DISSERTATION

A NET-RISK APPROACH TO DISPLACEMENT AND REOCCUPATION DECISION MAKING

Submitted by

Gerald Scott Braley

Department of Environmental and Radiological Health Sciences

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Doctoral Committee:

Advisor: Thomas E. Johnson

Alexander Brandl
Gwen Fisher
Ralf Sudowe

ABSTRACT

A NET-RISK APPROACH TO DISPLACEMENT AND REOCCUPATION DECISION MAKING

Decision makers and planners have a large body of information available concerning most aspects of a radiation disaster. International and national standards organizations, as well as national and local level policies and plans provide little guidance about the risks involved in relocating a population from a radiologically contaminated area. Populations displaced after all types of disasters have demonstrated poorer health outcomes, both physiological and psychological, than their non-displaced peers. These include a greater risk of diabetes and greater rates of post-traumatic stress disorder and depression when compared with other populations who experienced the disaster but were not relocated. Methodologies for population-level radiation dose prediction have improved, with recent data from contaminated areas in Japan providing real-world information about radiation doses. These improvements have not yet made their way into policies and guidance. The objective of this work is to quantify and incorporate multiple forms of risk, radiological and non-radiological, into a single model to improve decision making and minimize harm connected to displacement from and reoccupation of radiologically contaminated areas after a disaster.

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INTRODUCTION

Major disasters can result in large scale and long-term displacements of affected populations. Hurricane Katrina in March 2005 resulted in the initial dislocation of almost 1.5 million people; six months later, just over 40% of them – 600,000 people – still had not returned (Groen, 2008). The earthquake and tsunami that struck eastern Japan in March, 2011 resulted in the release of large quantities of radioactive material from the Fukushima Daiichi Nuclear Power Plant, some of which was deposited in populated areas of Fukushima, Iwate, and Miyagi Prefectures. Over several months, the Government of Japan ordered the relocations of almost 400,000 people in response to this triple disaster. (NCRP, 2014) While there is no formal dividing line between evacuation and displacement, this work considers evacuation to be a short-term relocation (days to weeks), while displacement is longer-term (months to years).

Experiences with these displacements have led to questions about the relative value of relocating people after a radiological incident. Historically, evacuating sensitive populations (such as hospital inpatients and nursing home residents) has led to excess mortality simply due to disruptions in care and the stress of the move (e.g. (Brown et al., 2012)), but the 2011 evacuations in Fukushima Prefecture led to a new wave of studies examining this phenomenon. Nomura et al., for example, found that nursing home residents had three times the mortality risk after being evacuated than they had before the earthquake (Nomura et al., 2013). Comparisons of health records from before and after the disaster have shown that increased

incidence of diabetes causes a greater loss of life expectancy (LLE) than radiation in affected areas (Murakami, Tsubokura, Ono, Nomura, & Oikawa, 2017).

The overall risks of displacement have historically been difficult to quantify and have been extremely situation dependent. Current U.S. and international standards for evacuation and displacement due to a radiological release are dose-based, with some policies accounting for special populations and local circumstances.

The hypothesis of this work is that a model can be created that will quantify and incorporate multiple forms of risk, radiological and non-radiological, to improve decision making and minimize harm connected to displacement from and reoccupation of radiologically contaminated areas after a disaster. The goal is quantify the risks of displacing a given population due to radioactive contamination, and to directly compare risks to a population for a given radiological release scenario with the risks of displacing that same population. The ultimate objective is to enable planners and emergency managers to make better judgements on when to consider evacuation and displacement. The specific aim is to provide a tool to advocate for the use of net risk instead of simply dose-based action criteria in public policy. This work does not aim to predict the actual probability of mortality in a given population; rather, it attempts to provide useful information for emergency planning and decision making.

While important, this work does not consider economic costs and impacts of evacuation, relocation, or remaining in place. Many of the psycho-social impacts of the disaster will be linked to economic damages and loss of livelihood, but these will not be explicitly considered.

POPULATION DOSE ASSESSMENT

Introduction: Dose as a Proxy for Risk

Most radiation policy is based on dose – whether for worker safety (0.005 Sv total effective dose equivalent/year)(U.S. Nuclear Regulatory Commission, 2015) or public safety (0.02 mSv per hour) (U.S. Nuclear Regulatory Commission, 2015). The International Commission on Radiation Protection (ICRP) states that the factors used to develop their standards include the reduction of life expectancy due to radiation as well as the increase in age-specific mortality rates. (ICRP, 2006a) There are regulations and policies based on other non-stochastic biological end states (such as cataracts or acute radiation sickness) but the current effort focuses on excess cancer mortality due to radiation exposures in affected populations, as this is the primary driver for displacement and reoccupation decision making.

Note that this work considers only gamma-emitting isotopes in the environment, although radiological incidents can include considerable releases of alpha- and beta-emitting materials. Further, this work focuses on stochastic effects, specifically increased cancer incidence, and assumes low dose rates (on the order of 20 µSv per hour or less) for exposed populations. Unless otherwise specified, this work uses the term *dose* to refer to the *total effective dose equivalent (TEDE)*, as defined in 10 CFR 20.1003. (U.S. Nuclear Regulatory Commission, 2015) A summary of the basis for TEDE can be found at Appendix 1.

Sources of Effects Information and Current Methodologies

Much of the radiation risk data used to develop radiation safety standards is from three major cohorts – survivors of the atomic bombs dropped by the United States at Hiroshima and Nagasaki, Japan, during World War Two; workers in the nuclear industry including those involved in uranium extraction; and persons exposed to fallout during above-ground nuclear weapons testing. Other radiation risk data comes from the medical community, from research on non-human subjects, and from various accidental exposures over roughly the last 100 years. (Committee to Assess Health Risks from Exposure to Low Levels of Ionizing Radiation, 2006)

The bulk of the discernable effects within a population (e.g. excess cancer mortalities) occur with doses exceeding 100 mGy in a short time frame. The effects of lower doses, or doses occurring at low dose rates over long time frames, become difficult to discern from background rates of cancers. (Committee to Assess Health Risks from Exposure to Low Levels of Ionizing Radiation, 2006) Regulators and advisory bodies have adopted a model in which dose and effect are extrapolated linearly to zero, known as the Linear-No-Threshold Model (LNT). (Committee to Assess Health Risks from Exposure to Low Levels of Ionizing Radiation, 2006)

Estimates of excess cancer mortality based on radiation exposure distill large variations in risk into a single risk value. Generally, risk values are developed by examining actuarial data for a variety of cancer types (such as bladder, stomach, lung, and others) as well as the associated demographic and radiation exposure information, then subtracting background rates of the same cancers in the same demographic, and normalizing for the estimated radiation dose. An

excess cancer mortality rate is then calculated based on a given dose of radiation for each considered cancer type. (Committee to Assess Health Risks from Exposure to Low Levels of Ionizing Radiation, 2006) These risk rates are then summed; typically radiation risks are grouped into two broad categories of cancers, solid cancers and leukemias.

Assessments of Cancer Risk from Radiation

Table 1 shows selected estimates of the nominal cancer mortality risk per unit radiation dose, including those from the BEIR (Biological Effects of Ionizing Radiation) VII committee (Committee to Assess Health Risks from Exposure to Low Levels of Ionizing Radiation, 2006), ICRP 103 (ICRP, 2007), the United States Environmental Protection Agency (EPA) (EPA, 1999), and (United Nations Scientific Committee on the Effects of Atomic Radiation (UNSCEAR) (United Nations Scientific Committee on the Effects of Atomic Radiation, 2000). Also included are ICRP 26 (ICRP, 1977) and ICRP 60 (ICRP, 1991), from which many of the U.S. and international regulations are derived. Note that the U.S. EPA attempts to set standards based on a 1×10^{-4} to 1×10^{-6} risk of cancer incidence, and presumes that cancer incidence attributable to radiation is 8×10^{-5} per mSv and cancer mortality risk is 6×10^{-5} per mSv.(EPA, 2017) Similarly, the ICRP considers cancer risks on the order of 1×10^{-6} to be "…a region in which people are usually content to dismiss the risk as approaching the trivial." Risks of 1×10^{-5} are considered "minor," and 1×10^{-4} intermediate.(ICRP, 2006a)

Table 1: Comparison of Estimates of Cancer Mortality Risk per Unit Dose, All Cancers

Source	Estimate (Excess Fatalities per 10,000 per Sv)	Reference
BEIR VII	474	(Committee to Assess Health Risks from Exposure to Low Levels of Ionizing Radiation, 2006)
EPA	600	(EPA, 1999)
ICRP 103	503	(ICRP, 2007)
ICRP 60	600	(ICRP, 1991)
ICRP 26	100	(ICRP, 1977)
UNSCEAR	520[1]	(United Nations Scientific Committee on the Effects of Atomic Radiation, 2000)

Note: Estimate is the average of male and female values

Table 2 is adapted from the BEIR VII report(Committee to Assess Health Risks from Exposure to Low Levels of Ionizing Radiation, 2006) and shows the detailed age and sex breakdown of cancer mortality risks. Generally, radiogenic cancer mortality risk is greater for females, and for persons under 20 years of age.

[1] All solid cancers (excludes leukemia)

Table 2 Lifetime Attributable Risk of Cancer Mortality by Age and Sex: Single dose, 0.1 Gy (Committee to Assess Health Risks from Exposure to Low Levels of Ionizing Radiation, 2006)

Age at Exposure (years)											
Cancer Site	0	5	10	15	20	30	40	50	60	70	80
Males											
Stomach	41	34	30	25	21	16	15	13	11	8	4
Colon	163	139	117	99	84	61	60	57	49	36	21
Liver	44	37	31	27	23	16	16	14	12	8	4
Lung	318	264	219	182	151	107	107	104	93	71	42
Prostate	17	15	12	10	9	7	6	7	7	7	5
Bladder	45	38	32	27	23	17	17	17	17	15	10
Other	400	255	200	162	134	94	88	77	58	36	17
All Solid	1028	781	641	533	444	317	310	289	246	181	102
Leukemia	71	71	71	70	67	64	67	71	73	69	51
All Cancers	1099	852	712	603	511	381	377	360	319	250	153
Females											
Stomach	57	48	41	34	29	21	20	19	16	13	8
Colon	102	86	73	62	53	38	37	35	31	25	15
Liver	24	20	17	14	12	9	8	8	7	5	3
Lung	643	534	442	367	305	213	212	204	183	140	81
Breast	274	214	167	130	101	61	35	19	9	5	2
Uterus	11	10	8	7	6	4	4	3	3	2	1
Ovary	55	47	39	34	28	20	20	18	15	10	5
Bladder	59	51	43	36	31	23	23	22	22	19	13
Other	491	287	220	179	147	103	97	86	69	47	24
All Solid	1717	1295	1051	862	711	491	455	415	354	265	152
Leukemia	53	52	53	52	51	51	52	54	55	52	38
All Cancers	1770	1347	1104	914	762	542	507	469	409	317	190

Note: Number of deaths per 100,000 persons exposed to a single dose of 0.1 Gy.

One interesting implication of these age- and sex-dependent risks is that different populations, exposed to the same radiation levels, might experience differing excess cancer mortality risks. For example, a community with a university might experience higher risks than a retiree-dominated community. By taking the demographic profile of the United States (U.S. Census Bureau, 2010) and cross referencing it with the mortality data in Table 2 one can determine an

expected excess mortality per 10,000 persons per Gy (or, for external gamma exposure, Sv) of 598 (see Appendix 1 for calculation details). This value compares well with the values in Table 1. Repeating the exercise for other populations yields differing results. Figure 1 shows the population distributions, by age and sex, of the United States (median age 37.5 in 2015), Nigeria (median age 17.9 in 2015), and Japan (median age 46.3 in 2015). (U.S. Census Bureau, 2010)

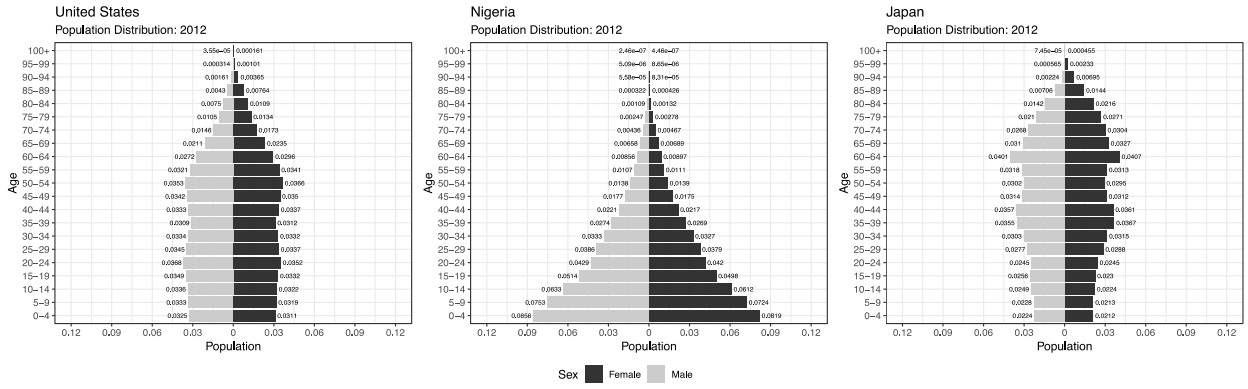


Figure 1 Population Distributions (by age and sex) of the United States, Nigeria, and Japan (U.S. Census Bureau, 2010)

For a country with a significantly older population, such as Japan, the calculation yields a result of 524 per 10,000 per Gy, while a population that skews much younger, such as Nigeria, yields a result of 869, as shown in Table 3. A strong, largely age-based, variation suggests that dose-based standards may be over- or under-protective in cases where the affected population diverges strongly from the demographics from which the risk estimates were developed. This work will utilize the age and sex distributions of these same populations, the United States, Nigeria and Japan, as representative middle-aged, young, and older populations.

Table 3 Calculated Excess Risk of Cancer Mortality from 1 Gy, in Deaths per 10,000 Persons

Country	Median Age in 2015 (U.S. Census Bureau, 2010)	Calculated Aggregate Cancer Mortality Risk
United States	37.5 years	598
Nigeria	17.9 years	869
Japan	46.3 years	524

The BEIR VII Committee also evaluated the cancer mortality for two chronic low-level exposure scenarios. In the first, the hypothetical population is exposed to 1 mGy per year from birth. The Committee utilized life tables based on Anderson et al. (Anderson & DeTurk, 2002), with a United States life expectancy at the time of 76.7 years. In the second scenario, the population is exposed to 10 mGy per year from ages 18 to 65. The cancer mortality risks were then tabulated by BEIR VII. The results are summarized in Table 4, below. Note that the total doses discussed are 76.7 mGy and 470 mGy respectively.

Table 4 Lifetime Attributable Risk of Solid Cancer Incidence and Mortality, Chronic Low-level Exposure based on BEIR VII (Committee to Assess Health Risks from Exposure to Low Levels of Ionizing Radiation, 2006)

	Exposure Scenario	
Cancer Site	1 mGy per year throughout life	10 mGy per year from ages 18 to 65
Males		
Stomach	13	66
Colon	53	273
Liver	14	72
Lung	99	492
Prostate	6.3	32
Bladder	16	80
Other	85	395
All Solid	285	1410
Leukemia	47	290
All Cancers	332	1700
Females		
Stomach	19	94
Colon	34	174
Liver	8	40
Lung	204	1002
Breast	53	193
Uterus	3.5	18
Ovary	18	91
Bladder	21	108
Other	98	449
All Solid	459	2169
Leukemia	38	220
All Cancers	497	2389

Note: Number of deaths per 100,000 persons exposed to 1 mGy per year throughout life or to 10 mGy per year from ages 18 to 64. Cumulative doses are roughly 90 mGy and 460 mGy respectively.

Note that, in all three of these tables, the unit of dose is the Gray. When considering external exposures to primarily gamma emitters, this is effectively equivalent to the Sievert, as the radiation weighting factor for photons is 1. (ICRP, 2007)

Focusing on excess mortality from all cancers, Table 4 can be reduced to the following:

Table 5 Excess Cancer Mortality for Two Scenarios, by Sex, per 10,000 people exposed

	Exposure Scenario		
Sex	100 mGy to mixed-age population	1 mGy per year throughout life	10 mGy per year from ages 18 to 65
Male	479	332	1700
Female	662	497	2389

Dose Limits Applied to Radiation Disasters

There have been two radiation disasters which resulted in the long-term displacement of large populations: Chernobyl (1983) and Fukushima (2011). Other radiation disasters that resulted in a release of contamination, such as the Windscale Fire (1957) (Eisenbud, 1997), the Palomares Crash (1966) (Eisenbud, 1997), or Three Mile Island (1979) (Eisenbud, 1997), did not lead to population displacements and are not considered here.

On April 26, 1986 workers conducting a test turned off critical safety systems at the Chernobyl Nuclear Power Plant in Ukraine, at the time part of the USSR. Absent these safety systems, a power surge caused a steam explosion that damaged the core and reactor vessel. This led to a graphite fire that burned intensely for about 10 days, spreading radioactive material over much of the northern hemisphere. Roughly 5.2 EBq of radioactive material was released, mainly short-lived isotopes. About 1,770 PBq of ^{131}I and 85 PBq of ^{137}Cs were released. Ultimately,

about 115,000 people were displaced as a result of the release. (United Nations Scientific Committee on the Effects of Atomic Radiation, 2008)

On March 11, 2011 a magnitude 9.0 earthquake struck just off the eastern coast of Japan, triggering a tsunami that killed nearly 20,000 people. (Nakahara & Ichikawa, 2013) In addition, the earthquake and tsunami disabled power to all six units of the Fukushima Daiichi Nuclear Power Plant, eventually leading to core melts in three of the units, as well as damage to the spent fuel pool. The damaged facility released approximately 770 PBq of radioactive material, primarily ^{131}I, ^{134}Cs and ^{137}Cs. This represented roughly 10% of the activity released by the Chernobyl disaster. As a result of the earthquake, tsunami, and power plant disasters, almost 400,000 people in the Fukushima, Iwate, and Miyagi Prefectures were displaced. (United Nations Scientific Committee on the Effects of Atomic Radiation, 2013)

Current Policy Guidance for Occupation of Contaminated Areas

Table 6 presents a summary of current policy guidance for occupation of or displacement from contaminated areas, from the United States Government and from other national and international standards bodies.

Table 6: Summary of Policy Guidance for Post-Emergency Occupation

Source	Dose Limit	Calculation	Source	Regulatory?
US EPA[2]	20 mSv / first year 5 mSv / following years	Worst Case, ambient dose rate @ 1 m	Protective Action Guides(EPA, 2017)	No
US NRC[3]	1 mSv / year	Calculated individually	10 CFR 20 (U.S. Nuclear Regulatory Commission, 2015)	Yes
ICRP[4]	1 mSv / year averaged over 5 years	95th Percentile "reference person"	ICRP 103 (ICRP, 2007)	No
ICRP	1 – 20 mSv / year	95th Percentile "reference person"	ICRP 111 (ICRP, 2009)	No
IAEA[5]	25 µSv / hour (~ 220 mSv / year)	Ambient dose rate @ 1 m	EPR-NPP Public Protective Actions (International Atomic Energy Agency, 2013)	No
IAEA	20 mSv / year	(per ICRP)	IAEA General Safety Requirements Part 7(International Atomic Energy Agency, 2015)	No
NCRP[6]	1-20 mSv / year	(per ICRP)	NCRP 175(NCRP, 2014)	No

The U.S. Environmental Protection Agency (EPA) produces the primary guidance for the United States in the form of the "PAG Manual: Protective Action Guides and Planning Guidance for

[2] *United States Environmental Protection Agency*

[3] *United States Nuclear Regulatory Commission*

[4] *International Commission on Radiological Protection*

[5] *International Atomic Energy Agency*

[6] *National Council on Radiation Protection and Measurements*

Radiological Incidents." The most recent version was published in 2017 (EPA, 2017). This manual (hereinafter "PAGs") is non-statutory, consisting only of non-binding recommendations to emergency planners and policy makers. The EPA divides a radiation emergency into three phases – the Early phase, the Intermediate phase, and the Late phase. Determinations about long-term displacement fall into the Late phase in EPA parlance.

