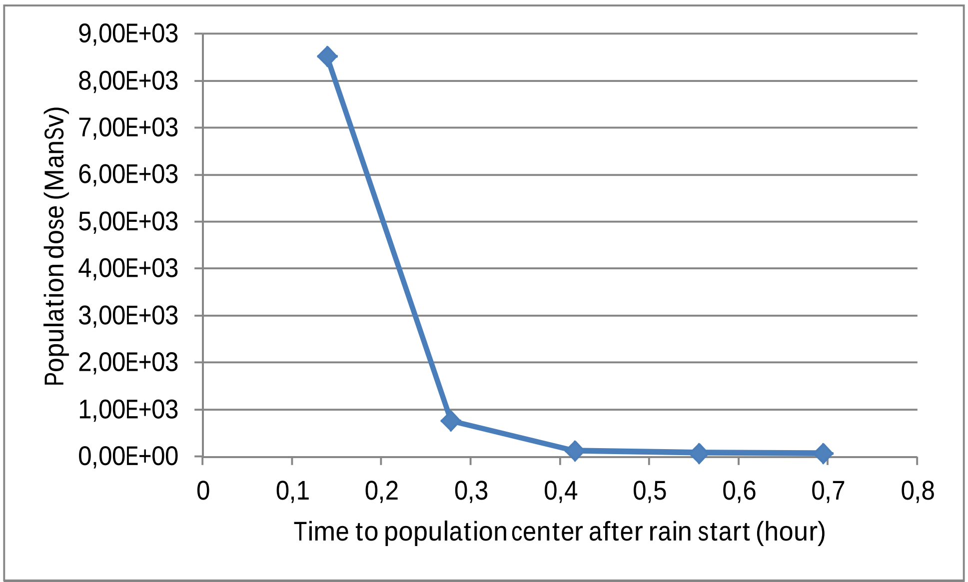

Figure 6: Population dose (manSv) as a function of the time (hours) it takes the plume to reach a population center after start of rain.

Various computational experiments were conducted. Of these, perhaps the most illuminating concerns the comparison of three situations:

- one in which there is no rain,
- one in which rain starts when the release plume is approaching a city but stops before the plume enters the city,
- one in which rain starts when the release plume is approaching a city and continues as the plume flows above the city.

The case of Iwaki was considered (48 km from Fukushima Daiichi, 345 000 inhabitants in 2011). The values of the weather variables are wind speed 4 m/s, rain intensity (when there is rain) 2 mm/h, stability class C, Table 3 summarizes the results.

Table 3. Effect of rain timing on individual and collective doses.

Rain timing	maximal individual dose (Sv)	collective population dose (manSv)
no rain	4,43E-03	1530
rain starts 4 km (about 17 min) before plume reaches city, and continues while the plume is above the city	1.67E-02	5770
rain starts 4 km (about 17 min) before plume reaches city, and stops 1 km before the plume reaches city	7,86E-04	271

The effect of rain timing is quite dramatic. If the rain starts and stops before the city, the doses are more than 20 times less the doses when the rain starts before the city but continues when the release plume is above the city. When compared to the case that there is no rain, the washing effect of rain before the city still reduces population dose to less than one-fifth.

The computational experiments confirm the intuitive idea that rainfall between the nuclear accident site and a population center is a blessing, but rainfall within the population center (after the release plume has arrived) is a curse.

4.4 Effect of the intensity of rain

Rain intensity affects deposition of volatile compounds in the release due to the washing effect: water droplets wash aerosol particles from the air, depositing the volatile compounds to where the rain falls. This washing effect does not affect noble gases, and so the plume still contains radioisotopes, but it is effectively stripped off the most harmful radioisotopes (Iodine and Cesium, in particular). In this section the effect of rain intensity is quantified.

Rainfall intensity is classified according to the rate of precipitation [American Meteorological Society 2015]:

- Light rain (precipitation rate is < 2.5 mm per hour)

- Moderate rain (precipitation rate is between 2.5 mm - 7.6 mm per hour)
- Heavy rain (precipitation rate is > 7.6 mm per hour)

The Met Office of United Kingdom [Met Office 2007] uses the scale slight 0 – 2 mm/h, moderate 2 – 10 mm/h, heavy 10 – 50 mm/h, and violent > 50 mm/h.

A complex relationship exists between rainfall intensity, rain duration and frequency (Koutsoyiannis et al. 1998), and this relationship probably has great effect on the probability that rain washes the aerosols of a release plume before it reaches a given geographical location. However, here only rainfall whose intensity is static in time is considered.

The first computational experiment concerned the effect of rainfall on the release plume moving from Fukushima Daiichi to Iwaki (48 km south of Fukushima Daiichi, 345 000 inhabitants). Its results are shown in Figure 7. As can be seen, rainfall more intensive than approximately 4 mm/h (moderate rain) will wash all aerosols from the plume. The only radionuclides that remain in the plume are noble gases, and they cause a rather small population dose (approximately 21.3 manSv).

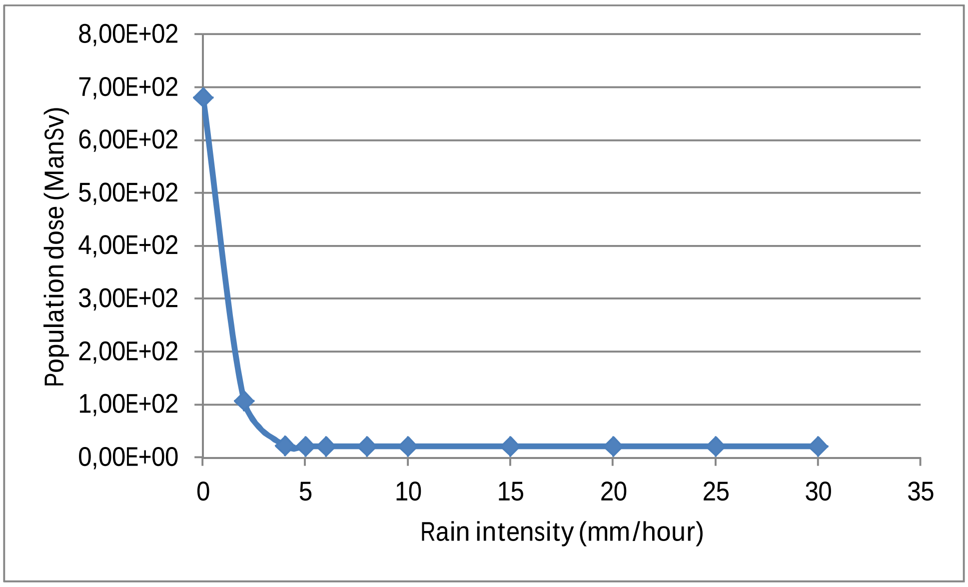

Figure 7. Population dose in Iwaki (48 km from Fukushima Daiichi) as a function of rainfall intensity. Wind speed 20 m/s, rain all the way from Fukushima Daiichi to Iwaki.

5. Dynamic models of evacuation

Evacuation is perhaps the most important early countermeasure, because if the population is transported away from the area before the plume arrival, radiation exposure is completely avoided.

The importance of evacuation has received attention in the nuclear safety community from early on (NUREG 1980). In practice, a nuclear power plant site is surrounded by a low population density zone. For the radiation protection purposes the NPP is surrounded by an emergency planning zone (EPZ), which spans up to 16-25 kilometers from the site, depending on the country. In Finland the EPZ is divided into two zones: the protection zone extends to about five kilometres from the power plant and the emergency planning zone is applied for an area within a radius of about 20 km. The planning principle of these zones is that there shall not be need for evacuation beyond the protective zone due to a severe reactor accident and no need for sheltering beyond the preparedness zone. As the

Fukushima accident demonstrated, there may be need for evacuation beyond the EPZ to reduce the collective dose.

Evacuation is a complex phenomenon, as there are many factors to be taken into account:

- Trip generation time is the time from the issuance of evacuation recommendation to the beginning of household's departure from the EPZ (Urbanik 2000). It consists of notification time, or the time from the decision to evacuate to getting the message through to people in the area to be evacuated, and mobilization time, or the time span between receiving notification and departure from home (Tweedie et al. 1986).

- The road network of the EPZ affects evacuation success in many ways. The road network near the Finnish NPP's is not very complex, but if evacuation would have to be extended to nearby cities, the models of the road network would become quite large. The location of workplaces and residences in the network is of importance, because people normally drive to home from work before they evacuate; if the workplaces are located so that this causes a lot of traffic crossing the radial evacuation traffic, this may cause delays. Also people who work outside the EPZ but live within it will return to their homes before they evacuate, which affects their evacuation time. Road capacity is of importance, too: big roads with more than two lanes will have larger capacity for the evacuation traffic, and traffic control actions affect evacuation times, too. If the rate of evacuation trip departures exceeds road capacity, traffic slows down and the time required by the excess trip demand has to be added to the evacuation times.

- The spatial distribution of population varies by time in ways that affect evacuation times. Holiday seasons have considerable effect (e.g. many inhabitants in the EPZ of the Loviisa power plant live there only in the summer holiday season). Time of day affects the distribution: in the daytime, people who work in or near the plant are at their workplaces, while they are at home in the night time; the reverse is true of people who live in the EPZ but work elsewhere.

- The number of available vehicles in relation to population size affects evacuation time. If there is sufficient vehicle capacity, each vehicle has to make only one trip; otherwise, some vehicles have to return and fetch more people. In addition to cars of the people living or working in the EPZ, also public transit has to be taken into account.

- Evacuation of public buildings such as schools and hospitals have to be considered by a model that concerns both building evacuation and evacuation trips through the road network according to the evacuation plans for those buildings; the model should take into account the fact that the population in such buildings have limited mobility.

- Evacuation management and control – e.g. the control of traffic by police, and evacuation instructions given by officials concerning e.g. evacuation timing and routing – affect evacuation times considerably as they e.g. prevent traffic congestion.

- Weather factors and time of day affect traffic. For example, rain, snowstorms, and heavy wind may cause traffic to slow down. If the nuclear accident being considered in the level 3 analysis has been caused by e.g. a flood or an earthquake, also the road network may have been damaged.

Some codes for evacuation modelling and analysis, such as I-DYNEV and OREMS, exist. Furthermore, the former is public domain, or at least was at the time of writing of (Urbanik 2000). However, I-DYNEV could not be found at the site of the U.S. Federal Emergency Management Agency (FEMA) for the purpose of this study, or even a contact address where it could be obtained. Even if the codes were available, proper modelling and analysis of evacuation would be a major undertaking due to the complicating factors listed above.

Statistical models that could have been used to provide evacuation time estimates for the level 3 model were not to be found for this study.

The way that evacuation is taken into account in the model was improved in the following way. Hitherto, if evacuation failed, the whole population was assumed to be in the city and be subjected to radiation for three days. This is overly conservative, because it is most probable that a part of the population has been evacuated when the plume arrives, even if the evacuation of all people has failed. Now, if evacuation fails, the population is assumed to be subjected to radiation for only the time from the plume arrival to three days. This is a conservative assumption, and still represents an upper limit to total population dose. In practice, this was implemented so that the total population doses, in the case that evacuation had failed, were scaled down with $(T_e – T) / T_e$, where T_e is the evacuation time distributed normally with mean 72 hours and standard deviation 7.2 hours and T is the time that the plume arrived in the city (in practice, T=S/v, where S is the city's distance from Fukushima Daiichi, and v is the wind speed). This is still an approximation, because the dose rates from cloudshine and inhalation are zero after the plume has moved past the person (population) considered.

6. Modelling of sheltering

Sheltering is another short-term countermeasure. Although not as effective as evacuation, it may significantly reduce the population dose.