The EPA recommends that, at doses projected to exceed 20 mSv in the first year, and 5 mSv in the following years, local officials consider relocation of the affected population.

For comparative purposes, the U.S. Nuclear Regulatory Commission, whose regulatory authority does not specifically apply to emergencies or evacuation decisions, enforces a whole-body public dose limit of 1 mSv per year for activities under its purview. (U.S. Nuclear Regulatory Commission, 2015)

The ICRP offers more nuanced guidance for post-emergency dose levels, having adopted several concepts of interest. Ultimately, the ICRP recommends public dose limits of less than 1 mSv per year. (ICRP, 2007) However, they acknowledge the challenges of reaching these levels, and consider a band of doses between 1 and 20 mSv per year to be more achievable. (ICRP, 2009) They incorporate a process of "optimization" into their recommendations, a term which evolved out of cost-benefit analysis and keeping doses As Low As Reasonably Achievable (ALARA) (ICRP, 1977). Acknowledging the complexities and uncertainties of population dose assessment and prediction, the ICRP recommends assessing the dose to the "representative

person"(ICRP, 2006b), effectively the 95th percentile of the population (described more fully in a later section).

The International Atomic Energy Agency (IAEA) provides two standards, differing in applicability and measurement, but generally defers to the ICRP (discussed in the following section). (International Atomic Energy Agency, 2015)

The (United States) National Council on Radiation Protection and Measurements (NCRP) directly adopts the ICRP standards. (NCRP, 2014)

Predicting Population Doses for Comparison to Dose Limits – Summary of Methodologies

Predicting population doses is a highly variable and uncertain process, especially in the early phases of an incident. The quantity and types of radionuclides released may be difficult to estimate. The distribution of those radionuclides in the environment is strongly affected by winds, terrain, initial particle size, temperature, the forces involved in the release (e.g. explosion, pressurized venting, et al.), and precipitation, to name some of the most important factors. Once the initial plume has passed, deposited particles of radioactive materials can be resuspended by winds, carried by rain or snow, incorporated into vegetation, or migrate deeper into soils and other surfaces. The dose to an individual will be affected by their behavior and personal characteristics such as time spent in contaminated areas, breathing rate, diet, and shielding (such as a building or vehicle). Selecting which individual(s) on which to base a population dose is also a complex process. A person who largely remains indoors will have a

very different exposure profile than an agricultural worker, for example. This type of assessment is considered a *prospective assessment*.(ICRP, 2006b) Note that these methodologies differ from those used in dose reconstruction, where available data is used to estimate past doses to individuals or populations. An example of these *retrospective* methodologies can be found at Akahane et al. (Akahane et al., 2013), which describes the estimation system for doses to residents of Fukushima during the first four months after the Great East Japan Earthquake of 2011 and subsequent radiological release from the Fukushima Daiichi NPP.

Policies for responding to radiological incidents include strict controls for foodstuffs and water. This work presumes that these controls are in place and effective and that contributions from the ingestion pathway are negligible. This was largely the case in Japan after the Fukushima release, for example. (United Nations Scientific Committee on the Effects of Atomic Radiation, 2013)

The inhalation pathway is important to large-scale radioactive releases under two circumstances – first, when a receptor is inside the plume, and secondly when deposited material is resuspended by traffic, winds, and other events. Many of the referenced policies (such as (EPA, 2017)) specifically consider the reseuspension pathway to be a near-negligible contributor during intermediate- and late-phase responses such as those under consideration here. Therefore, the inhalation pathway will not be considered in this work.

The U.S. EPA, the IAEA, the ICRP, the U.S. Nuclear Regulatory Commission, and the Government of Japan each have different formal methodologies for estimating population doses.

Summary of EPA Methodology

The most recent version of the U.S. EPA's Protective Action Guides (PAG) was published in 2017. (EPA, 2017) The PAG defines projected dose as the "sum of the effective dose from external radiation exposure … and the committed effective dose from inhaled radioactive material." (EPA, 2017) Note that this specifically excludes an ingestion pathway, as a base assumption that food and water intake of radionuclides will be managed to negligible levels. For EPA purposes, evacuation is defined as "the urgent removal of people from an area to avoid or reduce high-level, short-term exposure[s]" while relocation is "the removal or continued exclusion of people (households) from contaminated areas to avoid chronic radiation exposure. (EPA, 2017) Explicit assumptions also include that populations "remain in the contaminated area during the entire time," "do not account for shielding provided by being indoors part of each day of the projection year," and that "radionuclides are in the chemical and physical form that yields the highest dose." Partially offsetting this, the EPA selected the value of 20 mSv based on an expectation that actual doses would in fact be reduced based on the above factors, resulting in a first-year dose of roughly 10 mSv. (EPA, 2017)

For dose estimation, the EPA turns to an interagency methodology developed by the Federal Radiological Monitoring and Assessment Center (FRMAC). The FRMAC publishes a technical document entitled the "*FRMAC Assessment Manual*" (FRMAC, 2015). For the intermediate

phase, the Projected Public Dose (Method 1.5), is simply the sum of the doses from external exposure to the deposited material and the dose from deposited material that has been taken into the body via resuspension and inhalation. Coupled with the highly (and explicitly) worst-case assumptions above, this is a relatively simple calculation. The concentration of each individual radioisotope is estimated or measured, the concentration-to-dose conversion factor is selected, and the results are summed and multiplied by the exposure time. Equation 1, below, illustrates the summation, where the dose contributions during the time phase (*TP*) under consideration are summed. PPD_{TP} is the population dose during the time phase of interest; $Dp\_InhDP_{i,\ TP}$ is the contribution from inhaled radionuclide *i* based on deposition; $Dp\_ExDP_{i,\ TP}$ is the contribution from external exposure to radionuclide *i* based on deposition.

Equation 1 Projected Public Dose (Intermediate Phase)(FRMAC, 2015)

$$PPD_{TP} = \sum_{i} Dp\_InhDP_{i,TP} \ + Dp\_ExDP_{i,TP}$$

The EPA states that age-based dose coefficients account for less than 15% differences in dose, well within the conservatism of the assumptions, so only adult coefficients are utilized. (EPA, 2017) The EPA PAG recommends relocation if public doses are estimated to exceed 20 mSv in the first year, and 5 mSv in subsequent years.(EPA, 2017)

Summary of IAEA Methodology

The IAEA publishes two different methodologies for assessing doses to the public. In its technical publication *Actions to Protect the Public in an Emergency Due to Severe Conditions at*

a Light Water Reactor (International Atomic Energy Agency, 2013), Operational Intervention Levels (OIL) are based on dose rates measured at 1 m above the ground. The primary OIL for relocation of the public in the intermediate / late phase is OIL 2, set at 25 µSv per hour. This aggregates to roughly 220 mSv per year, which appears at first glance to be considerably higher than most of the other standards, including others published by the IAEA itself. After consideration of the other normal dose reduction factors, however, (such as time spent in other areas, time spent indoors, weathering and decay, etc.) this level is roughly in line with other references. Other OILs address food and water ingestion, inhalation, and doses to a fetus. The IAEA also explicitly adopts the ICRP methodology in its publication *Preparedness and Response for a Nuclear or Radiological Emergency.* (International Atomic Energy Agency, 2015)

Summary of ICRP Methodology

The ICRP has prepared a detailed methodology for assessing population-level doses in ICRP Publication 101, "Assessing dose of the representative person for the purpose of radiation protection of the public." (ICRP, 2006b). They acknowledge the complexity and range of methodologies available for calculating population doses. Their recommended process can be summed up as the following, all from publication 101:

1) Gather information about the source term (radionuclides quantities and distributions, radiation emitted)
2) Gather information about the environment, including terrain and climate information

3) Combine these quantities and human behavioral information into an “exposure scenario,” effectively a profile of the time course of human exposure to the various radionuclides
4) Use coefficients to relate concentrations in air or soil to pathway dose rates – primarily external and ingestion, then sum those dose rates into a composite rate

Figure 2illustrates this process.

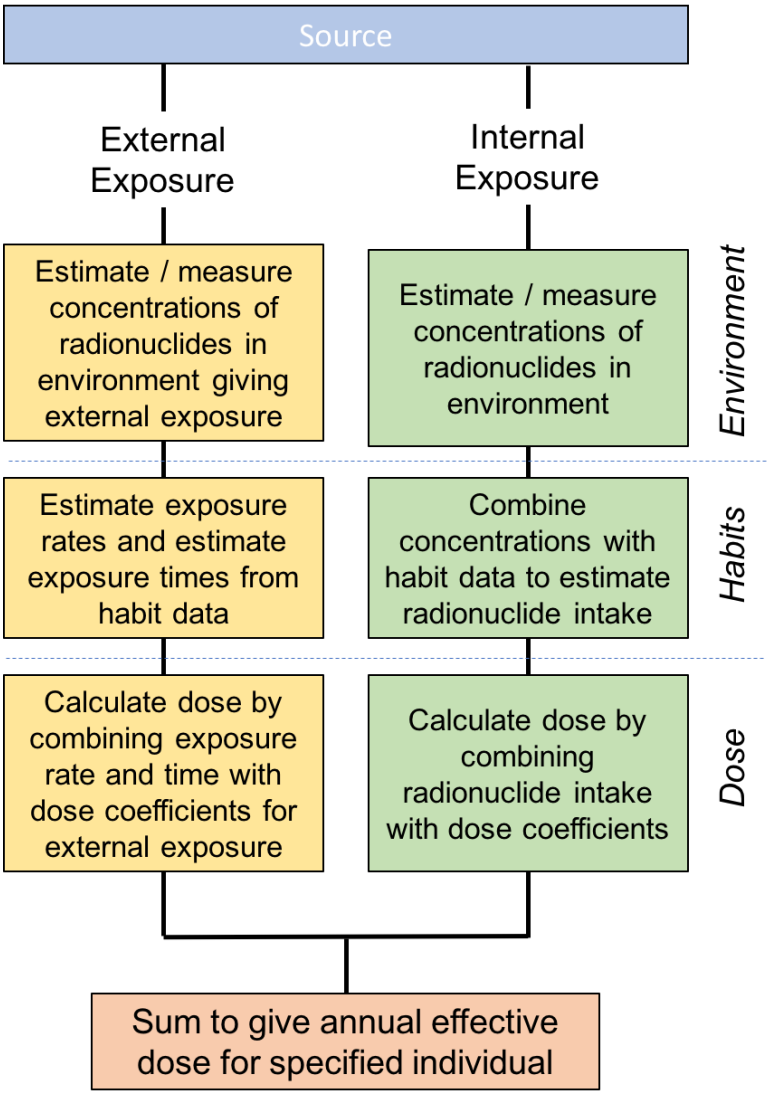


Figure 2 Dose-assessment process (adapted from ICRP 101, Figure 2.1, with permission)(ICRP, 2006b)

The ICRP does not provide a specific recommendation for deterministic versus probabilistic calculations, instead leaving the specific methodology to local authorities. They acknowledge that the two approaches "…may not necessarily yield mathematically equivalent results" (ICRP, 2006b) but that with transparency, appropriate peer review, and stakeholder involvement the goal of providing an appropriate estimate for determining the required protection can be met.

The ICRP introduced the concept of the "representative person" in 1985, in Publication 43 (ICRP, 1985). As currently described, the representative person is a hypothetical individual who "receives a dose that is representative of the more highly exposed individuals in the population." (ICRP, 2006b) The ICRP is careful to note that this person should not be developed using an extreme case, or entirely worst-case assumptions within the habit data (in contrast to the U.S. EPA). When a single pathway dominates the dose estimate (e.g. food intake) they recommend use of the 95th percentile habit profile, while other habits (such a breathing rate or outdoor time) should be closer to median values. Ultimately, the objective is to define the representative person such that "the probability is less that about 5% that a person drawn at random from the population will receive a greater dose." (ICRP, 2006b) The ICRP also suggests subdividing the population into three age bands: 0-6 years, 7-15 years, and 16-70 years, with each group utilizing dose coefficients for 1-year-olds, 10-year-olds and adults respectively.

ICRP Publication 103 sets a public dose reference level for relocation at 1 mSv per year (ICRP, 2007), but amended this for post-disaster response to a band of 1 – 20 mSv per year in ICRP Publication 111 (ICRP, 2009), acknowledging the difficulties of reaching 1 mSv per year after a major disaster.

U.S. NRC Methodology

The NRC is a special case, in that it only regulates certain activities and does not explicitly set criteria for relocation. The NRC sets a public exposure limit from regulated activities at 1 mSv per year. (U.S. Nuclear Regulatory Commission, 2015) If a radiological incident originates with

an NRC-licensed activity, it is conceivable that some decision-makers might attempt to apply this standard as an evacuation threshold. The NRC does not specify a calculation methodology.

Government of Japan, Ministry of the Environment Methodology

The Government of Japan (GOJ) uses a hybrid methodology for dose assessment.(Government of Japan, 2011) The total daily dose rate (DR_{total}) is calculated by summing the historical background dose rate (DR_{bg}) and a combination of two simple exposure scenarios. Using the ambient hourly dose rate (DR_{amb}) measured at 1 m above ground level, the GOJ assumes that the affected population spends 8 hours outdoors, unshielded, and 14 hours indoors, shielded by a wood frame house. The shielding factor used for the indoor period is 0.4. Equation 2 illustrates this relationship.

Equation 2 GOJ Daily Population Dose Estimate (Government of Japan, 2011)

$$DR_{total} = DR_{bg} + (8\ \text{hours} \times DR_{amb}) + (16\ \text{hours} \times 0.4 \times DR_{amb})$$

This results in a value that is less conservative than the U.S. EPA, while remaining simple to calculate. The equation simplifies to a daily dose rate of background plus 0.6 times the ambient hourly dose rate, or

Equation 3 Simplified GOJ Daily Population Dose Estimate

$$DR_{total} = DR_{bg} + (24\ \text{hours} \times 0.6 \times DR_{amb})$$

Modifications to Ambient Dose Rate for Improved Accuracy

At a coarse level, each of the population dose estimation methodology transforms measured or predicted deposition levels and ambient measurements into dose to an individual. The ICRP considers this in the "Habit" and "Dose" steps of its dose assessment process, shown in Figure 2. (ICRP, 2006b) The EPA relies on the deposition-to-dose coefficients in Federal Guidance Report 13 (EPA, 1999) and on a 1-to-1 conversion of ambient dose rates at 1 m above ground. (EPA, 2017) The Government of Japan uses a simple shielding factor to convert ambient doses to predicted population doses per Equation 3.

The radiological release at Fukushima Daiichi created an opportunity to test the conversion factors in areas which received radiological deposition, but which have since been decontaminated or did not receive significant contamination. Some areas still have residual ambient dose rates well above background levels, but do not reach levels that warrant relocation. Several municipalities and researchers have conducted research comparing ambient dose rates and actual external doses based on individual dosimetry.

Miyazaki et al. (Miyazaki & Hayano, 2016) described the efforts and data collected by Date City, in Fukushima Prefecture. The municipal government developed maps of the ambient dose rate at 1 m above ground for the entire city, divided into a grid of ~1 km squares. From July 2012 to June 2013 Date City issued glass dosimeters to ~65,000 residents. Combining the resulting measured doses with the household locations within the contamination map allows a comparison of mapped ambient dose rates versus the measured personal doses. The

researchers found that the ratio of individual dose rate to grid dose rates was 0.15 ± 0.03, or roughly one sixth of the ambient dose, or about one fourth of the values generated by the GOJ standard formula (Equation 3).

One limitation faced by simple dosimetry studies is that they are unable to distinguish between indoor and outdoor time, shielding factors, whether the dosimeter was actually worn, and other factors that may influence the resulting dose measurement. Naito et al. (Naito et al., 2016) provided 142 residents of Fukushima Prefecture with GPS-enabled dosimeters to measure their actual received doses, correlated with their locations. They demonstrated that overall dose rates were 0.18 of the nominal ambient dose rates, indoor dose rates were 0.14, and actual outdoor dose rates were only 0.32 of nominal ambient dose rates. The researchers suggest that the differences between the assumed shielding value of buildings (0.4) and the measured effective shielding value (0.14) could be attributed to more robust structures and time spent in buildings other than wood frame homes. They attribute the reductions in outdoor dose rates to the effects of incidental shielding (vehicles, buildings and vegetation) as well as time spent at heights higher than the measured 1 m elevation (e.g. on tractors). Additionally, they note that most people live and work in areas that were more intensely decontaminated than a general area measurement might account for in predicting dose rates.

Together, these papers suggest that the EPA's assumption of a 1-to-1 conversion of ambient dose rate to individual dose and the GOJ 0.6 conversion factor overstate received dose by

factors of roughly 6 and 4 respectively, a safety factor that may have strong impacts on evacuation and displacement decision making.

Introduction: Post-Disaster Health

Disasters carry long-term effects for the exposed population, even where the individual experiences no direct harm or loss. Studies following Hurricane Katrina identified increased overall mortality, physical disability, and degraded mental health among survivors. (Sastry & Gregory, 2013) A range of clinical outcomes have been identified; post-traumatic stress disorder (PTSD), anxiety, depression, and increased rates of substance abuse are the most commonly cited long-term effects (Neria, Nandi, & Galea, 2008; Porter & Haslam, 2005), with prevalence and duration varying with the affected population, proximity to the disaster, and time elapsed since the disaster took place. Interestingly, suicide rates appear to show little change after a disaster, though suicidal ideation and non-fatal self-harm showed increases in some cases. (Bonanno, Brewin, Kaniasty, & Greca, 2010) (Kolves, Kolves, & De Leo, 2013) Beyond mental health outcomes, researchers have studied changes in body composition and obesity (Ohira et al., 2016), metabolic syndrome(Hashimoto et al., 2017), physical performance (Ishii et al., 2015), cardiovascular health (Ohira et al., 2017), and effects on pregnancy and childbirth (Leppold et al., 2017).

Clinical outcomes due to evacuation and long-term displacement have been less studied, in part because separating the effects of the dislocation from the general effects of the disaster itself is difficult, and because relatively few disasters generate long-term, large-scale dislocation. A 2008 literature review of the health effects of relocation following disaster identified only 40

research articles published on this topic between 1950 and 2006, with only 24 of those containing quantitative data. (Uscher-Pines, 2009) This relatively small body of literature has been greatly enhanced since the 2011 Great East Japan Earthquake and the subsequent relocations due to potential radiation effects. The combination of a robust national health system and intense interest in the large displaced population has led to considerable study comparing populations relocated after the disaster with those similarly affected by the event, but not relocated, or which returned to their homes after a short evacuation.

In laying the groundwork for the parameters used to develop the risk model, this work presents a survey of clinical outcomes and post-disaster health.

General Effects of Disasters on Mortality Rates

Disasters have been identified as an indirect factor in mortality via increased risks of infectious disease (Kouadio, Aljunid, Kamigaki, Hammad, & Oshitani, 2012), impaired cardiovascular health (Kario, McEwen Bruce, & Pickering Thomas, 2003), and psychological disorders (Stephens et al., 2007).