There are several factors that affect the effectiveness of sheltering:

- Timing of sheltering recommendation.
- Time span to get the sheltering recommendation through to the general population. Several factors bring uncertainty to this: the communication channels available/used, the spatial distribution of the people.
- The proportion of people who choose not to obey the sheltering recommendation but e.g. decide to leave the EPZ.
- The time it takes each individual to arrive at a shelter, starting from where they were at the time they received sheltering recommendation.
- The quality of the shelters (ventilation, permeability of walls by ionizing radiation etc.).
- The time people leave the shelters (e.g. after the sheltering recommendation has been cancelled).

The authors of this report do not know of mathematical models of sheltering in scientific literature. Such models would contain many parameters for which statistical data is not available (e.g. the proportion of people who ignore the sheltering recommendation), and which should therefore be estimated by expert judgment. Such expert judgment exercises have been conducted e.g. by the European Union (Goossens et al. 2001). Large uncertainties would thus be associated with such models.

7. Results

The results from the simulation runs of the improved model (see Section 2) were as follows. The expected number of cancer deaths was 3.6. Direct comparison to the results in (Karanta et al. 2015) cannot be made because there was an input error in the calculations in the previous model. However, the model from (Karanta et al. 2015) was recalculated with correct input, and the expected number of cancer deaths was 1.2. The difference can be explained by the differences in wind speed modelling. Previously, the doses were assumed to be zero if the wind speed was smaller than 4 m/s, while speeds from 0.5 to 4 m/s can actually lead to high doses. Also, the probability of wind speed smaller than 4 m/s is large as can be seen from Figure 5.

The mean value of the probability of more than 0.1 cancer deaths was 0.16. The maximum of this probability was 0.22. Again, these higher numbers compared to (Karanta et al. 2015) can be explained by the wind speed modelling.

Figure 8 presents the complementary cumulative distribution of the number of cancer deaths. The probability for 20 cancer deaths is around 0.1. The probability for 60 cancer deaths is around 0.01, while the probability for 100 cancer deaths is less than 0.001.

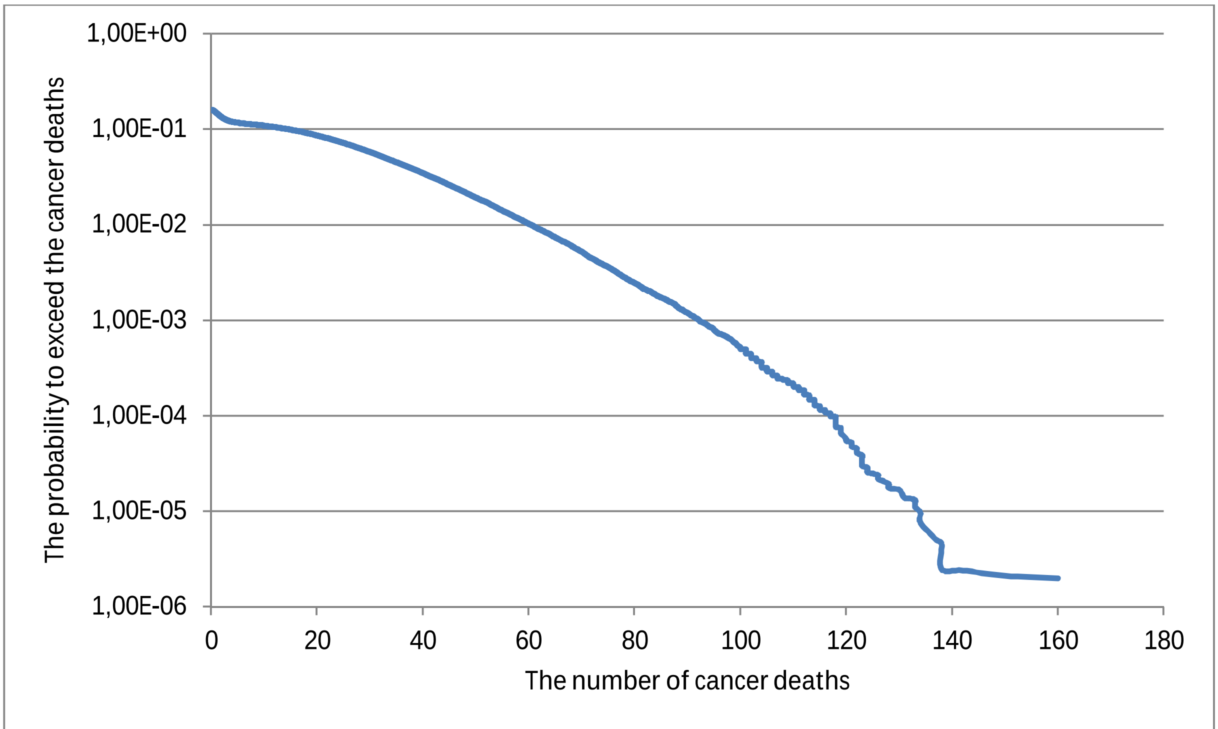

Figure 8: Complementary cumulative distribution of the number of cancer deaths.

Uncertainties on cancer deaths can also be viewed based on the scatter plot between the number of cancer deaths and the probability (‘Freq’) presented in Figure 9. This scatter plot contains a point (if not 0) from each sequence from each simulation round. Notice that the probability of anyone dying of cancer cannot be judged based on this graph because each point represents only one event. On one simulation round, the probability of cancer deaths is the sum of the probabilities of the sequences with non-zero population dose consequences. The two high density areas in the graph represent cases of rain and no rain; note that this bimodality is most probably an artefact of the model (with just two values for rain intensity), and would likely disappear if a continuous model for rain intensity would be introduced. The cancer death numbers are much lower with rain. The highest cancer death numbers are from southwest south direction where the largest and second nearest city is located, but around 100 cancer deaths can come also from directions west and north.