Ho et al. examined overall mortality rates in the 5 years following the 2004 earthquake and tsunami that killed 170,000 people in Aceh, Indonesia. They found that, for most groups, surviving the disaster had a small, negative affect on mortality rates (that is, fewer deaths) in the first two years following the event, while in the out years (3-5 years post-disaster), populations who lost their homes in the flooding had elevated mortality rates (+7.58%, 95% CI

3.75% - 11.41%).(Ho, Frankenberg, Sumantri, & Thomas, 2017) This particularly affected males over 50 years old. The authors note that the short-term reduction in mortality was in spite of the initial slow pace of reconstruction.

Morita et al. (Morita et al., 2017) evaluated vital records from Soma City and Minamisoma City for a baseline period of 5 years before the 2011 earthquake (2006-2010) against records for the period 2011-2015, excluding direct deaths due to the earthquake and tsunami. They found that overall mortality risks in Fukushima Prefecture more than doubled in the month following the disaster (relative risk: 2.64 for men and 2.46 for women), with the leading causes identified as pneumonia (28% of overall mortality), stroke (15%), coronary heart disease (10%) and cancer (9%). The excess risk overall, and these specific causes, were more prominent in older populations. Morita et al. cited degradation of access to primary care due to the disaster as a primary cause of the excess mortality. The mortality risks returned largely to baseline levels within 3 months, with risks for younger populations (under 65) returning to baseline within 1 month. The study did not consider evacuated/displaced populations separately.

Focusing on effects on the elderly, several studies have examined how disasters and evacuation impacted nursing home residents. Brown et al. examined death records following Hurricane Gustav, which made landfall in Louisiana in September 2008. They found elevated mortality among nursing home residents with dementia at 30 days post-evacuation (+2.8%) and 90 days (+3.9%) compared to non-evacuated residents. (Brown et al., 2012) The duration of the evacuation was not discussed. Murakami et al. compared the tradeoff of hypothetical radiation

risks to the residents and staff of three nursing homes under an evacuation order in Fukushima province with the actual mortality experienced due to evacuation. (Murakami et al., 2015) They found that the Loss of Life Expectancy (LLE) for the rapid evacuation that took place greatly exceeded the estimated LLE even from radiation exposures much higher than experienced in the area (11,000 person days for rapid evacuation, 5800 for 100 mSv total exposures).

Nomura et al. conducted the most general study of excess mortality on residents of elder care facilities (not necessarily nursing homes per se), finding that the experience of the disaster itself represented only a small increase in mortality risk (hazard ratio 1.10, 95% CI 0.84-1.43), while evacuation from the original facility was associated with significantly higher mortality (hazard ratio 1.82, 95% CI 1.22-2.70). He did not consider the duration of the evacuation in this work. (Nomura, Blangiardo, Tsubokura, Nishikawa, et al., 2016)

Psychosocial Outcomes

The effects of disaster on mental health has been well documented, though again, reports examining differences in outcomes between displaced and non-displaced populations have been sparse. Many of these mental health outcomes are difficult to isolate and quantify, as they are often comorbid with each other.

Post-Traumatic Stress Disorder

PTSD General Characteristics

One of the most common mental health pathologies affecting the victims of a disaster is Post-Traumatic Stress Disorder (PTSD) (Neria et al., 2008). The Diagnostic and Statistical Manual of Mental Disorders (DSM-5) (American Psychiatric Association, 2013) describes PTSD as the presence of several intrusive symptoms associated with a traumatic event, including recurring memories, flashbacks, and intense or prolonged psychological distress. In the United States, the general background prevalence is ~3.5%, with variation by sex (rates are higher among men) and ethnicity (rates are higher among Latinos, African Americans, and Native Americans). Symptoms usually begin within 3 months of the trauma, but can take up to a year (R. C. Kessler et al., 2008). Comorbidities include anxiety, depression, and substance abuse.

Morina et al. (Morina, Wicherts, Lobbrecht, & Priebe, 2014) conducted a meta-analysis of the time course of PTSD and found a ~44% remission rate at 3 years after the traumatic event, but also noted 60% remission in the case of natural disasters. Kessler et al. (Ronald C. Kessler, 1995) found that, with treatment, approximately 40% of cases are resolved within one year, and about 60% within six years. Roughly 30% of untreated cases resolved within one year, while at the 6-year point, the rates of resolved and unresolved cases were similar to the treated values. Table 7 summarizes these values.

Table 7 Remission rates for PTSD - Selected References

Source of PTSD	Remission Rate	Treatment	Timeframe	Reference
General	44%	Yes	40 months	(Morina, 2014)

Natural Disasters	60%	Yes	40 months	(Morina, 2014)
General	40%	Yes	1 Year	(Kessler, 1995)
General	30%	No	1 Year	(Kessler, 1995)
General	50%	Yes	6 Years	(Kessler, 1995)
General	50%	No	6 Years	(Kessler, 1995)

Post-Disaster PTSD

Bromet et al. (Bromet et al., 2017) reported that, in high-income countries, displacement following a disaster represented a 6-fold increase in risk for PTSD versus non-displaced populations, while human-made disasters presented a 3.3x greater risk of PTSD versus natural disasters. Neria et al. (Neria et al., 2008) found that the direct victims of a disaster experienced PTSD at rates between 30 and 40%, while 10-20% of rescue workers and 5-10% of the non-directly affected population experienced it as well.

Bryant et al. (Bryant et al., 2014) explored mental health outcomes based on the degree of impact from severe wildfires that passed through rural areas of Victoria, Australia in February of 2009. They defined impact at the community level based on property damage and number of fatalities; and at the individual level based on immediate danger during the fires, loss of personal property, and deaths of close friends/family during the fires. A move to temporary housing was considered among the stressors. Residing in highly affected communities correlated strongly with both PTSD (OR 4.57, 95% CI: 2.61-8.00) and heavy drinking (OR 1.39, 95% CI: 1.01-1.89), as did the individual factors.

Oe et al. (Oe et al., 2016) conducted a particularly detailed study of the population affected by the Fukushima disaster. Their study examined medical records and survey responses in 2012 (n=71,100), 2013 (n=53,162) and 2014 (n=44, 913) found that age, sex, and displacement all played strong roles in PTSD rates, with older persons experiencing greater morbidity than younger, women greater than men, and displaced greater than non-displaced. The authors suggest caution regarding the age sensitivity as a large portion of their study population was over 65, and previous studies have been contradictory regarding age as a factor. This study did not consider persons under 20 years old. Table 8 compares the identified PTSD prevalence in residents who were either never evacuated or had returned, against those who were still under an evacuation order (e.g those experiencing long-term displacement).

Table 8 PTSD Prevalence Among Fukushima Evacuation Zone Residents (Oe et al., 2016)

Sex	Displacement Status	Year		
		2012	2013	2014
Male	**Displaced**	23.5%	22.3%	21.9%
	Non-displaced	16.1%	15.2%	15.0%
	Δ	+7.4%	+7.1%	+6.9%
Female	**Displaced**	30.7%	28.5%	28.1%
	Non-displaced	22.0%	20.4%	20.1%
	Δ	+8.7%	+8.1%	+8.0%

Substance Abuse and Problem Drinking

Increased rates of substance abuse in general, and heavy alcohol use in particular are commonly reported after disasters. Bryant et al. (Bryant et al., 2014) found correlation between the degree of community and individual impact of a disaster with increased heavy drinking. Heavy drinking was identified as a coping mechanism for ~15% of Oklahoma City

bombing survivors (North, 1999), while almost 25% of New Yorkers reported increased alcohol use after the World Trade Center attacks in 2001 (Vlahov, 2002). 37% of Hurricane Katrina survivors were identified as binge drinkers 6-12 months post-event, compared to a Louisiana average of 14.2% (Flory, Hankin, Kloos, Cheely, & Turecki, 2009). Other studies, however, suggest that the overall prevalence increases only slightly, with problematic use occurring primarily in persons with prior substance abuse problems, or comorbid with other disorders such as PTSD, depression, or anxiety (Norris et al., 2002). Ueda et al. (Ueda et al., 2016) found that, within a year, about 9.8% of pre-disaster non-drinkers reported starting to drink, and also linked changed drinking behavior to a high risk of serious mental illness.

Quantitative discussions of the effects of post-disaster displacement on substance abuse in general are very sparse, and might represent a significant future research area. Bryant et al. (Bryant et al., 2014) identified property loss (not specifically relocation) as a minor risk factor (OR = 1.04, CI: 0.99 – 1.09) for heavy alcohol use after the 2009 wildfires in Victoria, Australia, with younger age and male sex showing the greatest risk. Oe et al. (Oe et al., 2016) provided the only study that specifically examined relocation and problem drinking. They found that, as of 2014, prevalence of problem drinking among populations still under evacuation orders (e.g. displaced) differed only slightly from those no longer or never under evacuation orders; see Table 9.

Table 9 Prevalence of Problem Drinking Among Fukushima Evacuees (Oe et al., 2016)

Sex	**Displacement Status**	**Year**	
		2013	**2014**

Male	**Displaced**	13.3%	13.1%
	Non-displaced	13.6%	13.3%
	Δ	-0.3%	-0.2%
Female	**Displaced**	2.9%	2.8%
	Non-displaced	2.6%	2.6%
	Δ	+0.3%	+0.2%

Smoking behavior also undergoes changes following a disaster. Flory et al. found that, in surveys taken 6-12 months after Hurricane Katrina, 53% of survivors were current smokers, compared to a Louisiana-wide prevalence of 23.5% (Flory et al., 2009) Hashimote et al. noted that smoking prevalence in Fukushima Prefecture as a whole jumped from 23% in 2010 to 39.7 in 2014. (Hashimoto et al., 2017). The increase was almost indistinguishable between displaced and non-displaced populations.

Suicidal Behaviors

In a systematic literature review published in 2012, Kõlves et al. examined trends in suicidal behaviors (suicide and non-fatal suicidal behaviors) after natural disasters. They found that, over the course of 3-5 years, suicidal behaviors dropped after a disaster, then appeared to rise to levels exceeding pre-disaster rates before returning to baseline. (Kolves et al., 2013) They described this as a "honeymoon phase," followed by a period of delayed increase. Though the effects described by Kõlves were weak and difficult to discern, they appear to have matched the experiences of Japan after the Fukushima disaster. Maeda et al. reviewed studies of mental health issues in Fukushima Prefecture (Maeda & Oe, 2017) and found that, indeed, suicide mortality ratios (SMR) dipped in the 2 years after the disaster, then rose to exceed previous baseline rates (2010 – 108, 2011 – 107, 2012 – 94, 2013 – 96, 2014 – 126). Similar results were

found in neighboring prefectures. SMR is the ratio prefectural suicide rate against the rate of the general population of Japan. These studies were conducted at the prefecture level, and did not distinguish between displaced and non-displaced populations.

Physiological Outcomes

Degradation of physiological markers has been well documented in post-disaster health literature, usually linked to disruption of ongoing medical care, loss of access to medical infrastructure, traumatic stress and anxiety, and the ongoing stressors of dislocation, recovery and reconstruction. Cardiovascular and metabolic outcomes, including changes in body-mass index (BMI), obesity, metabolic syndrome, diabetes, and other associated conditions have been studied in relation to disasters and displacement. These outcomes tend to be closely related and overlap – type 2 diabetes is tightly linked to obesity, for example (Golay & Ybarra, 2005). A major consideration in examining these sequelae is the disruption in care for chronic conditions surrounding a disaster (Callen & Homma, 2017).

General Cardiovascular Health

At the most acute end of the spectrum, sudden disasters have been shown to trigger sharp increases in mortality by cardiac death (Kloner, Leor, Poole, & Perritt, 1997) immediately

following the disaster. In the short-term post-disaster, cardiac events (such as acute myocardial infarction and tachyarrhythmia) appear to increase, likely due to increased stress. Feng et al. reported significantly more cardiac events in a study of admissions to a single hospital in New York City during the 60 days after the 9/11 attacks, for example (Feng, Lenihanx, Johnson, Karri, & Reddy, 2006). Kario et al. reported similar results in a review of cardiac health following major earthquakes (Kario et al., 2003), noting as well that increased hypertension persisted 4-6 weeks after a disaster, even when most other metabolic markers had returned to baseline. Kitamura et al. demonstrated that rate of cardiac arrest following the Great East Japan Earthquake rose by 70% in the first week, 50% in the second and 25% in the third and fourth weeks post-event.

Stroke admissions at one hospital in Minamisoma City in the 30 months following the Fukushima disaster rose from 10.7 to 13.9, for a relative risk of 1.62 (95% CI 1.23-2.14). (Gilmour, Sugimoto, Nomura, & Oikawa, 2015) Similarly,

No studies were found that discussed general cardiovascular health in the context of evacuation or displacement, but degradation of the cardiovascular system is an endpoint of and comorbid with both diabetes mellitus, excess body weight, and substance abuse.

Cardio-metabolic Metabolic End-States Other Than Diabetes

Studies examining the effect of the Great East Japan Earthquake of 2011 on clinical markers in evacuees began appearing shortly after the disaster. Significantly higher body weight, body mass index, waist circumference and blood glucose levels were identified in evacuees in a small

study (n=200) by Tsubokura et al. (Tsubokura et al., 2013) with data collection taking place less than 6 months after the disaster and compared to results prior to the event. A larger study (n=6528), by Takahashi et al. (Takahashi et al., 2016) compared measures at 8 and 18 months post-disaster between relocated and non-relocated populations, finding much greater increases in body weight and waist circumferences in the relocated populations, along with deterioration in physical activity; other findings will be discussed below.

A large study (n=27486) compared data collected on participants aged 40 and up during 2008-2010 and 2011-2013 (3 months to 2 years after the disaster), comparing mean body weight and proportion of overweight and obese evacuees and non-evacuees. (Ohira et al., 2016) The study team found that mean body weight among evacuees increased by 1.2 kg, while non-evacuees saw an increase of 0.3 kg; similarly, the proportion of overweight persons increased from 31.8% to 39.4% among evacuees, and from 28.3% to 30.3% among non-evacuees. Displacement presented a Hazard Ratio of 1.68 versus the non-displaced population. No significant change was found at the national-level during the same time period.

A similar study by Nomura et al. (Nomura, Blangiardo, Tsubokura, Ozaki, et al., 2016), conducted with a smaller subset of the population (n=6406) and health records through 2014, again found higher Body Mass Index among evacuees versus non-evacuees, but by 2014 BMI had essentially returned to baseline levels among evacuees (see Table 10). This study, however, only considered persons aged 40-74, excluding those 75 years of age and older.

Table 10 Comparisons of Body Mass Index 2008-2014 (Adapted from Nomura et. al, 2016)

Study Group	Baseline	2011	2012	2013	2014
Displaced	23.6	24.0	24.2	24.0	23.7
Non-Displaced	23.5	23.6	23.6	23.6	23.4
Δ	+0.1	+0.4	+0.8	+0.4	+0.3

Metabolic syndrome (METS), a set of conditions which are risk factors for diabetes mellitus and hypertension, was studied in displaced and non-displaced populations in Fukushima prefecture by Hashimoto et al (Hashimoto et al., 2017). They identified significantly higher body weight, waist circumference, triglycerides, and fasting plasma glucose among displaced populations than in non-displaced. Displaced persons also experienced significantly higher rates of metabolic syndrome (M: 19.2% vs. 11.0%, F: 6.6% vs. 4.6%), with displacement presenting an adjusted odds ratio of 1.72 (95% CI: 1.46-2.02) relative to non-displaced persons.

	Male			Female		
Clinical Marker	Non-Displaced	Displaced	P value	Non-Displaced	Displaced	P value
Δ weight, kg	0.4	2.0	<0.001	0.3	23.7	<0.001
Δ BMI, kg/m2	0.1	0.8	<0.001	0.2	0.4	<0.001
Δ FPG[7], mg/dL	0.0	3.0	<0.001	0.0	3.0	<0.001
METS, %	11.0	19.2	--	4.6	6.6	--

[7] FPG: Fasting Plasma Glucose

Diabetes Mellitus

The American Diabetes Association defines diabetes (more properly, *diabetes mellitus*) as "a group of metabolic diseases characterized by hyperglycemia resulting from defects in insulin secretion, insulin action, or both.(American Diabetes, 2010) Type 2 diabetes represents 90-95% of cases, and is a combination of insulin resistance and some degree of insulin deficiency. The symptoms of diabetes range from polyuria (excessive urination) and polydipsia (excessive thirst or drinking) to hyperglycemia with ketoacidosis (excess glucose and ketones in the bloodstream, potentially life-threatening). Long-term complications of Type 2 diabetes include loss of vision, renal failure, peripheral neuropathy (loss of sensation in the extremities), and cardiovascular symptoms.

Diabetes (in particular, Type 2 diabetes) has no cure per se, but can enter remission in certain cases. Severely obese patients who undergo gastric bypass surgery can achieve complete remission rates of up to 70%.(Arterburn et al., 2013) Short of gastric bypass surgery, type 2 diabetes does have a very small (<<1%) prolonged remission rate, generally when freshly-diagnosed cases are met with rigorous lifestyle changes and diabetes support and education.(Karter, Nundy, Parker, Moffet, & Huang, 2014) Both pathways to partial or complete remission can fail, with relapses hovering near 30% of remissions.

Studies examining Type 2 Diabetes after disasters generally focus on the disruptions to care – loss of access to dialysis, localized shortages of insulin, failure or inability to monitor blood glucose levels, and limitations on available diet. (see, for example, (Lee et al., 2016)).

Numerous studies indicate short-term increases in the severity and complications of existing diabetes cases after a disaster. Kamoi et al., in a small study, (Kamoi, Tanaka, Ikarashi, & Miyakoshi, 2006) identified short term degradation of glycemic control as well as increased incidence of some complications from diabetes after a major earthquake in Japan, but found that all measures returned to pre-earthquake levels within 12 months. On the other hand, A1C levels (a measure of hemoglobin with attached glucose) in diabetic Katrina survivors were continuing to increase 16 months after the event. (Fonseca et al., 2009) Leppold et al. (Leppold et al., 2016) identified this same pattern of deterioration in glycemic control after the Great East Japan Earthquake of 2011, but noted that there was no correlation with displacement status.

No studies were identified that specifically examined excess diabetes cases after disasters until after the Great East Japan Earthquake and Tsunami of 2011; some of these reflect a strong interest in the relative risks of displacement and radiation in affected areas.

The first major study examining diabetes prevalence in displaced and non-evacuated populations, compared with their pre-disaster rates, was published in 2015. This work, by Satoh et al. (Satoh et al., 2015) examined the clinical markers of diabetes in 27,486 subjects aged 40-90 from the disaster-affected provinces. The data was collected from the annual health checkups of patients who were examined before the disaster (2008-2010) and after (2011-2012). This study found that, prior to the disaster, the population had a diabetes incidence of 9.3%, while after the disaster the overall rate for both the displaced and non-

evacuated population was 11.0%. Of the previously non-diabetic population, 3.0% had become diabetic – this rate was 3.6% for evacuees, but only 2.6% for non-evacuees.

Takahashi et al. (Takahashi et al., 2016), as noted above, examined 6528 adults (18+ y.o.) in 3 affected provinces at 8 and 18 months post-disaster. Note that this study did not assess results before the disaster, only after. The relocated population had an overall incidence of diabetes of 7%, while the non-relocated population had an incidence of 6%.

A study by Ebner et al. (Ebner, Ohsawa, Igari, Harada, & Koizumi, 2016), similar to the Satoh et al. study noted above, examined the health records of ~700 residents of Kawauchi Village. The study compares 3 years of results prior to the disaster with 2 years after the event, a somewhat longer follow up period than found in the Satoh et al. study, in the population of adults over 40 years of age. The entire studied population was evacuated in March 2011, and began to return starting in April 2012. Mirroring Satoh et al., the incidence of lifestyle diseases was shown to have increased, but also was continuing to increase in 2013, the year after return was permitted. Diabetes prevalence in the village was 11.3% before the earthquake; in 2012 the rate in the same population was 14.7%, and in 2013 reached 17%. Of note, obesity rates had begun to decrease at the latter part of the study period (pre-event: 35.3%, 2012: 39.7%, 2013: 36.9%).