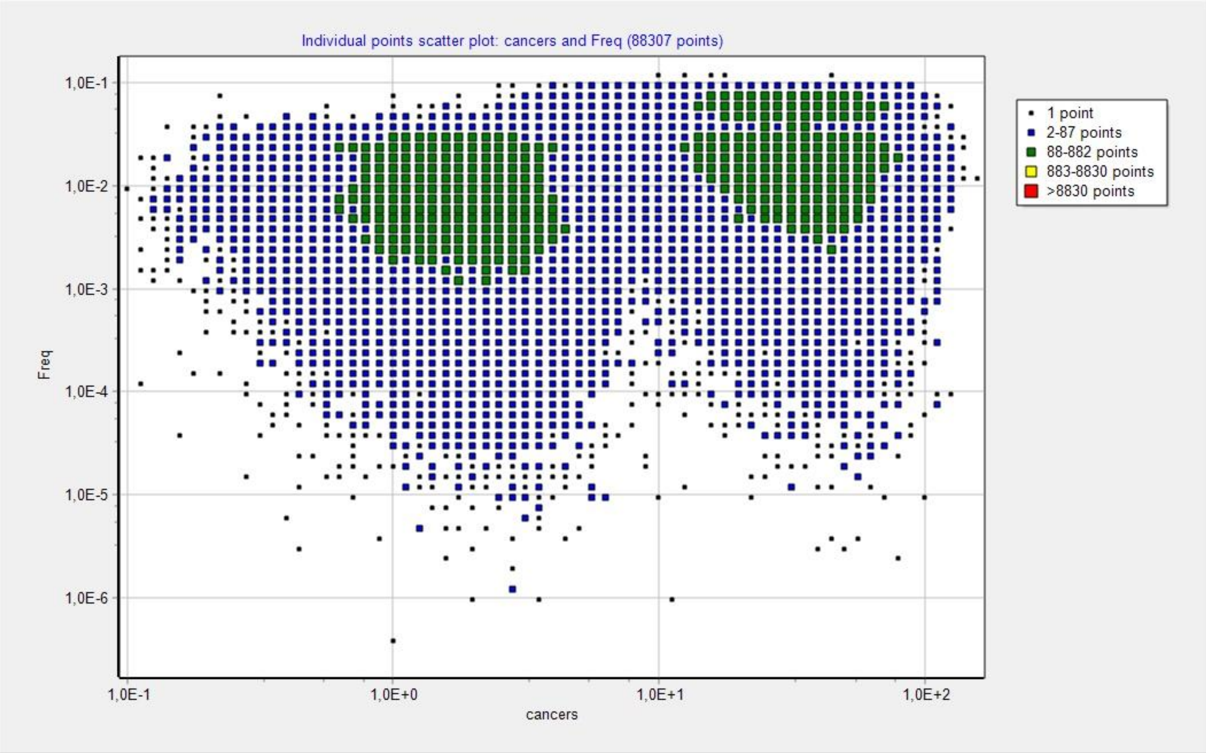

Figure 9: The scatter plot between the number of cancer deaths and the probability.

The effect of the wind speed on the number of cancers can be judged based on the scatter plot presented in Figure 10. This plot contains one weighted point from each simulation round (except from the rounds with very small population doses), and the cancer death numbers are therefore smaller than the largest values in Figure 9. The largest cancer death numbers are obtained with wind speeds from 1 to 10 m/s and especially from 1 to 2.5 m/s.

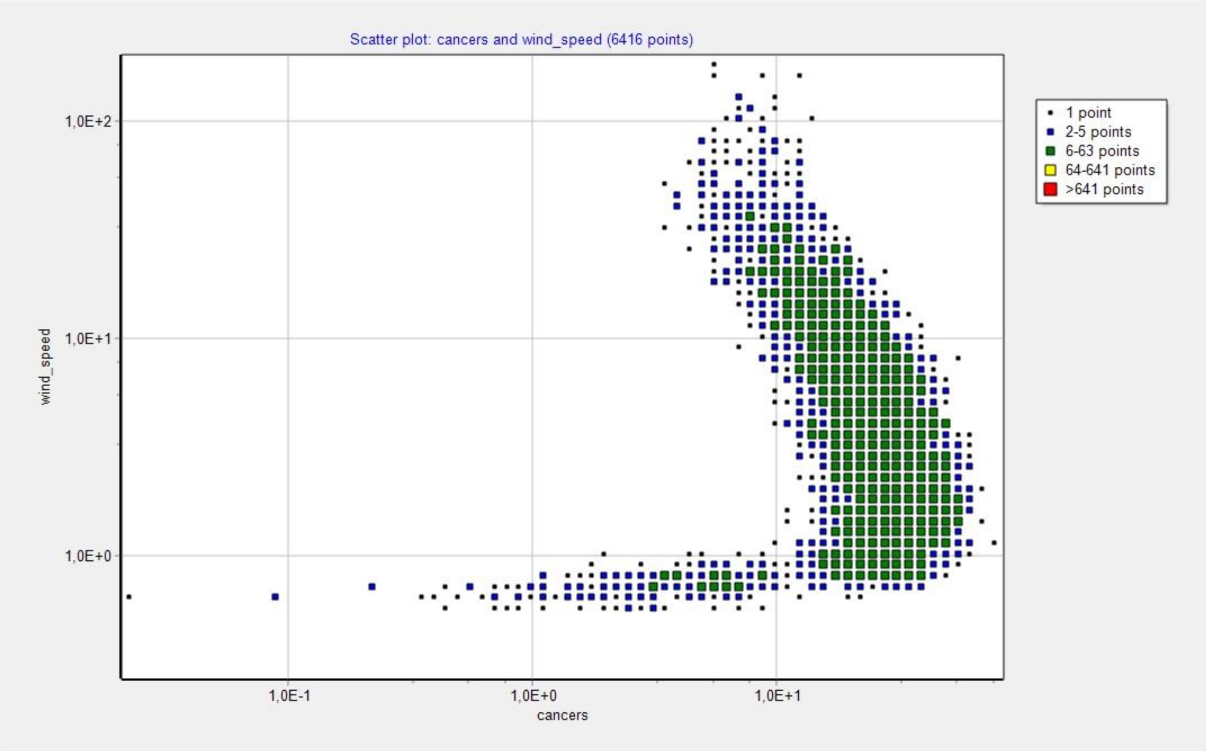

Figure 10: Scatter plot between the number of cancers and the wind speed.

8. Conclusions

The level 3 PSA model was improved compared to the one previously developed. The main improvement in the model is that wind speed is not handled coarsely in wind speed classes, but rather as a continuous random variable following the Weibull distribution; also the evacuation model has been improved. Source term uncertainty has been included and handling of wind speed and evacuation uncertainties has been improved in the model. Computational experiments on the effects of various weather factors on population dose have also been conducted.

The central factors affecting population dose are wind direction, wind speed, precipitation and evacuation. If the wind blows to the right direction (in the Fukushima case, towards the Pacific ocean) or if evacuation is conducted in time, the general population receives essentially no dose of ionizing radiation. High-speed wind takes the radioactive plume quickly away from a population center, with relatively little ground and surface deposition; low-speed wind does the opposite, and thus, increases the population dose. Rain washes aerosols from the radioactive plume, and leaves essentially only noble gases if long-lasting and/or intensive enough; if the rain starts well before a population center, this leads to lesser population dose, but if it starts above the population center, this leads to higher population dose due to increased ground deposition.

Considering the topic of the case study, the results support the conclusion indicated by results in (Karanta et al. 2015): the minor radiological consequences to the general population in the Fukushima Daiichi nuclear accident were not a matter of good luck, but rather what one would expect, given Fukushima Daiichi's location, weather in that part of Japan in March, and the effectiveness of evacuation in the region.

There are several important research issues that would need further work. The dynamics of precipitation (the relationship between rain intensity, duration and frequency), and its incorporation into level 3 PSA analyses, would merit a more thorough treatment. Proper evacuation modelling, with traffic modelling software, and the analysis of the model, would give more justified estimates of evacuation times and also uncertainty distributions for them. Modelling of sheltering would shed light on the actual effectiveness of sheltering, and would also increase the plausibility of the level 3 PSA model.