Like the Ebner et al. study, Nomura et al. (Nomura, Blangiardo, Tsubokura, Ozaki, et al., 2016) examined medical records for municipalities affected by the Great East Japan Earthquake. In this case, the study population was centered on Minamisoma City and Soma City. These cities

experienced partial evacuations, some immediately, some in April of 2011; small numbers of evacuees were permitted to return as zone boundaries were adjusted in 2012, while others remain displaced. Medical records for persons aged between 40 and 74 years from prior to the incident (2008-2010) and after (2011-2014) were compared. Table 11 shows the diabetes prevalence in the affected populations. As of 2014, diabetes prevalence among evacuees was significantly higher than among non-evacuees, and continuing to increase, while the rate among non-evacuees appears to have leveled off. Japanese national diabetes prevalence for all adults, (8.3% in 2012), was largely unchanged during the study period(Ikeda, Nishi, Noda, & Noda, 2017). Compared to baseline, the age-adjusted relative risk of diabetes among evacuees was 1.60 (95% CI: 1.18-2.16), while the relative risk to non-evacuees was 1.27 (95% CI: 1.11-1.45).

Table 11 Comparisons of Diabetes Prevalence 2008-2014 (Adapted from Nomura et. al, 2016)

Study Group	**Baseline**	**2011**	**2012**	**2013**	**2014**
Evacuees	7.7%	9.3%	10.2%	13.1	13.6
Non-Evacuees	7.7%	8.0%	9.5%	11.6	11.2
Δ	0.0%	+1.3%	+0.7%	+1.5%	+2.4%

Radiological Effects on Non-Displaced Populations

Surprisingly, only one study was found that specifically examined clinical parameters for a non-displaced population with a focus on non-cancer radiological effects. Ishii et al. conducted a small study (n = 155) in the Tamano district of Soma City, Japan. (Ishii et al., 2016) Tamano had

levels of radiation of 1.0 to 1.9 µSv per hour at the time of the study (July 2012), equating to roughly 8 mSv per year using the Government of Japan dose calculation, Equation 3 above. Internal uptake was low, with no study participant estimated to receive more that 1 mSv per year from internally incorporated ^{137}Cs. The researchers found small but statistically significant decreases in blood pressure and in body mass index, while other clinical markers were either unchanged or clinically negligible.

The Nomura et al. study noted above (Nomura, Blangiardo, Tsubokura, Ozaki, et al., 2016) found no significant association between the disease risks studied and the radiation levels in the non-evacuated/temporarily evacuated residents of Minamisoma City and Soma City. Radiation levels were estimated at an air dose rate of 0.25 to 0.5 µSv per hour (~2-4 mSv per year using the Government of Japan methodology).

Introduction: Modeling Radiogenic and Displacement Risks

With access to at least some quantitative information about risks connected to displacement, it becomes possible to consider modeling the comparative risks of displacing a given population vice allowing them to remain in place despite some level of radiation risk. Development of such a model makes up the heart of this work.

The first step to development of the model is the selection of which clinical outcomes to model. While an ideal case would include a comprehensive suite of outcomes, with detailed values and associated uncertainties, the paucity of published data limits the possibilities. Further, many of the outcomes are closely associated and/or comorbid with each other. Degradation of cardiovascular health is associated with disasters and displacement, but is also comorbid with and an end state of diabetes mellitus, for example. After assessing the available information, three clinical outcomes were selected.

Since the bulk of radiation regulation and standards are based on excess cancer risk, radiogenic cancer mortality was a straightforward choice on which to base the radiation risks. Other end states, such as cataract formation or Acute Radiation Syndrome, are extremely unlikely to occur at the low exposure rates being considered here.

Two displacement risks were selected: Post-Traumatic Stress Disorder and diabetes mellitus. While some data were available for other outcomes, they were unsuitable for use for several reasons. First, many of the general outcomes, such as increased mortality, lacked specific details on life shortening. There was limited data available on several clinical outcomes closely related to (and often comorbid with) diabetes mellitus, such as increased obesity rates, degraded cardiovascular health, and conditions such as metabolic syndrome and hypertension. Similar difficulties limited the potential mental health outcomes – difficulties separating depression, anxiety, suicidal behaviors and substance abuse, coupled with a paucity of quantitative studies. These outcomes were excluded because of the complexity that would be introduced with the comorbidities, especially given the relatively small number of studies available.

Strict vs. Extrapolated Model

Some data were only available for limited age groups, discussed in more detail below. As such, two variants of the model were prepared. The *strict* model only applies excess risk to the populations matching those described – for example, excess diabetes mellitus was only studied in persons aged 40-75 at the time of the Fukushima disaster. The strict model applies that excess morbidity to the matching age groups. A second variant, the *extrapolated* model, ascribes some moderate level of excess morbidity to other age groups; for example, again in the case of diabetes, 50% of the excess for persons aged 40-49 was assigned to persons aged 30-39.

Modeling Radiation Doses

As noted previously, predicting radiation doses to a population is a highly subjective proposition, with several available methodologies, each subject to a range of interpretations. In order to model the *risk*, several elements are needed. First, some estimate of the *dose* rate is needed, which requires in turn a starting *exposure* rate, and an effective half-life. The model handles radiation in a simple manner, as its purpose is not to provide a sophisticated population dose estimate. An initial exposure rate ($\dot{D}_0$) is provided (default is 0.04 Gy per year, or 40 mGy/y), along with an effective half-life (default is 5 years) and the duration of exposure (default is 20 years). These parameters are used to generate two integrated doses provided in the output. The first, and worst case, is a dose based on the U.S. EPA methodology, which holds the exposed population in place, without shielding or time spent elsewhere, for the entire exposure period. The second, more realistic (but still quite conservative) method is based on the methodology employed by the Government of Japan (GOJ). The primary difference between the two is that the GOJ methodology results are 60% of the EPA results, accounting modestly for time spent indoors and in places with little or no excess radiation exposure. With the youngest age groups divided into 5-year blocks (e.g. 0-4, 5-9, etc.) the model integrates the dose (*D*) over 5 year periods according to Equation 4. The dose is recalculated and reapplied for each 5-year block of the supplied duration.

Equation 4 Total Dose During Time Interval t (Johnson, 2017)

$$D = \frac{\dot{D}_0}{\lambda_E}\left(1 - e^{-\lambda_E t}\right)$$

where

Equation 5 Effective Decay Constant

$$\lambda_E = \frac{0.693}{T_E}$$

There are several built-in assumptions to the radiation code. First, that the measured ambient dose rate is the H*(10) dose, requiring no conversion or weighting to relate to whole-body doses among the affected populations. Second, that the population and its demographic distribution are stable – the number of people in entering and leaving each age and sex grouping remains the same. Third, that the effective half-life remains stable over the period of interest. In this work, the effective half-life includes the effects of weathering, decay, and decontamination. The effective half-life of radiation exposures in the areas affected by the releases from the Fukushima disaster, for example, have been estimated to be 3.2 ± 0.5 years. (Hayes, 2019).

Units for Quantifying Risk

A net risk model necessarily requires quantification of both the risks of the potential radiation exposure and the risks of displacement. Ideally, a decision maker would be able to make a determination to displace a given population due to a potential radiation hazard only when the

risk of remaining is greater than the risk of relocation, essentially scoring each risk separately and comparing the two. This requires a common scale of risk, with units that cover both radiological and non-radiological impacts.

The World Health Organization (WHO) has developed a system for assessing the global burden of disease, including measures of detriment due to a wide range of conditions. (World Health Organization, 2017) A *Disability-Adjusted Life Year* (DALY) is a summary measure combining years of life lost through premature death (YLL) with years of healthy life lost due to disability (YLD). A set of tabulated *Disability Weights* accounts for differing detriments of 234 different diseases and injuries. The WHO includes data on cancers, post-traumatic stress disorder (included under anxiety disorders), diabetes, obesity, hypertension and more. Years of life lost have also been considered by radiation standards-setting bodies such as BEIR, who found that the typical fatal solid cancer resulted in the loss of 11 years of life in both males and females, while fatal leukemias resulted in the loss of 12 years of life in males and 13 years of life in females. (Committee to Assess Health Risks from Exposure to Low Levels of Ionizing Radiation, 2006)

In calculating DALYs for a given clinical outcome, Equation 6 is used:

Equation 6 Disability-adjusted Life Year Calculation

$$DALY(c,s,a) = YLL(c,s,a) + YLD(c,s,a)$$

where *c* is the cause, *s* is the sex, and *a* is the age.

The typical years of life lost for many conditions can be found in the literature or, as noted above, have been assessed by standards-setting bodies, and is a measure of premature death based on a hypothetical lifespan, "thought likely to be achievable by a substantial number of people who are alive today." (World Health Organization, 2017) Literature values may differ from the WHO values in that the WHO methodology assumes an ideal, disease- and injury-free lifespan of 91.9 years for both males and females, while other authors may use other values, based on national or regional life tables (e.g. Pham et al., who used the Japan Life Tables for 1995 in their study of cancer YLLs. (T. M. Pham et al., 2009)) The general formula for YLL at an attained age *a* is shown in equation 5.

Equation 7 General formula for YLL

$$YLL_c(a) = \frac{\sum_{a,s} m_c(a,s) \times L(a,s)}{\sum_{a,s} m_c\,(a,s)}$$

where *m* is the number of mortalities at age *a* and sex *s* from cause *c*, and *L* is the loss function describing the standard expected life remaining for an individual of sex *s* in good health at age *a*.

The calculation of YLD for each cause *c* is shown in Equation 8:

Equation 8 Calculation of YLD

$$YLD_c(s,a) = \sum_{s,a} p_c(s,a) \times n(s,a) \times d_c \times dw_c$$

where *p* is the prevalence of a given condition, *n* is the size of the affected population, *d* is the duration of the condition, and *dw* is the weight assigned to the condition. If the condition persists for the remainder of life, then d_c becomes:

Equation 9 Calculation of Duration of Condition When it Extends to End of Life

$$d_c = 91.9 - a - YLL_c(a)$$

in accordance with the WHO methodology.

Selection of Modeled Clinical Outcomes and Quantitative Basis

To construct DALYs for the outcomes under consideration, values are required for the incidence and duration of the condition, the disability weights (per WHO), and the associated Years of Life Lost.

Excess Radiogenic Cancer - DALYs

As noted previously, cancer mortality is the primary endpoint considered by standards-setting bodies and regulators in low-dose and low-dose-rate scenarios. For this work, the BEIR age- and sex-based cancer mortality risk values in Table 2 form the starting point for the radiation module.

Cancer YLLs (sometimes Average YLL (AYLL) is used) have been well studied, and some standards-setting bodies have developed consensus values. Table 12 summarizes YLL values for cancer from selected sources.

Table 12 Years of Life Lost Due to Cancer Mortality - Selected References

Author/Source	Region	Male YLL (years)	Female YLL (years)	Data Year	Reference
BEIR	Global	11 (solid) 12 (leukemia)	11 (solid) 13 (leukemia)	Not specified	(Committee to Assess Health Risks from Exposure to Low Levels of Ionizing Radiation, 2006)
Brustugun et al.	Norway	12.7 (all cancers)	14.9 (all cancers)	2012	(Brustugun, Moller, & Helland, 2014)
Burnet et al.	UK	12.5 (solid)8 13.6 (leukemia)8		2004	(Burnet, Jefferies, Benson, Hunt, & Treasure, 2005)
NIH	US	14.7 (all cancers)	16.6 (all cancers)	2015	(National Institutes of Health, 2019)
Pham et al.	Japan	13.6	17.5	2003	(T. M. Pham et al., 2009)

The WHO, in assessing the global burden of cancer, estimates that YLL makes up 96% of the total DALY for cancer (Global Burden of Disease Cancer et al., 2017). That is, YLD makes up only 4% of the DALY. Other studies addressing the proportions making up the overall DALY found similar results, with allowances for variations in methodologies. Table 13 summarizes the percentages of YLL that make up the overall DALY for all cancers found in selected references. The Shimada et al. study was somewhat of an outlier, having used an older 2004 WHO

[8] Results were for entire population

methodology (World Health Organization, 2004) with sharply different disability weights. (Shimada & Kai, 2015) Disability weights for cancer were heavily revised in 2010 and have been only slightly modified since. (World Health Organization, 2017)

Table 13 Percentage of YLL in DALY, all cancers - selected references

Author/Source	Region	% YLL in DALY	Data Year	Reference
WHO	Global	96%	2015	(Global Burden of Disease Cancer et al., 2017)
Shimada et al.	Japan	88%	2010	(Shimada & Kai, 2015)
Pham et al.	Japan	93.8%	2000	(T.-M. Pham et al., 2011)
Sakia et al.	Asia	95.6% (male) 92% (female)	2008	(Saika & Machii, 2013)
Murillo-Zamora et al.	Colima, Mexico	87.4% (male) 93.7% (female)	2014	(Murillo-Zamora et al., 2018)
GBD Collaboration	US	93.4% (male) 93.1% (female)	2017	(Global Burden of Disease Collaborative Network, 2018)
GBD Collaboration	Global	97.1% (male) 96.1% (female)	2017	(Global Burden of Disease Collaborative Network, 2018)
GBD Collaboration	India	98.5% (male) 97.8% (female)	2017	(Global Burden of Disease Collaborative Network, 2018)

For model use, a decision was taken to consider only YLL from cancer, as the YLD would contribute only on the order of 4-6% to the value. Cancer YLLs for males were generally found to be lower than YLLs for females. The male YLL for all cancers was chosen to be 14 years, in between published values for Japan and the United States noted in Table 12. Female YLL was chosen as 17 years for all cancers. Table 14 summarizes the model parameters for radiogenic cancers.

Table 14 Summary of Model Parameters for Radiogenic Cancer

Incidence	Per Table 2
Duration	n/a (only YLL considered)
Disability Weight	n/a (only YLL considered)
Male YLL	14 years
Female YLL	17 years

Displacement Effects – DALYs

Selecting effects suitable for modeling posed several challenges. Even with the increased reporting of clinical outcomes attributable to displacement, many outcomes had only limited sample size or a small number of studies, or both. Further, many outcomes were intertwined and difficult to impossible to assess separately. After consideration of comorbidity and data strength, the two primary measures selected for inclusion were PTSD and diabetes milletus. For reasons noted below, AUD was selected as an additional measure.

Post-Traumatic Stress Disorder – DALYs

PTSD is one of the most well-documented and quantified outcomes of disasters in general, and some data is available regarding the time course and the relative prevalence among evacuees. PTSD is not directly associated with mortality, though it is routinely comorbid with conditions that are, such as depression or substance abuse.

DALYs for PTSD, therefore, are derived from YLDs. The disability weights assigned to PTSD fall under the health state of Anxiety Disorders under the WHO rubric (World Health Organization, 2017). The WHO assigns weights to Mild (0.030), Moderate (0.133) and Severe (0.523) Anxiety

Disorders. Lacking data on the specific clinical states of individual patients suffering from PTSD, the model makes use of the Moderate disability weight of 0.133. For model purposes, excess incidence of PTSD is selected to be +7% for male evacuees, and +8% for females, in line with Oe et al. (Oe et al., 2016). Information about the correlation of age with PTSD morbidity is conflicted; Oe et al. is one of the primary sources of information on PTSD in displaced populations and did not discuss results for persons aged 0-19, so the strict model does not apply any excess PTSD to these age groups. The extrapolated model applies the same values to these age groups as for 20+ year age groups. PTSD is modeled to begin immediately after the event.

Duration for PTSD was selected based on the mean values identified by Kessler et al. for man-made disasters of 41.3 months (R. C. Kessler et al., 2017). Table 15 summarizes the model parameters used for Post-Traumatic Stress Disorder.

Table 15 Summary of Model Parameters for Post-Traumatic Stress Disorder

Incidence	Male +7%, Female +8%
Duration	41.3 months
Disability Weight	0.133
Male YLL	n/a (only YLD considered)
Female YLL	n/a (only YLD considered)

Diabetes Mellitus – DALYs

Diabetes was selected for several reasons. First, quantitative studies of diabetes prevalence among disaster evacuees are relatively new, with the first being identified only in 2015 (Satoh

et al., 2015). Second, diabetes is well studied, with documented time-course and detriment. Finally, it is one of the major end-states of some of the other clinical outcomes reported, such as obesity and waist size.

Quantitative values for excess diabetes for use in the model were drawn from Nomura et al. (Nomura, Blangiardo, Tsubokura, Ozaki, et al., 2016), as this study directly compared pre- and post-event health records among both displaced and non-displaced populations (see Table 11). Staying within the bounds of the published results, the model assumes that excess diabetes incidence occurs in the affected population for three years, increasing linearly at 0.8% per year to reach the 2.4% differential reported by Nomura et al. at the third year. It is further assumed (again, staying within the bounds of the published results) that this increased incidence occurs only in persons aged 40-75 at the time of the displacement. Given the very small (<<1%) remission rates noted by Karter et al. (Karter et al., 2014), remission is ignored.

The life-shortening impacts of diabetes have been studied for some time, with peer-reviewed papers dating back into the early 1970s (see, for example, (I. I. Kessler, 1971). While some papers report crude estimates of life shortening overall (e.g. a worldwide YLL of 5-10 years, (Panzram, 1987)), most lay out a loss of life expectancy by age and sex. Improvements in diagnosis and treatment have resulted in decreases in detriment – the loss of LE for men diagnosed within a year of birth in Canada dropped from 12.8 years in 1995/6 (Manuel & Schultz, 2004) to 9.3 years in 2004/6 (Loukine, Waters, Choi, & Ellison, 2012). Table 16, Table 17, and Table 18 summarize YLLs by age and sex from several studies. Each study used

somewhat differing (but comparable) methodologies to derive an *expected* YLL based on *attained age*. Table 19 shows the loss of life expectancy from birth(Manuel & Schultz, 2004), and Table 20 summarize YLLs from Narayan et al. (Narayan, Boyle, Thompson, Sorensen, & Williamson, 2003), who elected to identify the age at which a diagnosis was made and estimate YLL from that point.

Table 16 Years of Life Lost for Diabetes – Per Magliano et al.

Study Region: Australia	Data Year: 2004/5	Reference: (Magliano et al., 2008)
Age (attained)	Male YLL	Female YLL
25	10	7.6
35	8.3	6.8
45	6.9	5.9
55	5.5	4.8
65	4.0	3.4

Table 17 Years of Life Lost for Diabetes – Per Loukine et al.

Study Region: Canada	Data Year: 2004-2006	Reference: (Loukine et al., 2012)
Age (attained)	Male YLL	Female YLL
1	9.3	10.1
20	8.8	9.2
55	5.0	6.0
80	1.9	2.6

Table 18 Years of Life Lost for Diabetes – Per Turin et al.

Region: Japan	Data Year: (not specified)	Reference: (Turin et al., 2012)
Age (attained)	Male YLL	Female YLL
40	8.8	6.6
45	4.4	6.8
50	4.9	7.0
55	4.9	6.5
60	4.0	5.6

65	3.4	5.9
70	2.8	4.3
75	2.2	4.6
80	2.3	3.0
85	0.9	1.9

Table 19 Years of Life Lost in Ontario Canada for Diabetes

Study Region: Ontario, Canada	Data Year: 1996/7	Reference: (Manuel & Schultz, 2004)
Age (attained)	Male YLL	Female YLL
12+	12.8 (from birth)	12.2 (from birth)

Table 20 Years of Life Lost in the United States for Diabetes (Narayan et al., 2003)

Region: United States	Data Year: 2000	Reference: (Narayan et al., 2003)
Age (at diagnosis)	Male YLL	Female YLL
10	18.7	19.0
20	17.2	17.9
30	14.5	16.5
40	11.6	14.3
50	9.2	12.1
60	7.3	9.5
70	5.3	6.5
80	3.8	4.1

As the primary study that considered excess diabetes morbidity due to displacement only considered persons aged 40-74, the strict model calculates DALYs for the same age range, to avoid unsupported extrapolation and overestimation of risk. The age- and sex-based YLLs from Narayan et al. were selected for model use. The extrapolated model expands on this slightly, setting values for ages 30-40 and 80+ at half that of the 40-50 range.

The WHO-assigned disability weights for diabetes vary depending on the particular stage of the disease, and for specific sequelae (e.g. neuropathy, or gastric bleeding). Lacking data on the specific clinical states for individual patients, the primary health state of interest is what the WHO terms *chronic kidney disease stage IV*, for which the weight is 0.104 (World Health Organization, 2017). This represents the general condition of controlled diabetes, without need for dialysis and lacking other side effects; this is also least-severe state considered by the WHO for diabetes. As diabetes is effectively a remainder-of-life disease, the duration of the condition, for modeling purposes, is set per Equation 9.

Table 21 summarizes the model parameters used for diabetes mellitus.

Table 21 Summary of Model Parameters Used for Diabetes Mellitus

Incidence	+0.8% per year over 3 years for ages 40-75
Duration	Remainder of life per Equation 9
Disability Weight	0.104
Male YLL	Per Table 20 for ages 40+
Female YLL	Per Table 20 for ages 40+

Uncertainties and Significance

The model makes use of many parameters for which uncertainties are not available. Many of the published YLLs, for example, do not include uncertainties, and the weighting factors in the DALYs are based on consensus standards developed by the World Health Organization. Rather than mix these values with those for which uncertainties are available, the decision was made

to rely on significant figures to express uncertainty. The model outputs will be presented with 2 significant figures.

Model Description

The model is coded in R (R Core Team, 2017); the code is included and described in detail at Appendices 1-3. Table 22 shows the model inputs and default values. Default values in this case are those utilized by the model if the user provides no other input.

Table 22 Model Inputs and Default Values

Field	Description	Default Value
`fips_code`	2-letter country codes used by US Census Bureau	"US"
`year`	4-digit year for census data	2012
`starting_exposure_rate`	The starting exposure rate for estimating dose (Gy/y)	0.04
`effective_half_life`	The effective half-life of exposure rates, including weathering and decay (years)	5
`duration`	Duration for exposure (years)	20
`pop_size`	Size of the affected population (#)	100,000

Population data is drawn from the US Census Bureau (U.S. Census Bureau, 2010). A function was developed in R to obtain national-level population data, broken down by age and sex. This data was then combined to match the age categories utilized by the BEIR VII (e.g. Table 2). Additional functions were developed for data visualization as described in Appendix 1, but were not central to the function of the model.

Description of Model Inputs

The U.S. Census Bureau (U.S. Census Bureau, 2010) maintains a set of international population data, accessible via the internet. The model includes a pre-constructed data call, requiring only two inputs, *fips_code* and *year*. Although the National Institutes for Science and Technology have since replaced the Federal Information Processing Standard (FIPS) 2-letter codes with a set of codes based on ISO 3166 (Federal Geographic Data Committee, 2008), the current application programming interface (API) still utilizes the older codes. The default country for the model is the United States (*fips_code* "US") and the default year for population data is 2012.

The inputs *starting_exposure*_rate and *effective_half_life* are used in the radiation model as explained above. The default value for starting_exposure_rate of 0.04 Gy/y is double the EPA standard for population displacement, but is only utilized when the user provides no other value.

The input population size is a convenience; the model works internally entirely based on proportions of age and sex. The default value, 100,000, is arbitrary. A value of 1 will yield the results equivalent to DALYs per capita for the affected population as used, for example, by Murakami et al. in their paper on diabetes risks. (Murakami et al., 2017)

Description of Model Outputs

The core function of the model does not produce user-readable output; rather, it produces a data frame intended for further processing and plotting. Table 23 summarizes the output fields of the risk comparison module, described further in Appendix 2 – Risk Comparison Codes.

Table 23 Description of Model Output Fields

Field	Description
Country	2-letter FIPS code (as provided by user)
Pop_Size	Population size (as provided by user)
Start_Exp	Starting exposure rate (as provided by user)
Eff_Half	Effective half-life (as provided by user)
Duration	Duration of exposure under consideration (as provided by user)
EPA_DALY	DALY generated using US EPA methodology with all dose applied at the beginning of exposure period (depreciated)
GOJ_DALY	DALY generated using Government of Japan methodology with all dose applied at the beginning of exposure period (depreciated)
BLOCK_EPA_DALY	DALY generated using US EPA methodology with dose applied in 5-year blocks
BLOCK_GOJ_DALY	DALY generated using Government of Japan methodology with dose applied in 5-year blocks
PTSD	DALY generated from excess PTSD as a result of displacing the modeled population
Diabetes	DALY generated from excess diabetes mellitus as a result of displacing the modeled population
Displaced_DALY	Total DALY generated as a result of displacing the modeled population (sum of the PTSD and diabetes mellitus DALYs)

Of note, the fields EPA_DALY and GOJ_DALY are generated, but not utilized further in this work. They represent the DALY assuming that the total dose derived from the entire exposure period is delivered at once. This is an absolute worst case, and sharply exaggerates the radiation risk. These output fields were left in place but not processed further.

MODEL RESULTS

Broadly speaking, the model calculates two radiation DALYs, based on the EPA and GOJ methodologies respectively, which depend on the demographics of the population, the starting dose rate, and the effective half-life of that dose rate. It also calculates a strict and an extrapolated DALY for displacement, depending on the demographics of the population. In the case of a single run of the model, using a US-proportioned population, a starting dose rate of 20 mSv/y, and an effective half-life of 5 years, the radiation DALYs would be 0.070 y for the EPA methodology and 0.042 y for the GOJ methodology. These DALYs represent the per-capita disability-adjusted years of life lost due to excess cancers if the population remained in the elevated radiation area. The calculated DALYs for displacement, shown in Table 24, total 0.15 y for the strict model, and 0.19 for the extrapolated version; both exceed the radiation DALY by a large margin.

Table 24 Sample of Displacement DALYs for a US-Proportioned Population

	Strict		Extrapolated	
Data Year	**PTSD DALY (y)**	**Diabetes DALY (y)**	**PTSD DALY (y)**	**Diabetes DALY (y)**
2012	0.0074	0.14	0.020	0.17

Continuing this example, we can vary the starting dose rate. Plotting the results, as shown in Figure 3, allows the user to consider the “crossover” points at which the anticipated DALY cost of excess cancer mortality begins to exceed the DALY cost of displacement. In this example, the radiation risk utilizing the EPA methodology exceeds the strict displacement DALY at a starting

dose rate of 42 mSv/y, while the GOJ methodology does not exceed the strict displacement DALY until a starting dose rate of 70 mSv/y.

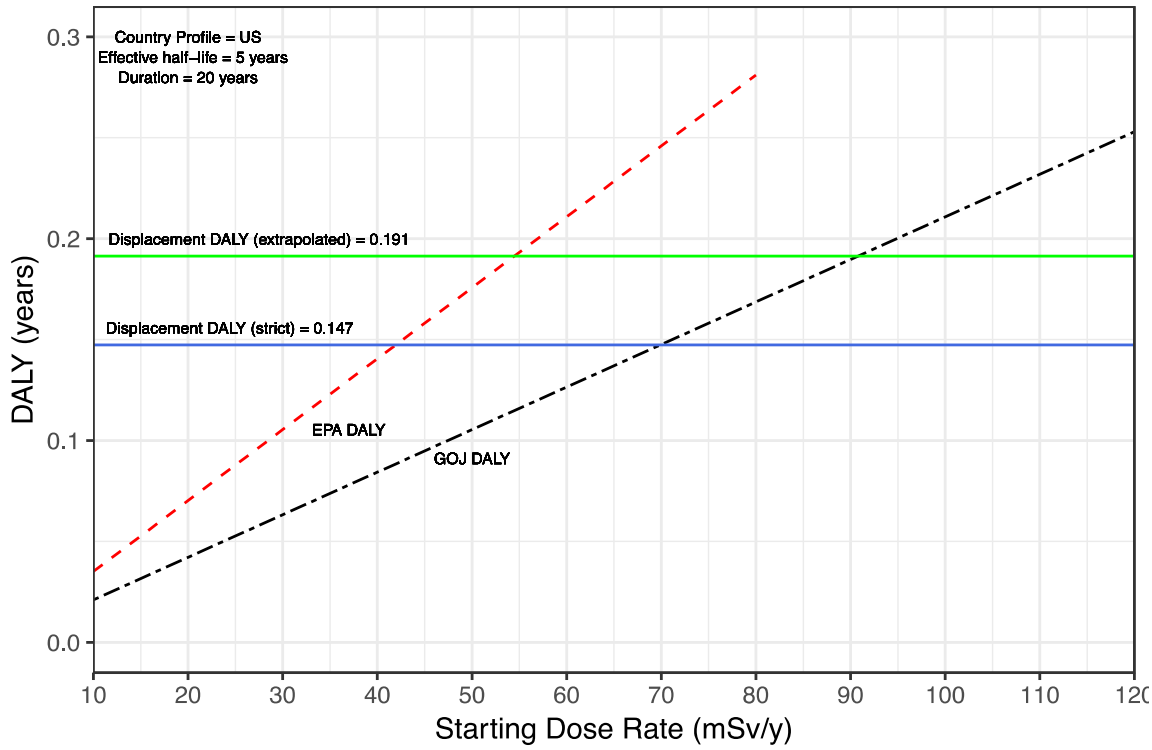


Figure 3 Sample DALYs for a US proportioned Population, with T_{eff} of 5 years

The slope of the radiation DALY line depends on the effective half-life and is unique to each population demographic mix. Figure 4 shows DALYs for the same US-proportioned population, with effective half-lives of 3, 5, and 7 years.

Calculated DALYs

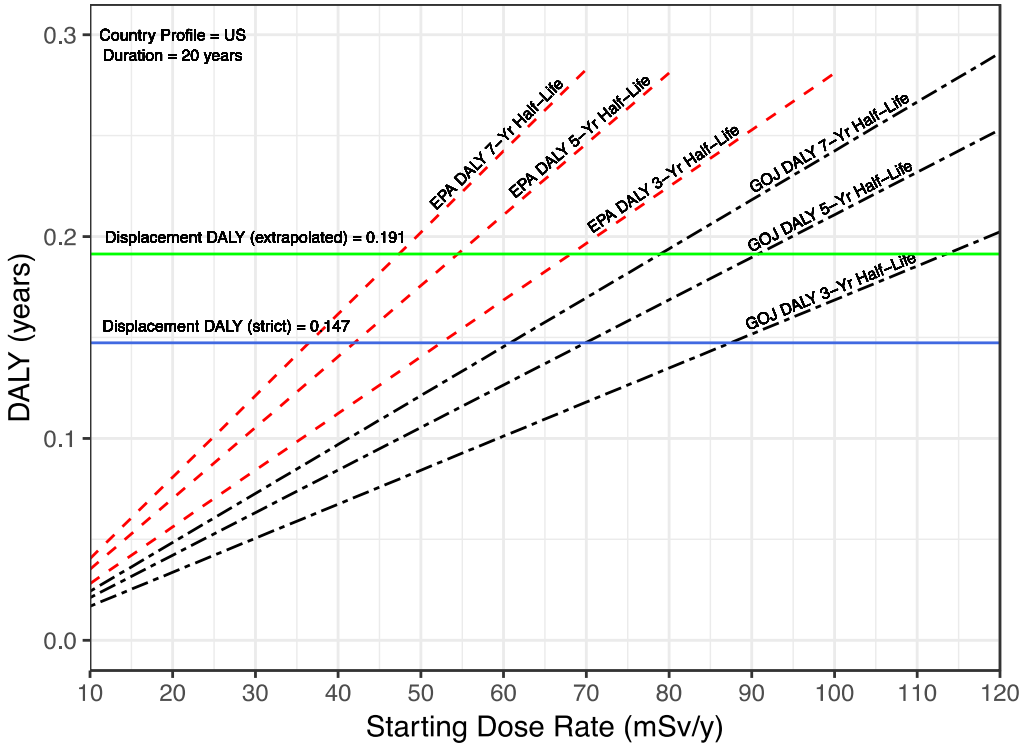


Figure 4 Sample DALYs for a US-proportioned Population, with 3-, 5-, and 7-year T_{eff}

As expected, for a given starting dose rate, a longer half-life generates a larger cumulative dose and hence a larger DALY. This lowers the crossover point, meaning that displacement becomes the less-costly (in terms of DALY) option at a lower starting dose rate.

Similar results are obtained when examining other populations. The next example shows the effect of demographic profile, with Nigeria for a younger population, and Japan for an older one.

Displacement DALYs for a Nigerian-proportioned population differed somewhat from the United States-proportioned previous calculation, as portrayed in Table 25. The strict model, which excludes PTSD in persons under 20 years of age, and diabetes mellitus in persons under 40, yields significantly lower DALYs for a Nigerian population. The extrapolated model reduces this effect somewhat, but major contributor to the DALY in either case is excess diabetes. The extrapolated model still excludes persons under 30 years of age, so effects on Nigeria's very young population (see Figure 1) might still not be adequately captured by the model.

Table 25 Sample of Displacement DALYs for a Nigerian-Proportioned Population

	Strict		Extrapolated	
Data Year	**PTSD DALY (y)**	**Diabetes DALY (y)**	**PTSD DALY (y)**	**Diabetes DALY (y)**
2012	0.0046	0.060	0.020	0.089

When the DALYs from excess radiogenic cancers are brought in, as in Figure 5, differences between the two examples become more stark. With ages skewed much younger, a Nigerian-proportioned population is more at risk from radiation. The crossover point with the strict model for a 5-year half-life using the EPA methodology is only 14 mSv/y, whereas the US-proportioned population it was 42 mSv/y. The crossover for the extrapolated displacement line, likely more appropriate for such young demographic, is still only 23 mSv. This wide difference suggests, as anticipated, that the radiation risks for a young population may exceed the risks of displacement at much lower levels than for an older one.

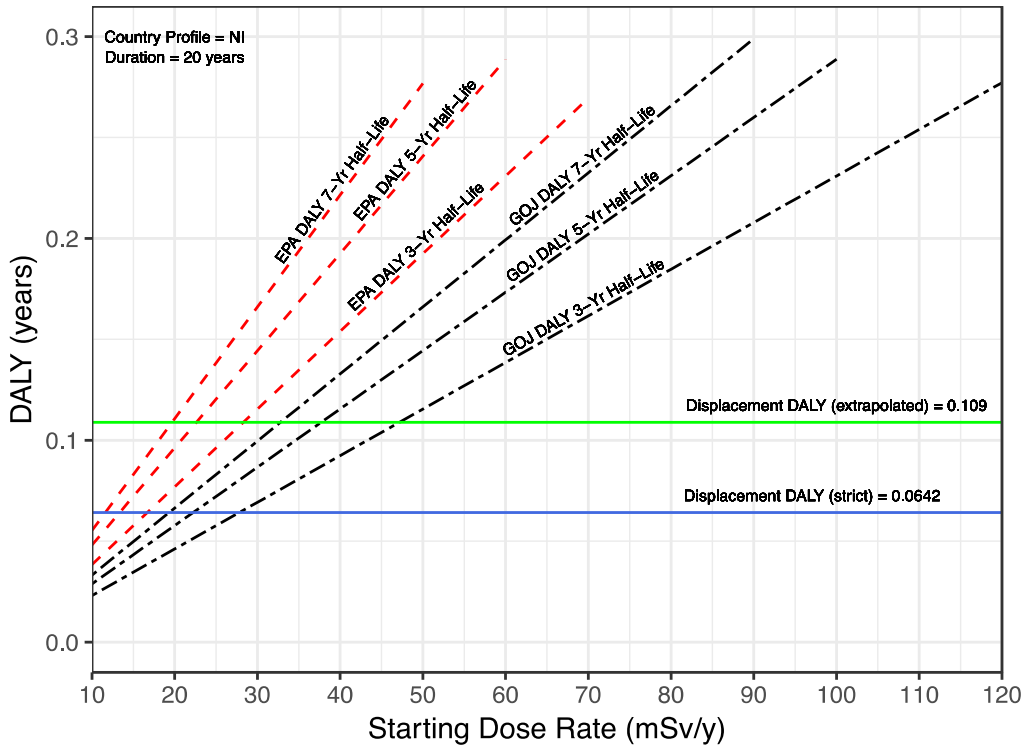


Figure 5 Sample DALYs for a Nigerian-proportioned Population, with 3-, 5-, and 7-year T_{eff}

Finally, we look at an older population. Here we see the largest DALYs for displacement, shown in both in the strict and in the extrapolated models.

Table 26 Sample of Displacement DALYs for a Japanese-Proportioned Population

	Strict		Extrapolated	
Data Year	**PTSD DALY (y)**	**Diabetes DALY (y)**	**PTSD DALY (y)**	**Diabetes DALY (y)**
2012	0.0082	0.16	0.020	0.19

Reflecting the greater age of the population, the crossover points, shown in Figure 6, are pushed much further to the right; the EPA methodology with a 5-year half-life crosses the strict

model for displacement at 53 mSv/y, far higher than the 42 mSv/y seen for the US population or the 14 mSv/y for the Nigerian population.

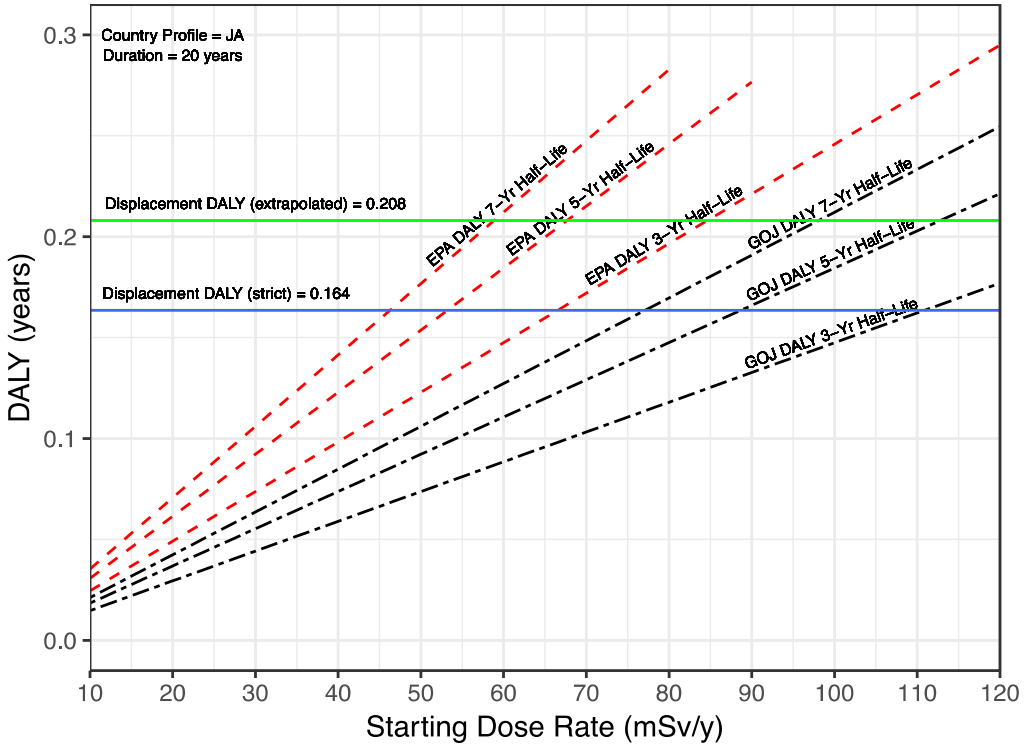


Figure 6 Sample DALYs for a Japanese-proportioned Population, with 3-, 5-, and 7-year T_{eff}

Comparisons between countries can be illustrated for each given effective half-life; the data remains unchanged, but is merely plotted differently for illustrative purposes. Figure 7, Figure 8, Figure 9 show the DALYs for 3-, 5- and 7-year half-lives respectively, with the crossover points for each population highlighted.