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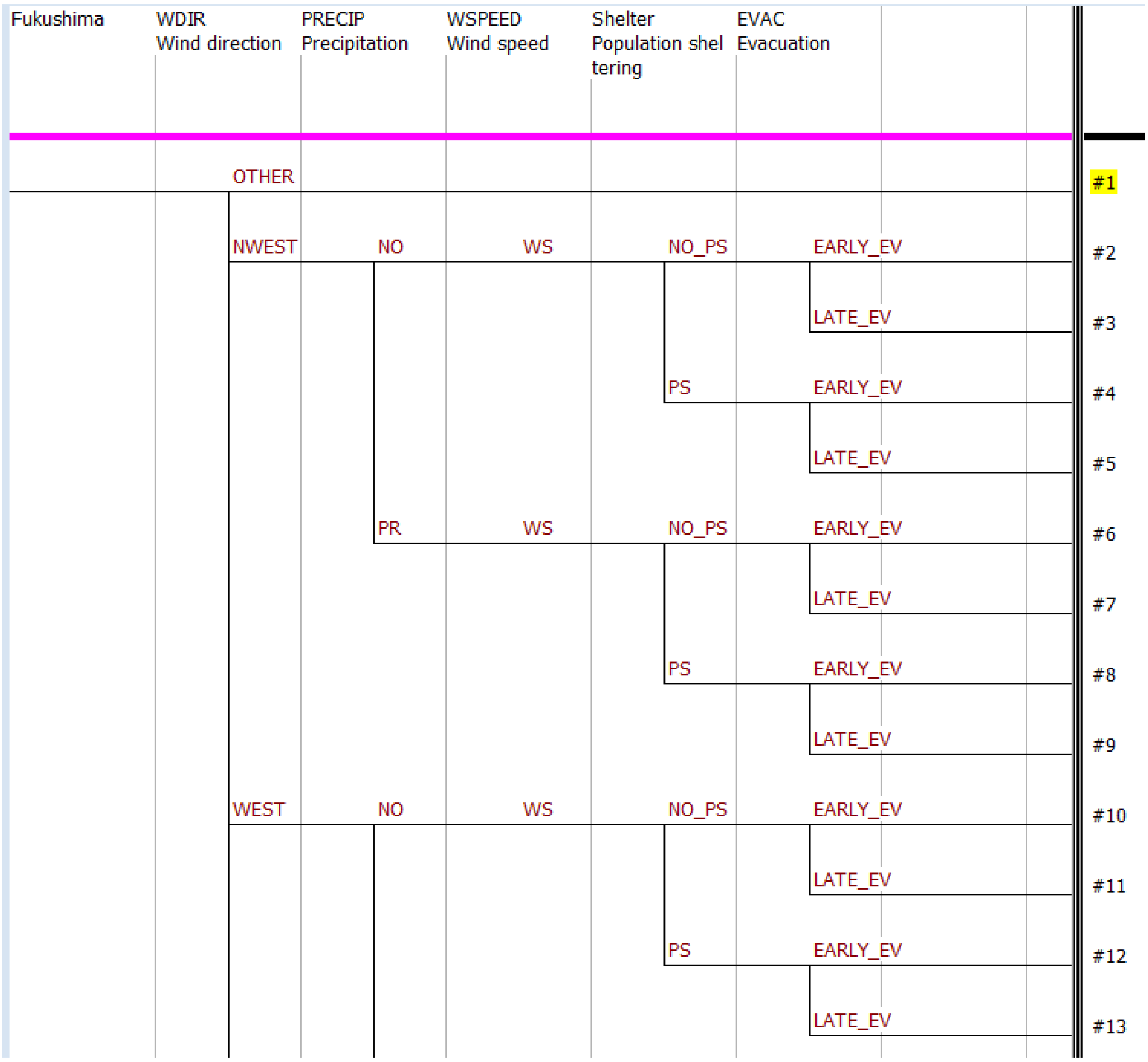
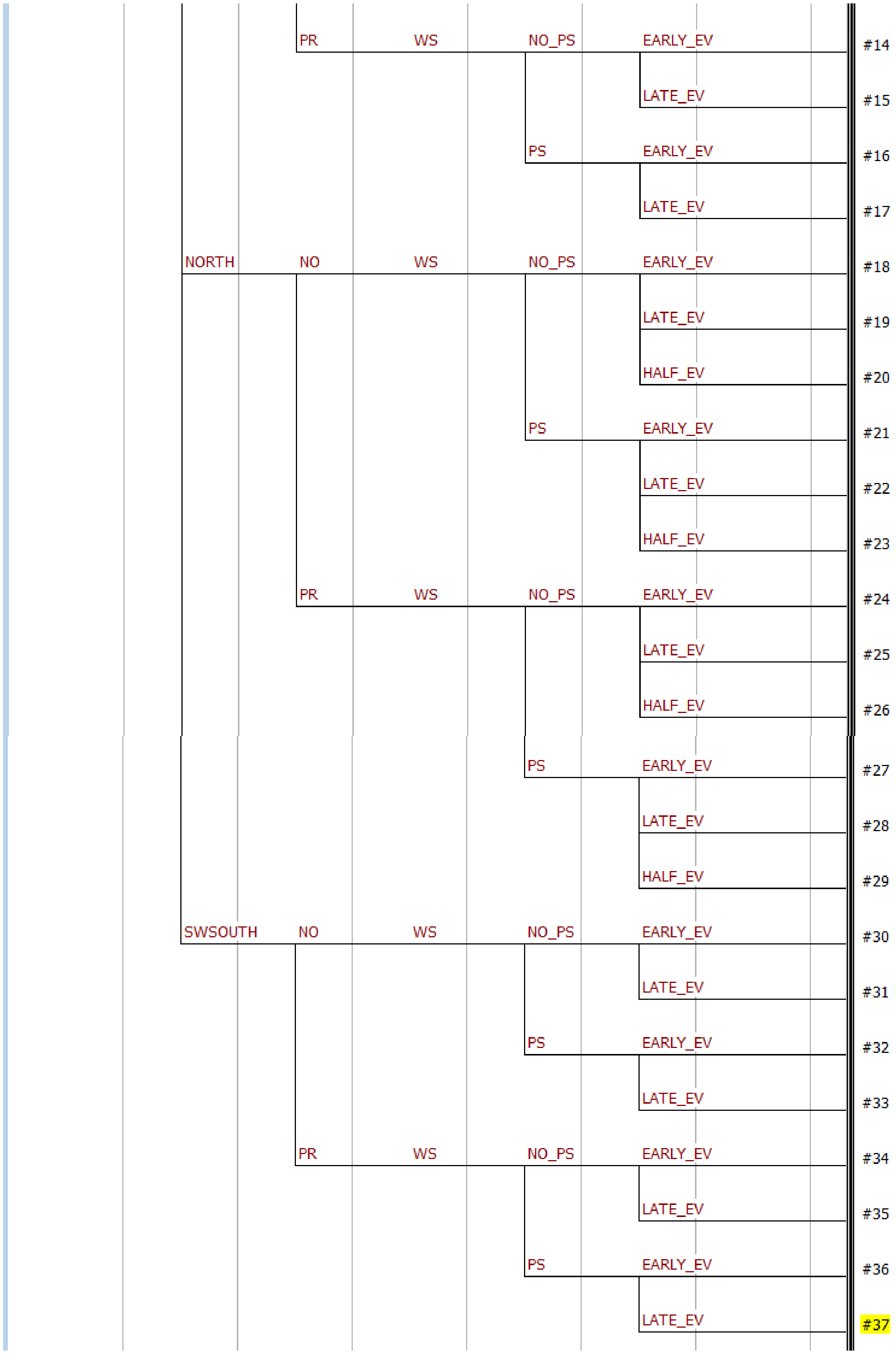
Appendix A: the event tree model

The event tree model is presented in the following. Some function names are explained in Table 4.

Table 4. Descriptions of functions in the event tree model.

Function	Desciption
NO	No rain
PR	Precipitation 5 mm/hour
WS	Wind speed computation
NO_PS	No population sheltering
PS	Successful population sheltering
EARLY_EV	Evacuation completely successful
LATE_EV	Evacuation not completely successfully
HALF_EV	In the case wind direction north, Kakuda is evacuated but Minamisoma is not.




PR
WS
NO_PS
EARLY_EV
#14
LATE_EV
#15
PS
EARLY_EV
#16
LATE_EV
#17
NORTH
NO
WS
NO_PS
EARLY_EV
#18
LATE_EV
#19
HALF_EV
#20
PS
EARLY_EV
#21
LATE_EV
#22
HALF_EV
#23
PR
WS
NO_PS
EARLY_EV
#24
LATE_EV
#25
HALF_EV
#26
PS
EARLY_EV
#27
LATE_EV
#28
HALF_EV
#29
SWSOUTH
NO
WS
NO_PS
EARLY_EV
#30
LATE_EV
#31
PS
EARLY_EV
#32
LATE_EV
#33
PR
WS
NO_PS
EARLY_EV
#34
LATE_EV
#35
PS
EARLY_EV
#36
LATE_EV
#37

The initial section:

```
real cancers, $ the number of cancer deaths
     wind_speed,
     dist1, $ distance from the plant
     dist2,
     time1, $ time when the plume arrives
     time2,
     shfactor, $ sheltering factor
     pdose, $ baseline population dose based on wind
     pdose2,
     st, $ factor of source term uncertainty
     st2,
     cancer_factor $ number of cancers multiplied from pdose

real cor, evac_factor, evac_factor2
real te, i, xe, cs134, cs136, cs137

boolean rain

string dir

source cancers

collect wind_speed, st

routine init
  BinFreq = 1

  $ the number of cancer death multiplied from the population
dose
  cancer_factor = raneven(0.03, 0.07)

  $ source term uncertainty computation
  cor = rannorm(0.5, 0.0875) $ correlation factor
  i = rannorm(0.525, 0.0919)
  te = (1-cor)*rannorm(0.11, 0.0193)+i*0.11/0.525*cor
  xe = rannorm(0.06, 0.0105)
  cs134 = (1-cor)*rannorm(0.115, 0.0201)+i*0.115/0.525*cor
  cs136 = (1-cor)*rannorm(0.01, 0.00175)+i*0.01/0.525*cor
  cs137 = (1-cor)*rannorm(0.18, 0.0315)+i*0.18/0.525*cor
  st = te+i+xe+cs134+cs136+cs137 $ factor of source term
uncertainty
  st2 = te+i+xe+cs134+cs136+cs137
return

routine finish
  if rain then
  begin
    $ when it rains, the whole population dose comes from
xenon
    st = xe/0.06
    st2 = xe/0.06
```

```
  end
  else
  begin
    $ factor of source term uncertainty changed according to
wind speed
    $ the fraction of xenon depends on wind speed
    $ st2 is for Minamisoma and st for other cities
    if wind_speed > 16 then
    begin
      st = (st-xe)*103/100+xe*0.5
      st2 = (st2-xe)*103/100+xe*0.5
    end
    else if wind_speed > 8 then
    begin
      st = (st-xe)*104/100+xe*4/6
      st2 = (st2-xe)*103/100+xe*0.5
    end
    else if wind_speed > 4 then
    begin
      st = (st-xe)*105/100+xe*5/6
      st2 = (st2-xe)*104/100+xe*4/6
    end
    else if wind_speed > 1 then
    begin
      st = (st-xe)*98/100+xe*8/6
    end
    else
    begin
      if samestr(dir, 'NWest') then
      begin
        st = (st-xe)*80/100+xe*26/6
      end
      else if samestr(dir, 'SWSouth') then
      begin
        st = (st-xe)*93/100+xe*13/6
      end
      else
      begin
        st = (st-xe)*84/100+xe*22/6
      end
      st2 = (st2-xe)*98/100+xe*8/6
    end
  end

  $ The number of cancer deaths calculated.
  $ Baseline population dose is scaled according to
  $ source term uncertainty, evacuation factor, sheltering
factor.
  $ Population dose is multiplied by the cancer factor.
  $ When wind direction is north, there are two cities with
different
```

```
  $ population doses, evacuation factors and source term
uncertainty factors.
  if samestr(dir, 'North') then
  begin
    cancers =
(pdose2*evac_factor2*st+pdose*evac_factor*st2)*shfactor*cancer
_factor
  end
  else
  begin
    cancers = pdose*shfactor*st*evac_factor*cancer_factor
  end

  if cancers < 0.1 then dir = 'Other'
return

class dir
routine binner active
  ('NWest',    'Expo'),
  ('West',     'Expo'),
  ('North',    'Expo'),
  ('SWSouth',  'Expo'),
  ('Other',    'Other')
return
```

WDIR section

```
real nw, w, n, sws

routine init
  nw = raneven(0.018, 0.058)
  w = raneven(0.007, 0.047)
  n = raneven(0.094, 0.134)
  sws = raneven(0.077, 0.117)
return

$ Fukushima city is located in northwest
function real NWEST
  dist1 = 64
  dist2 = 0
  dir = 'NWest'
return nw

$ Koriyama is located in west
function real WEST
  dist1 = 56
  dist2 = 0
  dir = 'West'
return w

$ Minamisoma and Kakuda are located in north
function real NORTH
  dist1 = 27
```

```
  dist2 = 58 $ dist2 for Kakuda
  dir = 'North'
return n

$ Iwaki is located in southwest south
function real SWSOUTH
  dist1 = 48
  dist2 = 0
  dir = 'SWSouth'
return sws

$ No cities in other directions
function nil OTHER
  dist1 = 0
  dist2 = 0
  dir = 'Other'
  pdose = 0
  pdose2 = 0
return nil
```

PRECIP section

```
real hp

routine init
  hp = raneven(0.158, 0.358)
return

function real PR
  rain = true
return hp

function nil NO
  rain = false
return nil
```