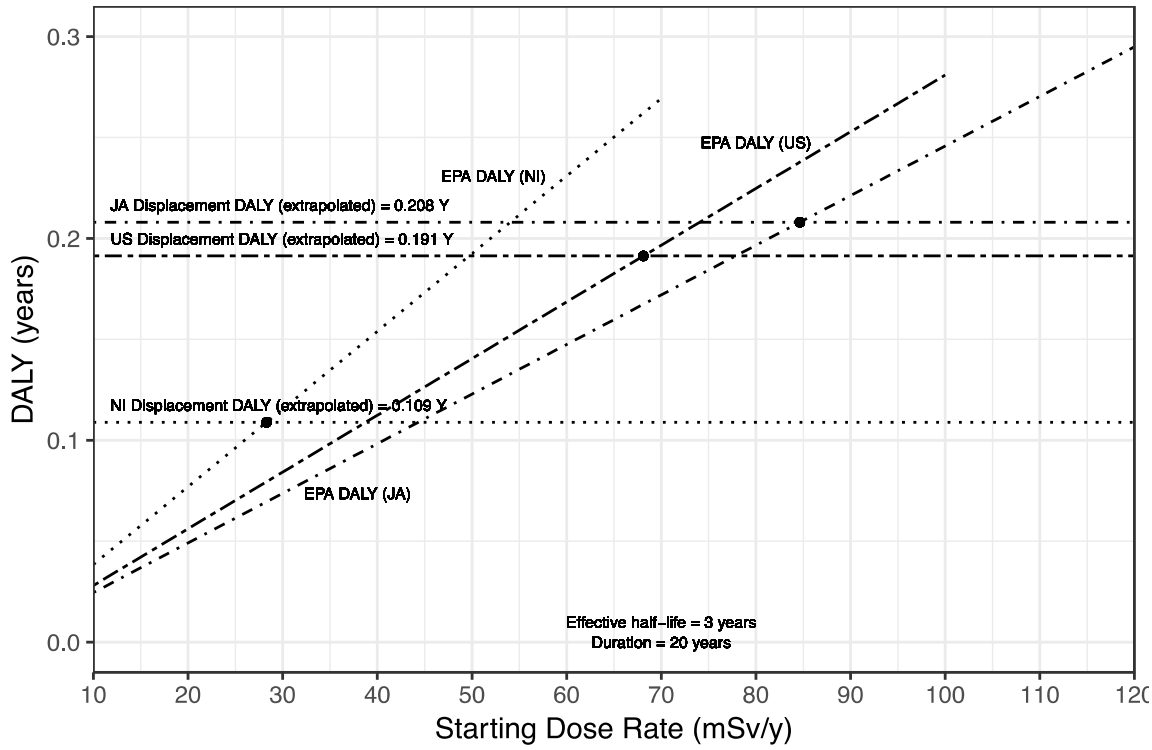


Figure 7 Comparison of DALYs for US, JA, and NI populations at T_{eff} = 3 years

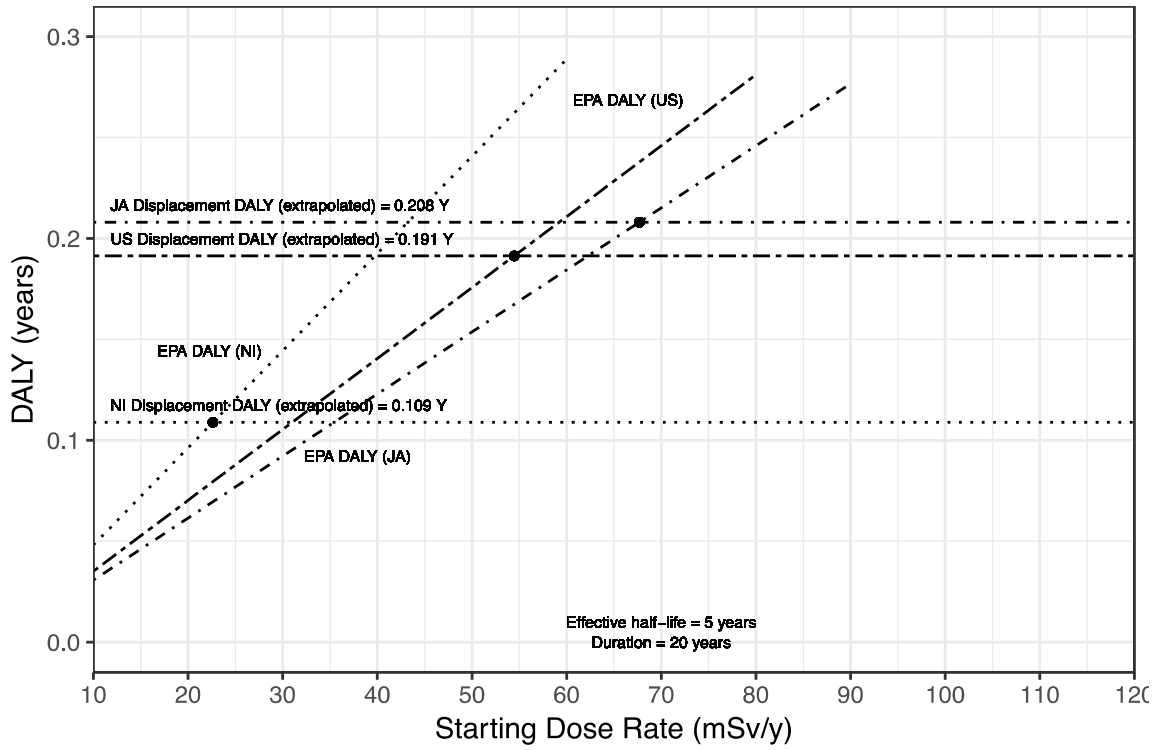


Figure 8 Comparison of DALYs for US, JA, and NI populations at T_{eff} = 5 years

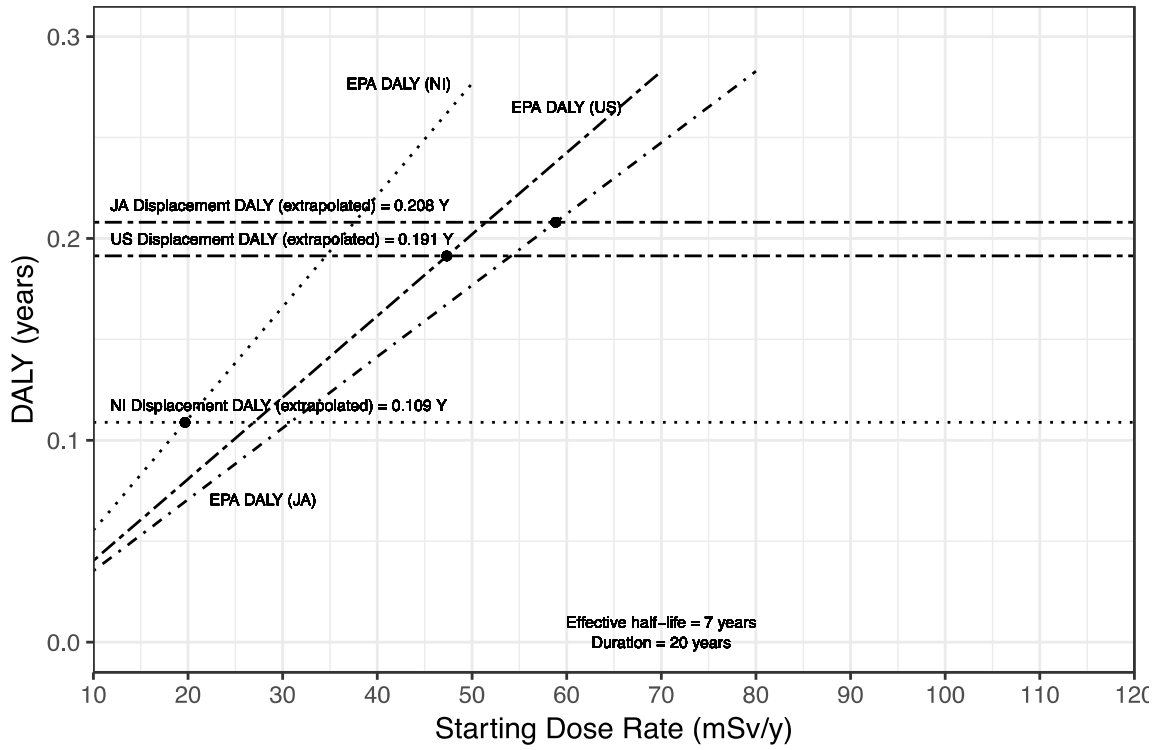


Figure 9 Comparison of DALYs for US, JA, and NI populations at T_{eff} = 7 years

DISCUSSION

Few papers have examined the relative health impacts of displacement against the hazard or disaster causing relocation. Some works focused on economics have suggested that post-disaster displacement costs go far beyond the up-front costs of housing and supporting evacuees (see Waddington et al. (Waddington, Thomas, Taylor, & Vaughan, 2017), Park et al. (Park, Cho, & Rose, 2010) and Deryungina et al. (Deryugina T., 2014) for discussions related to the Chernobyl and Fukushima disasters, as well as Hurricane Katrina).

Some research has been done comparing the avoided risks of radiation after Fukushima to the loss of life during the evacuation process among older populations in care facilities, finding that the risk to patients and staff from radiation was dwarfed by the excess mortality among residents. (Murakami et al., 2015)

More interestingly, Murakami et al. followed up their 2015 paper with one examining the overall risk of excess diabetes versus that of radiogenic cancers. (Murakami et al., 2017) They reviewed about 28,000 medical records from the cities of Minamisoma and Soma, with some of the same limitations noted above (only considering excess diabetes in 40-74 year olds, for example). They did not distinguish evacuees from non-evacuees, but did note that 15.1% of the population considered had lived in mandatory evacuation areas, that is, locations experiencing long-term dislocation. They then considered the estimated LLEs from excess diabetes post-disaster and from radiogenic cancers based on doses estimated for each resident. They used a detailed estimate for radiation doses in the first year of the incident, then generalized to 0.55

μSv/hr (4.8 mSv/year) based on post-decontamination measurements in the area. Their model gave an LLE for the estimated radiation exposures of 0.69 x 10^{-2} years (95% CI: 0.61-0.79) for the entire population, while excess diabetes gave 2.6-4.1 x 10^{-2} years (the paper considered several scenarios for future diabetes prevalence).

Murakami et al. used very different methodologies to arrive at their conclusions from this work, as well as a different measure – LLE versus DALY. Nonetheless, as a very rough comparison, Table 27 presents model results using 4.8 mSv/year as a starting effective dose rate, along with a 3.5 year half-life and a Japanese population distribution. Murakami et al. used tailored factors (e.g. in line with the ICRP methodology noted above) which generated significantly smaller radiation effect sizes than allowed for in either the EPA or GOJ model, while this work considers not just the LLE for diabetes but the DALY as a whole. Murakami found that the ratio of diabetes LLE to radiation LLE was between 3.7 and 5.9; this work put that ratio at roughly 2.

Table 27 Model results for a Japanese population using parameters adapted from Murakami et al.

		DALY (10^{-2} y)			
Dose Methodology		Diabetes		Total Displacement	
EPA	GOJ	Strict	Extrapolated	Strict	Extrapolated
12	7.6	16	19	16	21

Policy Implications

Overall, this work suggests that, at low radiation levels, the risks of displacement can exceed those of the avoided radiation exposures, especially in older populations. Within the United

States, with a median age of 37.5 years old, county-level populations range in age from 22.4 to 66.6 (U.S. Census Bureau, 2010). These populations, in turn, have widely differing levels of risk from both radiation exposure and from displacement.

It is highly unlikely that the US public would accept a purely risk-based relocation policy, responding to a hazard differently due to demographic variations in the affected populations. Rather, this work aims to show that the risks of dislocation are of a similar magnitude to, and can readily exceed, those of chronic low-level radiation exposures. The US relocation guide – 20 mSv per year in the first year, 5 mSv per year in the following years – is quite low and, depending on the effective half-life and demographics of the population involved, may drive relocations that cause greater net harm than the averted radiation hazard. Efforts by the ICRP to reduce the guidelines to 1 mSv per year (ICRP, 2009) may not represent a risk reduction, but rather a risk increase. Policy makers might consider comparing these excess risks in developing new guidance. It may be possible, long-term, to increase risk awareness in the general population, allowing better risk-informed policy decisions in the future.

An intermediate step towards a risk-based policy for disaster management might include steps such as pre-assessing populations at the county or regional level for displacement risk, then assessing specific hazard scenarios – this could take place at the direction of the NRC under the auspices of its disaster planning mission.

Future work should include a broad, multidisciplinary effort to examine disaster risks holistically, to potentially establish a framework for inserting risk-based decision making into

disaster response policy. Additional focused effort should examine improving broad public understanding of risk and risk assessment, particularly as applied to governance and public policy.

Further, most of the effects on displaced populations are mutable – PTSD is a treatable condition; excess diabetes mellitus appears to be related to lifestyle changes and loss of social networks, and so forth. More intense efforts to treat and prevent these conditions may result in reduced risk. Pre-planning for, and post-disaster implementation of mitigation strategies can reduce both incidence and duration of negative clinical outcomes. This work assumes a "steady-state" support network for both displaced and non-displaced populations – no significant changes to resource availability and services that would affect lifestyles and community health.

Limitations of This Work

The primary limitation of this work is the relative paucity of quantitative data on clinical outcomes among displaced populations. This work relies heavily on research originating in the Fukushima disaster of 2011, and as such is based on the affected Japanese populations. Generalizing from this specific disaster to others in other parts of the world is difficult, and so the results of this model should be used with caution. The diabetes papers, in particular, focused on persons 40-74 based on the timing of annual checkups in the Japanese National

Healthcare System, with no data available on excess morbidity among younger or older populations.

Future Development

A number of areas are ripe for future work in this area. First and foremost, expanded research on the health of displaced populations would greatly improve the model, and give it a much more firm statistical foundation. As the primary health outcome of interest, examination of diabetes mellitus rates in other regions of the world affected by disasters and displacement should be a priority as it appears to be a significant risk. Substance use and abuse rates are culturally linked – examining post-disaster behaviors in multiple cultural contexts would also be fruitful.

Two aspects of the code would reward future development. On a pragmatic level, coding of a user interface would ease the use of the model, currently run on a command-line interface within the R Studio development environment. (R Core Team, 2017) Secondly, the US Census Bureau provides access to a number of databases for population information. This work made use of the national-level databases, but the Bureau also maintains a different database down to the census block level. Future work might include developing code to access that database to generate model populations tailored to specific regions of the country, perhaps at the county level, to allow emergency planners to consider what dislocation risks might be for the areas for which they have responsibility.

REFERENCES

Akahane, K., Yonai, S., Fukuda, S., Miyahara, N., Yasuda, H., Iwaoka, K., . . . Akashi, M. (2013). NIRS external dose estimation system for Fukushima residents after the Fukushima Dai-ichi NPP accident. *Scientific Reports, 3*, 1670. doi:10.1038/srep01670

American Diabetes, A. (2010). Diagnosis and classification of diabetes mellitus. *Diabetes Care, 33 Suppl 1*, S62-69. doi:10.2337/dc10-S062

American Psychiatric Association. (2013). *Diagnostic and Statistical Manual of Mental Disorders (DSM-5)*: American Psychiatric Publishing.

Anderson, R. N., & DeTurk, P. B. (2002). United States life tables, 1999. *Natl Vital Stat Rep, 50*(6), 1-39.

Arterburn, D. E., Bogart, A., Sherwood, N. E., Sidney, S., Coleman, K. J., Haneuse, S., . . . Selby, J. (2013). A multisite study of long-term remission and relapse of type 2 diabetes mellitus following gastric bypass. *Obes Surg, 23*(1), 93-102. doi:10.1007/s11695-012-0802-1

Bonanno, G. A., Brewin, C. R., Kaniasty, K., & Greca, A. M. (2010). Weighing the Costs of Disaster: Consequences, Risks, and Resilience in Individuals, Families, and Communities. *Psychol Sci Public Interest, 11*(1), 1-49. doi:10.1177/1529100610387086

Bromet, E. J., Atwoli, L., Kawakami, N., Navarro-Mateu, F., Piotrowski, P., King, A. J., . . . Kessler, R. C. (2017). Post-traumatic stress disorder associated with natural and human-made disasters in the World Mental Health Surveys. *Psychol Med, 47*(2), 227-241. doi:10.1017/S0033291716002026

Brown, L. M., Dosa, D. M., Thomas, K., Hyer, K., Feng, Z., & Mor, V. (2012). The effects of evacuation on nursing home residents with dementia. *Am J Alzheimers Dis Other Demen, 27*(6), 406-412. doi:10.1177/1533317512454709

Brustugun, O. T., Moller, B., & Helland, A. (2014). Years of life lost as a measure of cancer burden on a national level. *Br J Cancer, 111*(5), 1014-1020. doi:10.1038/bjc.2014.364

Bryant, R. A., Waters, E., Gibbs, L., Gallagher, H. C., Pattison, P., Lusher, D., . . . Forbes, D. (2014). Psychological outcomes following the Victorian Black Saturday bushfires. *Aust N Z J Psychiatry, 48*(7), 634-643. doi:10.1177/0004867414534476

Bureau International des Poids et Mesures. (2006). *The International System of Units (SI)*. Retrieved from

Burnet, N. G., Jefferies, S. J., Benson, R. J., Hunt, D. P., & Treasure, F. P. (2005). Years of life lost (YLL) from cancer is an important measure of population burden--and should be considered when allocating research funds. *Br J Cancer, 92*(2), 241-245. doi:10.1038/sj.bjc.6602321

Callen, J., & Homma, T. (2017). Lessons Learned in Protection of the Public for the Accident at the Fukushima Daiichi Nuclear Power Plant. *Health Phys, 112*(6), 550-559. doi:10.1097/HP.0000000000000666

Committee to Assess Health Risks from Exposure to Low Levels of Ionizing Radiation. (2006). *Health Risks from Exposure to Low Levels of Ionizing Radiation: BEIR VII Phase 2*. Retrieved from Washington, DC:

Deryugina T., K. L., and Levitt S. (2014). *The Economic Impact of Hurricane Katrina on its Victims: Evidence from Individual Tax Returns*. (Working Paper 20713).

Ebner, D. K., Ohsawa, M., Igari, K., Harada, K. H., & Koizumi, A. (2016). Lifestyle-related diseases following the evacuation after the Fukushima Daiichi nuclear power plant accident: a retrospective study of Kawauchi Village with long-term follow-up. *BMJ Open, 6*(7), e011641. doi:10.1136/bmjopen-2016-011641

Eisenbud, G. G., T. (1997). *Environmental Radioactivity from Natural, Industrial and Military Sources* (4 ed.). San Diego: Academic Press.

EPA. (1999). *Cancer Risk Coefficients for Environmental Exposure to Radionuclides*. (EPA 402-R-99-001). Washington, DC.

EPA. (2017). *PAG Manual: Protective Action Guides and Planning Guidance for Radiological Incidents*. (EPA-400/R-17/001).

Federal Geographic Data Committee. (2008). FGDC ENDORSES GEOPOLITICAL ENTITIES, NAMES, AND CODES (GENC) STANDARD EDITION 1. Retrieved from https://www.fgdc.gov/standards/news/GENC

Feng, J., Lenihanx, D. J., Johnson, M. M., Karri, V., & Reddy, C. V. R. (2006). Cardiac sequelae in Brooklyn after the September 11 terrorist attacks. *Clinical Cardiology, 29*(1), 13-17. doi:10.1002/clc.4960290105

Flory, K., Hankin, B. L., Kloos, B., Cheely, C., & Turecki, G. (2009). Alcohol and cigarette use and misuse among Hurricane Katrina survivors: psychosocial risk and protective factors. *Subst Use Misuse, 44*(12), 1711-1724. doi:10.3109/10826080902962128

Fonseca, V. A., Smith, H., Kuhadiya, N., Leger, S. M., Yau, C. L., Reynolds, K., . . . John-Kalarickal, J. (2009). Impact of a natural disaster on diabetes: exacerbation of disparities and long-term consequences. *Diabetes Care, 32*(9), 1632-1638. doi:10.2337/dc09-0670

FRMAC. (2015). *FRMAC Assessment Manual Volume 1: Overview and Methods*. (SAND2015-2884 R).

Gilmour, S., Sugimoto, A., Nomura, S., & Oikawa, T. (2015). Long-Term Changes in Stroke-Related Hospital Admissions After the Fukushima Triple Disaster. *J Am Geriatr Soc, 63*(11), 2425-2426. doi:10.1111/jgs.13812

Global Burden of Disease Cancer, C., Fitzmaurice, C., Allen, C., Barber, R. M., Barregard, L., Bhutta, Z. A., . . . Naghavi, M. (2017). Global, Regional, and National Cancer Incidence, Mortality, Years of Life Lost, Years Lived With Disability, and Disability-Adjusted Life-years for 32 Cancer Groups, 1990 to 2015: A Systematic Analysis for the Global Burden of Disease Study. *JAMA Oncol, 3*(4), 524-548. doi:10.1001/jamaoncol.2016.5688

Global Burden of Disease Collaborative Network. (2018). Global Burden of Disease Study 2017 (GBD 2017) Results. In. Seattle, United States: Institute for Health Metrics and Evaluation (IHME).

Golay, A., & Ybarra, J. (2005). Link between obesity and type 2 diabetes. *Best Pract Res Clin Endocrinol Metab, 19*(4), 649-663. doi:10.1016/j.beem.2005.07.010

Government of Japan. (2011). *View of Additional Annual Dose of 1 mSv*. Retrieved from https://www.env.go.jp/press/files/jp/18437.pdf.

Groen, J. P., A. (2008). Hurricane Katrina evacuees: who they are, where they are, and how they are faring. *Monthly Labor Review*, 32-51.

Hashimoto, S., Nagai, M., Fukuma, S., Ohira, T., Hosoya, M., Yasumura, S., . . . Fukushima Health Management Survey, G. (2017). Influence of Post-disaster Evacuation on Incidence of Metabolic Syndrome. *J Atheroscler Thromb, 24*(3), 327-337. doi:10.5551/jat.35824

Hayes, J. J., T. E.; Anderson, D.; Nanba, K. (2019). Effective Half Life of 134Cs and 137Cs in Fukushima Prefecture When Compared to

Theoretical Decay Models. *Health Physics*.

Ho, J. Y., Frankenberg, E., Sumantri, C., & Thomas, D. (2017). Adult Mortality Five Years after a Natural Disaster. *Popul Dev Rev, 43*(3), 467-490. doi:10.1111/padr.12075

ICRP. (1977). *ICRP PUBLICATION 26 Recommendations of the International Commission on Radiological Protection*. Retrieved from New York:

ICRP. (1985). ICRP Publication 43: Principles of Monitoring for the Radiation Protection of the Population. *Annals of the ICRP, 15*(1).

ICRP. (1991). 1990 Recommendations of the International Commission on Radiological Protection. *Annals of the ICRP, 21*.

ICRP. (2006a). Analysis of the Criteria Used by the ICRP to Justify the Setting of Numerical Protection Level Values. . *Annals of the ICRP, 36*(4).

ICRP. (2006b). ICRP Publication 101a: Assessing Dose of the Representative Person for the Purpose of the Radiation Protection of the Public. *Annals of the ICRP, 36*(3).

ICRP. (2007). ICRP Publication 103: The 2007 Recommendations of the International Commission on Radiological Protection. . *Annals of the ICRP, 37*(2-4).

ICRP. (2009). ICRP 111: Application of the Commission's Recommendations to the Protection of People Living in Long-term Contaminated Areas after a Nuclear Accident or a Radiation Emergency. *Annals of the ICRP, 39*(3).

Ikeda, N., Nishi, N., Noda, H., & Noda, M. (2017). Trends in prevalence and management of diabetes and related vascular risks in Japanese adults: Japan National Health and Nutrition Surveys 2003-2012. *Diabetes Res Clin Pract, 127*, 115-122. doi:10.1016/j.diabres.2017.03.011

International Atomic Energy Agency. (2013). *Actions to Protect the Public in an Emergency due to Severe Conditions at a Light Water Reactor*. Vienna: International Atomic Energy Agency.

International Atomic Energy Agency. (2015). *Preparedness and Response for a Nuclear or Radiological Emergency*. International Atomic Energy Agency.

Ishii, T., Ochi, S., Tsubokura, M., Kato, S., Tetsuda, T., Kato, J., . . . Tachiya, H. (2015). Physical performance deterioration of temporary housing residents after the Great East Japan Earthquake. *Prev Med Rep, 2*, 916-919. doi:10.1016/j.pmedr.2015.10.009

Ishii, T., Tsubokura, M., Ochi, S., Kato, S., Sugimoto, A., Nomura, S., . . . Tachiya, H. (2016). Living in Contaminated Radioactive Areas Is Not an Acute Risk Factor for Noncommunicable Disease Development: A Retrospective Observational Study. *Disaster Med Public Health Prep, 10*(1), 34-37. doi:10.1017/dmp.2015.102

Johnson, T. E. (2017). *Introduction to Health Physics, Fifth Edition*: McGraw-Hill Education.

Kamoi, K., Tanaka, M., Ikarashi, T., & Miyakoshi, M. (2006). Effect of the 2004 Mid Niigata Prefecture earthquake on glycemic control in type 1 diabetic patients. *Diabetes Res Clin Pract, 74*(2), 141-147. doi:10.1016/j.diabres.2006.03.028

Kario, K., McEwen Bruce, S., & Pickering Thomas, G. (2003). Disasters and the Heart: a Review of the Effects of Earthquake-Induced Stress on Cardiovascular Disease. *Hypertension Research, 26*(5), 355-367. doi:10.1291/hypres.26.355

Karter, A. J., Nundy, S., Parker, M. M., Moffet, H. H., & Huang, E. S. (2014). Incidence of remission in adults with type 2 diabetes: the diabetes & aging study. *Diabetes Care, 37*(12), 3188-3195. doi:10.2337/dc14-0874

Kessler, I. I. (1971). Mortality experience of diabetic patients. *The American Journal of Medicine, 51*(6), 715-724. doi:10.1016/0002-9343(71)90299-3

Kessler, R. C. (1995). Posttraumatic Stress Disorder in the National Comorbidity Survey. *Archives of General Psychiatry, 52*(12). doi:10.1001/archpsyc.1995.03950240066012

Kessler, R. C., Aguilar-Gaxiola, S., Alonso, J., Benjet, C., Bromet, E. J., Cardoso, G., . . . Koenen, K. C. (2017). Trauma and PTSD in the WHO World Mental Health Surveys. *Eur J Psychotraumatol, 8*(sup5), 1353383. doi:10.1080/20008198.2017.1353383

Kessler, R. C., Galea, S., Gruber, M. J., Sampson, N. A., Ursano, R. J., & Wessely, S. (2008). Trends in mental illness and suicidality after Hurricane Katrina. *mol psychiatry, 13*(4), 374-384. doi:10.1038/sj.mp.4002119

Kloner, R. A., Leor, J., Poole, W. K., & Perritt, R. (1997). Population-Based Analysis of the Effect of the Northridge Earthquake on Cardiac Death in Los Angeles County, California. *Journal of the American College of Cardiology, 30*(5), 1174-1180. doi:10.1016/s0735-1097(97)00281-7

Kolves, K., Kolves, K. E., & De Leo, D. (2013). Natural disasters and suicidal behaviours: a systematic literature review. *J Affect Disord, 146*(1), 1-14. doi:10.1016/j.jad.2012.07.037

Kouadio, I. K., Aljunid, S., Kamigaki, T., Hammad, K., & Oshitani, H. (2012). Infectious diseases following natural disasters: prevention and control measures. *Expert Rev Anti Infect Ther, 10*(1), 95-104. doi:10.1586/eri.11.155

Lee, D. C., Gupta, V. K., Carr, B. G., Malik, S., Ferguson, B., Wall, S. P., . . . Goldfrank, L. R. (2016). Acute post-disaster medical needs of patients with diabetes: emergency department use in New York City by diabetic adults after Hurricane Sandy. *BMJ Open Diabetes Res Care, 4*(1), e000248. doi:10.1136/bmjdrc-2016-000248

Leppold, C., Nomura, S., Sawano, T., Ozaki, A., Tsubokura, M., Hill, S., . . . Anbe, H. (2017). Birth Outcomes after the Fukushima Daiichi Nuclear Power Plant Disaster: A Long-Term Retrospective Study. *Int J Environ Res Public Health, 14*(5). doi:10.3390/ijerph14050542

Leppold, C., Tsubokura, M., Ozaki, A., Nomura, S., Shimada, Y., Morita, T., . . . Hill, S. (2016). Sociodemographic patterning of long-term diabetes mellitus control following Japan's 3.11 triple disaster: a retrospective cohort study. *BMJ Open, 6*(7), e011455. doi:10.1136/bmjopen-2016-011455

Loukine, L., Waters, C., Choi, B. C., & Ellison, J. (2012). Impact of diabetes mellitus on life expectancy and health-adjusted life expectancy in Canada. *Popul Health Metr, 10*(1), 7. doi:10.1186/1478-7954-10-7

Maeda, M., & Oe, M. (2017). Mental Health Consequences and Social Issues After the Fukushima Disaster. *Asia Pac J Public Health, 29*(2_suppl), 36S-46S. doi:10.1177/1010539516689695

Magliano, D. J., Shaw, J. E., Shortreed, S. M., Nusselder, W. J., Liew, D., Barr, E. L. M., . . . Peeters, A. (2008). Lifetime risk and projected population prevalence of diabetes. *Diabetologia, 51*(12), 2179-2186. doi:10.1007/s00125-008-1150-5

Manuel, D. G., & Schultz, S. E. (2004). Health-related quality of life and health-adjusted life expectancy of people with diabetes in Ontario, Canada, 1996-1997. *Diabetes Care, 27*(2), 407-414. doi:10.2337/diacare.27.2.407

Miyazaki, M., & Hayano, R. (2016). Individual external dose monitoring of all citizens of Date City by passive dosimeter 5 to 51 months after the Fukushima NPP accident (series): 1. Comparison of individual dose with ambient dose rate monitored by aircraft surveys. *J Radiol Prot, 37*(1), 1-12. doi:10.1088/1361-6498/37/1/1

Morina, N., Wicherts, J. M., Lobbrecht, J., & Priebe, S. (2014). Remission from post-traumatic stress disorder in adults: a systematic review and meta-analysis of long term outcome studies. *Clin Psychol Rev, 34*(3), 249-255. doi:10.1016/j.cpr.2014.03.002

Morita, T., Nomura, S., Tsubokura, M., Leppold, C., Gilmour, S., Ochi, S., . . . Kami, M. (2017). Excess mortality due to indirect health effects of the 2011 triple disaster in Fukushima, Japan: a retrospective observational study. *J Epidemiol Community Health, 71*(10), 974-980. doi:10.1136/jech-2016-208652

Murakami, M., Ono, K., Tsubokura, M., Nomura, S., Oikawa, T., Oka, T., . . . Oki, T. (2015). Was the Risk from Nursing-Home Evacuation after the Fukushima Accident Higher than the Radiation Risk? *plos one, 10*(9), e0137906. doi:10.1371/journal.pone.0137906

Murakami, M., Tsubokura, M., Ono, K., Nomura, S., & Oikawa, T. (2017). Additional risk of diabetes exceeds the increased risk of cancer caused by radiation exposure after the Fukushima disaster. *plos one, 12*(9), e0185259. doi:10.1371/journal.pone.0185259

Murillo-Zamora, E., Mendoza-Cano, O., Rios-Silva, M., Sanchez-Pina, R. A., Higareda-Almaraz, M. A., Higareda-Almaraz, E., & Lugo-Radillo, A. (2018). Disability-Adjusted Life Years for Cancer in 2010(-)2014: A Regional Approach in Mexico. *Int J Environ Res Public Health, 15*(5). doi:10.3390/ijerph15050864

Naito, W., Uesaka, M., Yamada, C., Kurosawa, T., Yasutaka, T., & Ishii, H. (2016). Relationship between Individual External Doses, Ambient Dose Rates and Individuals' Activity-Patterns in Affected Areas in Fukushima following the Fukushima Daiichi Nuclear Power Plant Accident. *plos one, 11*(8), e0158879. doi:10.1371/journal.pone.0158879

Nakahara, S., & Ichikawa, M. (2013). Mortality in the 2011 Tsunami in Japan. *Journal of Epidemiology, 23*(1), 70-73. doi:10.2188/jea.JE20120114

Narayan, K. M., Boyle, J. P., Thompson, T. J., Sorensen, S. W., & Williamson, D. F. (2003). Lifetime risk for diabetes mellitus in the United States. *JAMA, 290*(14), 1884-1890. doi:10.1001/jama.290.14.1884

National Institutes of Health. (2019). Online Summary of Trends in US Cancer Control Measures. Retrieved from https://progressreport.cancer.gov/end/life_lost

NCRP. (2014). *Decision Making for Late-Phase Recovery From Major Nuclear or Radiological Incidents*. Retrieved from Bethesda, MD:

Neria, Y., Nandi, A., & Galea, S. (2008). Post-traumatic stress disorder following disasters: a systematic review. *Psychol Med, 38*(4), 467-480. doi:10.1017/S0033291707001353

Nomura, S., Blangiardo, M., Tsubokura, M., Nishikawa, Y., Gilmour, S., Kami, M., & Hodgson, S. (2016). Post-nuclear disaster evacuation and survival amongst elderly people in Fukushima: A comparative analysis between evacuees and non-evacuees. *Prev Med, 82*, 77-82. doi:10.1016/j.ypmed.2015.11.014

Nomura, S., Blangiardo, M., Tsubokura, M., Ozaki, A., Morita, T., & Hodgson, S. (2016). Postnuclear disaster evacuation and chronic health in adults in Fukushima, Japan: a long-term retrospective analysis. *BMJ Open, 6*(2), e010080. doi:10.1136/bmjopen-2015-010080

Nomura, S., Gilmour, S., Tsubokura, M., Yoneoka, D., Sugimoto, A., Oikawa, T., . . . Shibuya, K. (2013). Mortality risk amongst nursing home residents evacuated after the Fukushima nuclear accident: a retrospective cohort study. *plos one, 8*(3), e60192. doi:10.1371/journal.pone.0060192

Norris, F. H., Friedman, M. J., Watson, P. J., Byrne, C. M., Diaz, E., & Kaniasty, K. (2002). 60,000 Disaster Victims Speak: Part I. An Empirical Review of the Empirical Literature, 1981–2001. *Psychiatry: Interpersonal and Biological Processes, 65*(3), 207-239. doi:10.1521/psyc.65.3.207.20173

North, C. S. (1999). Psychiatric Disorders Among Survivors of the Oklahoma City Bombing. *JAMA, 282*(8). doi:10.1001/jama.282.8.755

Oe, M., Fujii, S., Maeda, M., Nagai, M., Harigane, M., Miura, I., . . . Abe, M. (2016). Three-year trend survey of psychological distress, post-traumatic stress, and problem drinking among residents in the evacuation zone after the Fukushima Daiichi Nuclear Power Plant accident [The Fukushima Health Management Survey]. *Psychiatry Clin Neurosci, 70*(6), 245-252. doi:10.1111/pcn.12387

Ohira, T., Hosoya, M., Yasumura, S., Satoh, H., Suzuki, H., Sakai, A., . . . Fukushima Health Management Survey, G. (2016). Effect of Evacuation on Body Weight After the Great East Japan Earthquake. *Am J Prev Med, 50*(5), 553-560. doi:10.1016/j.amepre.2015.10.008

Ohira, T., Nakano, H., Nagai, M., Yumiya, Y., Zhang, W., Uemura, M., . . . Fukushima Health Management Survey, G. (2017). Changes in Cardiovascular Risk Factors After the Great East Japan Earthquake. *Asia Pac J Public Health, 29*(2_suppl), 47S-55S. doi:10.1177/1010539517695436

Panzram, G. (1987). Mortality and survival in Type 2 (non-insulin-dependent) diabetes mellitus. *Diabetologia, 30*(3), 123-131. doi:10.1007/bf00274216

Park, J., Cho, J., & Rose, A. (2010). Modeling a major source of economic resilience to disasters: recapturing lost production. *Natural Hazards, 58*(1), 163-182. doi:10.1007/s11069-010-9656-9

Pham, T.-M., Kubo, T., Fujino, Y., Ozasa, K., Matsuda, S., & Yoshimura, T. (2011). Disability-Adjusted Life Years (DALY) for Cancer in Japan in 2000. *Journal of Epidemiology, 21*(4), 309-312. doi:10.2188/jea.JE20110017

Pham, T. M., Fujino, Y., Ide, R., Tokui, N., Kubo, T., Mizoue, T., . . . Yoshimura, T. (2009). Years of life lost due to cancer in a cohort study in Japan. *Eur J Public Health, 19*(2), 189-192. doi:10.1093/eurpub/ckp020

Porter, M., & Haslam, N. (2005). Predisplacement and postdisplacement factors associated with mental health of refugees and internally displaced persons: a meta-analysis. *JAMA, 294*(5), 602-612. doi:10.1001/jama.294.5.602

R Core Team. (2017). R: A language and environment for statistical computing. Vienna, Austria: R Foundation for Statistical Computing,. Retrieved from https://www.r-project.org/

Saika, K., & Machii, R. (2013). Estimated Disability-adjusted Life Year (DALY) in Asia in GLOBOCAN 2008. *Japanese Journal of Clinical Oncology, 43*(8), 846-847. doi:10.1093/jjco/hyt107

Sastry, N., & Gregory, J. (2013). The effect of Hurricane Katrina on the prevalence of health impairments and disability among adults in New Orleans: differences by age, race, and sex. *Soc Sci Med, 80*, 121-129. doi:10.1016/j.socscimed.2012.12.009

Satoh, H., Ohira, T., Hosoya, M., Sakai, A., Watanabe, T., Ohtsuru, A., . . . Abe, M. (2015). Evacuation after the Fukushima Daiichi Nuclear Power Plant Accident Is a Cause of Diabetes: Results from the Fukushima Health Management Survey. *J Diabetes Res, 2015*, 627390. doi:10.1155/2015/627390

Shimada, K., & Kai, M. (2015). Calculating disability-adjusted life years (DALY) as a measure of excess cancer risk following radiation exposure. *J Radiol Prot, 35*(4), 763-775. doi:10.1088/0952-4746/35/4/763

Stephens, K. U., Sr., Grew, D., Chin, K., Kadetz, P., Greenough, P. G., Burkle, F. M., Jr., . . . Franklin, E. R. (2007). Excess mortality in the aftermath of Hurricane Katrina: a preliminary report. *Disaster Med Public Health Prep, 1*(1), 15-20. doi:10.1097/DMP.0b013e3180691856

Takahashi, S., Nakamura, M., Yonekura, Y., Tanno, K., Sakata, K., Ogawa, A., & Kobayashi, S. (2016). Association between relocation and changes in cardiometabolic risk factors: a longitudinal study in tsunami survivors of the 2011 Great East Japan Earthquake. *BMJ Open, 6*(5), e011291. doi:10.1136/bmjopen-2016-011291

Tsubokura, M., Takita, M., Matsumura, T., Hara, K., Tanimoto, T., Kobayashi, K., . . . Tachiya, H. (2013). Changes in metabolic profiles after the Great East Japan Earthquake: a retrospective observational study. *BMC Public Health, 13*, 267. doi:10.1186/1471-2458-13-267

Turin, T. C., Murakami, Y., Miura, K., Rumana, N., Kadota, A., Ohkubo, T., . . . Group, N. D. R. (2012). Diabetes and life expectancy among Japanese - NIPPON DATA80. *Diabetes Res Clin Pract, 96*(2), e18-22. doi:10.1016/j.diabres.2012.01.003

U.S. Census Bureau. (2010). American Factfinder. Retrieved from https://factfinder.census.gov/faces/nav/jsf/pages/index.xhtml

STANDARDS FOR PROTECTION AGAINST RADIATION, 10 C.F.R. (2015).