WSPEED section:

```
real u, a, b, w

integer j

$ wind speeds and corresponding baseline population dose for
$ each city in both rain and no rain conditions.
vector(31) speeds = (0.5, 1, 1.5, 2, 2.5, 3, 3.5, 4, 4.5, 5,
5.5, 6, 6.5, 7, 8, 10, 12, 14, 16, 18, 20, 22, 24, 26, 28, 30,
32, 34, 36, 38, 40),
           doseMn = (2360, 1680, 1290, 1080, 954, 870, 814,
768, 729, 696, 667, 640, 614, 591, 551, 489, 430, 384, 348,
313, 284, 259, 238, 216, 197, 182, 168, 156, 146, 137, 129),
           doseIn = (3760, 3430, 2800, 2350, 2040, 1810, 1650,
1530, 1430, 1350, 1290, 1250, 1200, 1170, 1100, 996, 908, 838,
```

```
781, 734, 681, 635, 596, 562, 532, 503, 473, 447, 424, 403,
384),
           doseKOn = (2840, 2560, 2160, 1860, 1610, 1430,
1290, 1190, 1110, 1050, 995, 952, 920, 891, 841, 762, 703,
649, 606, 569, 538, 508, 477, 450, 386, 369, 350, 333, 317),
           doseKAn = (241, 220, 188, 162, 140, 125, 113, 104,
97, 91.4, 86.6, 82.5, 79.7, 77.2, 72.8, 66.1, 60.9, 56.4,
52.6, 49.5, 46.8, 44.5, 41.7, 39.4, 37.3, 35.4, 33.8, 32.3,
30.9, 29.4, 28),
           doseFn = (1830, 1740, 1530, 1320, 1160, 1030, 932,
855, 794, 748, 709, 675, 645, 624, 589, 534, 493, 460, 429,
404, 382, 363, 347, 328, 310, 295, 282, 269, 258, 248, 238),
           doseMp = (190, 100, 70.3, 54.6, 45, 38.7, 34.4,
31.1, 28.5, 26.3, 24.5, 23, 21.6, 20.5, 18.6, 15.8, 13.3,
12.1, 12.4, 14.7, 19.2, 26.3, 36, 48.1, 62.2, 78.3, 95.7, 114,
134, 154, 174),
           doseIp = (482, 258, 177, 137, 112, 95.8, 83.7,
74.5, 67.3, 61.5, 57.1, 53.5, 50.3, 47.6, 43, 36.4, 31.8,
28.4, 25.8, 23.7, 21.4, 19.7, 18.6, 18.2, 18.6, 19.8, 22.2,
25.6, 30.2, 36.1, 43.1),
           doseKOp = (608, 212, 146, 112, 92, 78.4, 68.5,
60.9, 55, 50.2, 46.2, 43, 40.5, 38.2, 34.6, 29.2, 25.5, 22.7,
20.6, 18.9, 17.5, 16.2, 14.9, 13.9, 13.3, 13, 13.1, 13.7,
14.8, 16.5, 18.7),
           doseKAp = (54.1, 18.7, 12.9, 9.85, 8.1, 6.9, 6.03,
5.36, 4.84, 4.41, 4.06, 3.77, 3.55, 3.35, 3.03, 2.56, 2.23,
1.99, 1.8, 1.66, 1.53, 1.43, 1.32, 1.22, 1.16, 1.12, 1.11,
1.14, 1.2, 1.31, 1.46),
           doseFp = (472,, 158, 109, 83.5, 68.4, 58.3, 50.9,
45.3, 40.8, 37.2, 34.3, 31.8, 29.7, 28, 25.3, 21.3, 18.6,
16.6, 15, 13.8, 12.8, 11.9, 11.2, 10.4, 9.68, 9.15, 8.78, 8.6,
8.63, 8.88, 9.38)

routine init
  $ wind speed is sampled from Weibull distribution
  a = raneven(0.4365, 0.5335)
  b = raneven(1.7487, 2.1373)
  u = random()
  wind_speed = b*pow(-ln(1-u),1/a) $ a = 0.485, b = 1.943
return

$ population dose is calculated based on wind speed
function nil WS
  $ finding right place (index j) in the vector
  j = 1
  while (wind_speed > speeds(j)) and (j < 31) do
  begin
    j = j+1
  end

  $ w is a weight for interpolation between two values
  if same(j, 1) then
```

```
    begin
      $ pdose is the dose of wind speed 0.5
      w = 0
      j = 2
    end
    else
    begin
      w = (wind_speed-speeds(j-1))/(speeds(j)-speeds(j-1))
    end
    if w > 1 then w = 1 $ pdose is the dose of wind speed 40

    $ population dose is calculated by interpolation
    if rain then
    begin
      if samestr(dir, 'NWest') then
      begin
        pdose = (1-w)*doseFp(j-1)+w*doseFp(j)
      end
      else if samestr(dir, 'West') then
      begin
        pdose = (1-w)*doseKOp(j-1)+w*doseKOp(j)
      end
      else if samestr(dir, 'North') then
      begin
        pdose = (1-w)*doseMp(j-1)+w*doseMp(j)
        pdose2 = (1-w)*doseKAp(j-1)+w*doseKAp(j) $ pdose2 for
  Kakuda
      end
      else if samestr(dir, 'SWSouth') then
      begin
        pdose = (1-w)*doseIp(j-1)+w*doseIp(j)
      end
    end
    else
    begin
      if samestr(dir, 'NWest') then
      begin
        pdose = (1-w)*doseFn(j-1)+w*doseFn(j)
      end
      else if samestr(dir, 'West') then
      begin
        pdose = (1-w)*doseKOn(j-1)+w*doseKOn(j)
      end
      else if samestr(dir, 'North') then
      begin
        pdose = (1-w)*doseMn(j-1)+w*doseMn(j)
        pdose2 = (1-w)*doseKAn(j-1)+w*doseKAn(j) $ pdose2 for
  Kakuda
      end
      else if samestr(dir, 'SWSouth') then
      begin
        pdose = (1-w)*doseIn(j-1)+w*doseIn(j)
```

```
    end
  end
return nil
```

SHELTER section

```
real sp, sf

routine init
  sp = raneven(0.6, 1) $ sheltering probability
  sf = raneven(0.5, 0.9) $ sheltering factor
return

function real PS
  time1 = dist1/wind_speed
  time2 = dist2/wind_speed $ time2 for Kakuda
  shfactor = sf
return sp

function nil NO_PS
  time1 = dist1/wind_speed
  time2 = dist2/wind_speed $ time2 for Kakuda
  shfactor = 1
return nil
```

EVAC section

```
real l1, l2, evtime

routine init
  evtime = rannorm(72, 7.2) $ evacuation completed at this
time
return
$ to how large portion of the dose the population is exposed
$ evac_factor2 is for Kakuda, evac_factor for others
function nil LATE_EV
  evac_factor = (evtime-time1)/evtime
  evac_factor2 = (evtime-time2)/evtime
  if evac_factor < 0 then evac_factor = 0
  if evac_factor2 < 0 then evac_factor2 = 0
return nil

$ if the plume comes after evacuation time, population dose is
0
function real EARLY_EV
  l1 = time1/evtime
  if l1 > 1 then l1 = 1 else l1 = 0
  pdose = 0
  pdose2 = 0
  dir = 'Other'
return l1

$ Kakuda evacuated, but Minamisoma not
```

```
function real HALF_EV
  if (time1/evtime < 1) and (time2/evtime > 1) then
  begin
     l2 = 1
  end
  else
  begin
     l2 = 0
  end

  pdose2 = 0

  evac_factor = (evtime-time1)/evtime
  if evac_factor < 0 then evac_factor = 0
return l2
```