Ueda, Y., Yabe, H., Maeda, M., Ohira, T., Fujii, S., Niwa, S., . . . Fukushima Health Management Survey, G. (2016). Drinking Behavior and Mental Illness Among Evacuees in Fukushima Following the Great East Japan Earthquake: The Fukushima Health Management Survey. *Alcohol Clin Exp Res, 40*(3), 623-630. doi:10.1111/acer.12984

United Nations Scientific Committee on the Effects of Atomic Radiation. (2000). *SOURCES AND EFFECTS OF IONIZING RADIATION UNSCEAR 2000 Report to the General Assembly, with Scientific Annexes VOLUME II: EFFECTS*. Retrieved from New York:

United Nations Scientific Committee on the Effects of Atomic Radiation. (2008). *Sources and Effects of Ionizing Radiation: Volume II: EFFECTS Scientific Annexes C, D and E*.
United Nations Scientific Committee on the Effects of Atomic Radiation. (2013). *SOURCES, EFFECTS AND RISKS OF IONIZING RADIATION United Nations Scientific Committee on the Effects of Atomic Radiation UNSCEAR 2013 Report to the General Assembly with Scientific Annexes VOLUME I Scientific Annex A*. Retrieved from New York:
Uscher-Pines, L. (2009). Health effects of relocation following disaster: a systematic review of the literature. *Disasters, 33*(1), 1-22. doi:10.1111/j.1467-7717.2008.01059.x
Vlahov, D. (2002). Increased Use of Cigarettes, Alcohol, and Marijuana among Manhattan, New York, Residents after the September 11th Terrorist Attacks. *American Journal of Epidemiology, 155*(11), 988-996. doi:10.1093/aje/155.11.988
Waddington, I., Thomas, P. J., Taylor, R. H., & Vaughan, G. J. (2017). J-value assessment of relocation measures following the nuclear power plant accidents at Chernobyl and Fukushima Daiichi. *Process Safety and Environmental Protection, 112*, 16-49. doi:10.1016/j.psep.2017.03.012
World Health Organization. (2004). Global Burden of Disease 2004 Update: Disability Weights for Diseases and Conditions.
World Health Organization. (2017). *WHO methods and data sources for global burden of disease estimates 2000-2015*. Geneva, Switzerland.

APPENDIX 1 – DEMOGRAPHIC CALCULATIONS AND ASSOCIATED R CODE

This work utilizes several demographic tools, generated in the R programming language (R Core Team, 2017). Each is described briefly in the following sections, followed by the code.

Appendix 1A – R Function get_data_secure()

The function get_data_secure() is a generic tool that gathers national-level demographic data from the United States Census Bureau via a secure Application Programming Interface (API). This API depends on an API key, which is unique to each user and is obscured here. This function defaults to 2012 census data for the United States; the user can supply any 2-letter country code and year for which the Census Bureau has data. The function divides the data into the 5-year age bins for ages 0-99 years, and a final "100+" bin; it is also divided by sex. The output is a data frame of age bins, sex, and population. The male population figures are returned as negative values for graphing convenience.

This is the complete command line:

```
get_data_secure(country = "US", year = 2012)
```

Where a variable in the command line is followed by an equals sign, it represents a default value.

This command will obtain the dataset for the U.S. in 2012, since this is the default:

```
get_data_secure()
```

This command line will obtain the dataset for Japan in 2015:

```
get_data_secure("JA", 2015)
```

The code is below:

```
# created 8 Jan 2019

# function get_data_secure(country="US", year=2012)
# function that grabs US census data population data from census.gov
# requires an API key
# returns a dataframe with Age, Sex, and Population for every 5 year group
# 0-4, 5-9, 10-14, etc.
#
# default country is US, year is 2012
# example call: get_data_secure(country="JA", year=2010)
#
# does not depend on any other custom functions
#
library(reshape2)
library(plyr)
library(jsonlite)

# country is the 2-letter FIPS code, default is "US"
# also takes 2-letter state codes without problem
# year is the 4-digit year of interest, default is 2012
# for my purposes other country codes of note are NIgeria,
# JApan, GM (Germany), BRazil, UK

get_data_secure <- function(country="US", year=2012) {
  # construct URLs for data request
  # had to separate male and female because the URL gets too long!

  # my_key is an API key specific to myself
  # for distribution - change my_key
  my_key <- "XXXXXXXXX"
  c1 <- "https://api.census.gov/data/timeseries/idb/5year?"
  m1 <- "get=MPOP0_4,MPOP5_9,MPOP10_14,MPOP15_19,MPOP20_24,MPOP25_29,MPOP30_34"
  m2 <- ",MPOP35_39,MPOP40_44,MPOP45_49,MPOP50_54,MPOP55_59,MPOP60_64,MPOP65_69"
  m3 <- ",MPOP70_74,MPOP75_79,MPOP80_84,MPOP85_89,MPOP90_94,MPOP95_99,MPOP100_"
  f1 <- "get=FPOP0_4,FPOP5_9,FPOP10_14,FPOP15_19,FPOP20_24,FPOP25_29,FPOP30_34"
  f2 <- ",FPOP35_39,FPOP40_44,FPOP45_49,FPOP50_54,FPOP55_59,FPOP60_64,FPOP65_69"
  f3 <- ",FPOP70_74,FPOP75_79,FPOP80_84,FPOP85_89,FPOP90_94,FPOP95_99,FPOP100_"
  c3 <- paste0("&FIPS=", country, "&time=", year, "&key=")
  male_url <- paste0(c1, m1, m2, m3, c3, my_key)
  female_url <- paste0(c1, f1, f2, f3, c3, my_key)
  # I've frequently had to rerun these, maybe due to delays in establishing
  # secure connections or downloading.  Not sure how to handle in the context
  # of a function.  I don't think it's a code problem, just connectivity.
  male_df <- fromJSON(male_url)
  female_df <- fromJSON(female_url)

  # because of the way the data comes in from census.gov, have to do some
  # reshaping.  Drop cols 22 and 23, which echo the input country code and
```

```
  # year.  Drop row 1 which is the variable names.  Leaves a char vector
  male_df2 <- male_df[,-(22:23)]
  male_df2 <- male_df2[-1,]
  female_df2 <- female_df[,-(22:23)]
  female_df2 <- female_df2[-1,]

  # fold cleaned up male and female vectors together with a pretty set of
  # age ranges into a single data frame, then clean up
  ages <- c("0-4","5-9","10-14","15-19","20-24","25-29","30-34","35-39","40-44",
            "45-49","50-54","55-59","60-64","65-69","70-74","75-79","80-84",
            "85-89","90-94","95-99","100+")
  df <- data.frame(ages, male_df2, female_df2, stringsAsFactors = FALSE)
  colnames(df) <- c("Age", "Male", "Female")
  df$Female <- as.numeric(df$Female)
  df$Male <- as.numeric(df$Male)
  # set male pops as negative for later graphing.  Obviously delete
  # or reset if actually using the numbers.  Just easier to do at this
  # point than later
  df$Male <- -1 * df$Male
  df$Age <- factor(df$Age, levels = df$Age, labels = df$Age)
  # take to long form, with Age (factor), Sex (factor), Pop (numeric)
  df.melt <- melt(df,
                  value.name='Population',
                  variable.name = 'Sex',
                  id.vars='Age' )
  # rev 6 Jan 2019 melt stopped correctly naming the columns so brute force
  colnames(df.melt) <- c("Age", "Sex", "Population")

  return(df.melt)
}
```

Appendix 1B – R Function demo_risk()

The function demo_risk() performs two tasks; first, based on the demographic profile of the input country, it prints the overall value of cancer risk per 10,000 people per gray. Then, it generates a plot pairing the population proportions with the cancer mortality risk proportions for the input country. This function depends on both get_data_secure() and on a data file, beir_vii_cancers.txt, set in the working directory. Calls are similar to get_data_secure(), in that the user supplies a 2-letter country code (default, “US”) and year (default, 2012). Note: this function was one of the first developed, and is only used for generating a few graphics. It was not updated.

This is the complete command line:

```
demo_risk(country = "US", year = 2012)
```

Where a variable in the command line is followed by an equals sign, it represents a default value.

This command line will generate the risk value and plot for Japan in 2015:

```
demo_risk("JA", 2015)
```

The output would be:

```
[1] "JA Total Cancer Mortality Risk per 10000 per Gy =  516.418061602261"
```

and a plot (Figure 10)

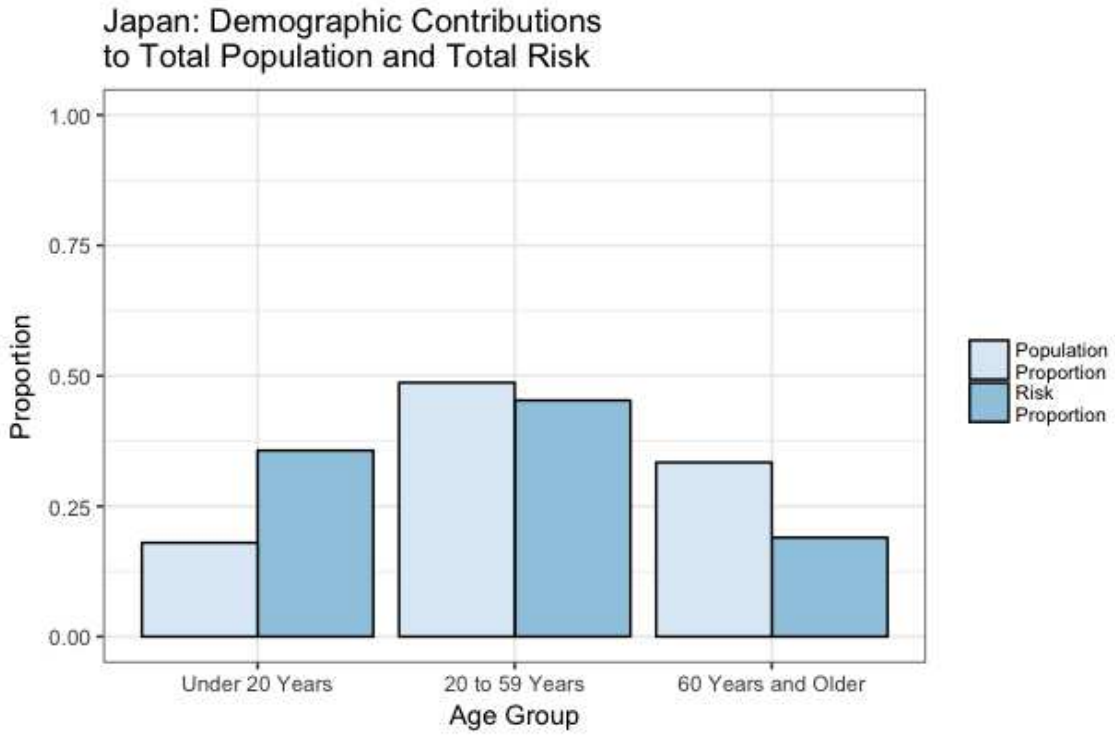


Figure 10: Example plot for function demo_risk()

The code is below:

```
# reviewed, tested, comments revised 13 Feb 2018
#
# depends on my function get_data_secure(), found in file get_pop_data secure.R
# requires the file "beir_vii_cancers.txt" in the working directory
#
#this function produces a plot of all demographic contributions
# to cancer risk, paired with their population proportions.
# it also prints the value of excess cancer risk per 10000 people
# per Gy of low LET radiation
#
library(tidyverse)
library(reshape2)
library(countrycode)

demo_risk <- function(country = "US", year=2012) {
  # pull in the BEIR VII table, peel out male and female mortality figures
  beirvii_mm <- read_delim("beir_vii_cancers.txt", delim = " ", col_names = FALSE)
  temp_names <- unlist(beirvii_mm[,1])
  beirvii_t <- t(beirvii_mm[, 2:ncol(beirvii_mm)])
  beirvii_t <- as.data.frame(beirvii_t, row.names = FALSE)
  colnames(beirvii_t) <- temp_names

  # convert to 1 Gy, and per-person
  beirvii_t$male_incidence <- beirvii_t$male_incidence*10/100000
  beirvii_t$female_incidence <- beirvii_t$female_incidence*10/100000
  beirvii_t$male_mortality <- beirvii_t$male_mortality*10/100000
  beirvii_t$female_mortality <- beirvii_t$female_mortality*10/100000

  male_mort_table <- select(beirvii_t, male_mortality)
  female_mort_table <- select(beirvii_t, female_mortality)

  #pull in country pop fractions, fold bins to match BEIR
  # a lot of tedious manual combining
  # 0-4  5-9  10-14  15-19  20-29 (up by 10, 80 max)
  pop_raw <- get_data_secure(country, year)
  total_pop <- sum(abs(pop_raw$Population))
  pop_raw$Population <- pop_raw$Population/total_pop
  pop_raw$Age <- as.character(pop_raw$Age)
  pop_raw$Sex <- as.character(pop_raw$Sex)
  pop_raw$Population <- abs(pop_raw$Population)
  pop_frac_beir <- tibble(Age = "0", Sex = "0", Population = 0)
  pop_frac_beir[1,] <- pop_raw[1,]
  pop_frac_beir[2,] <- pop_raw[2,]
  pop_frac_beir[3,] <- pop_raw[3,]
  pop_frac_beir[4,] <- pop_raw[4,]
  pop_frac_beir[5,] <- c("20-29", "Male",
                         pop_raw[5,3] + pop_raw[6,3])
  pop_frac_beir[6,] <- c("30-39", "Male",
                         pop_raw[7,3] + pop_raw[8,3])
  pop_frac_beir[7,] <- c("40-49", "Male",
                         pop_raw[9,3] + pop_raw[10,3])
  pop_frac_beir[8,] <- c("50-59", "Male",
                         pop_raw[11,3] + pop_raw[12,3])
  pop_frac_beir[9,] <- c("60-69", "Male",
                         pop_raw[13,3] + pop_raw[14,3])
  pop_frac_beir[10,] <- c("70-79", "Male",
                         pop_raw[15,3] + pop_raw[16,3])
  pop_frac_beir[11,] <- c("80+", "Male",
                         pop_raw[17,3] + pop_raw[18,3] +
                         pop_raw[19,3] + pop_raw[20,3] +
                         pop_raw[21,3])
```

```
  pop_frac_beir[12,] <- pop_raw[22,]
  pop_frac_beir[13,] <- pop_raw[23,]
  pop_frac_beir[14,] <- pop_raw[24,]
  pop_frac_beir[15,] <- pop_raw[25,]
  pop_frac_beir[16,] <- c("20-29", "Female",
                          pop_raw[26,3] + pop_raw[27,3])
  pop_frac_beir[17,] <- c("30-39", "Female",
                          pop_raw[28,3] + pop_raw[29,3])
  pop_frac_beir[18,] <- c("40-49", "Female",
                          pop_raw[30,3] + pop_raw[31,3])
  pop_frac_beir[19,] <- c("50-59", "Female",
                          pop_raw[32,3] + pop_raw[33,3])
  pop_frac_beir[20,] <- c("60-69", "Female",
                          pop_raw[34,3] + pop_raw[35,3])
  pop_frac_beir[21,] <- c("70-79", "Female",
                           pop_raw[36,3] + pop_raw[37,3])
  pop_frac_beir[22,] <- c("80+", "Female",
                           pop_raw[38,3] + pop_raw[39,3] +
                             pop_raw[40,3] + pop_raw[41,3] +
                             pop_raw[42,3])
  pop_frac_beir$Population <- as.numeric(pop_frac_beir$Population)
  male_frac <- pop_frac_beir[pop_frac_beir$Sex == "Male",3]
  female_frac <- pop_frac_beir[pop_frac_beir$Sex == "Female",3]

  #demographic risk contribution
  male_risk <- male_frac * male_mort_table
  female_risk <- female_frac * female_mort_table
  total_risk <- sum(male_risk) + sum(female_risk)
  # uncomment to see total pop risk - just a check
  out_string <- paste(country,
            "Total Cancer Mortality Risk per 10000 per Gy = ",total_risk*10000)
  print(out_string)
  # parsing out the age-based risk for plotting
  under_20_risk <- sum(male_risk[1:4,]) + sum(female_risk[1:4,])
  mid_risk <- sum(male_risk[5:8,]) + sum(female_risk[5:8,])
  over_60_risk <- sum(male_risk[9:11,]) + sum(female_risk[9:11,])

  #parsing out the age-based population fractions for plotting
  under_20_frac <- sum(male_frac[1:4,]) + sum(female_frac[1:4,])
  mid_frac <- sum(male_frac[5:8,]) + sum(female_frac[5:8,])
  over_60_frac <- sum(male_frac[9:11,]) + sum(female_frac[9:11,])

  #create vectors for plotting
  risk_vec <- c(under_20_risk, mid_risk, over_60_risk)
  risk_vec_proportion <- risk_vec/sum(risk_vec)
  risk_vec_proportion <- signif(risk_vec_proportion, digits = 3)
  pop_vec <- c(under_20_frac, mid_frac, over_60_frac)
  pop_vec <- signif(pop_vec, digits = 3)

  # Plotting
  table_names <- c("Under 20 Years", "20 to 59 Years", "60 Years and Older")

  pop_data <- tibble(
    age_group = factor(table_names),
    pop = pop_vec,
    risk = risk_vec_proportion
  )
  pop_data$age_group <- factor(pop_data$age_group, levels = table_names)
  # A quick conversion of 2-letter (fips) country code to full name
  country_name <- countrycode(country, "fips", "country.name")
  pop_data <- as.data.frame(pop_data)
  pop_data_m <- melt(pop_data)
  country_demo_risk <- ggplot(pop_data_m, aes(x = age_group, y = value, fill = variable)) +
    geom_bar(stat = "identity", position = "dodge", color = "black") +
    theme_bw() +
    theme(legend.text=element_text(size=8)) +
    labs(x = "Age Group", y = "Proportion") +
    labs(title = paste0(country_name, ": Demographic Contributions\nto Total Population and Total
Risk")) +
    scale_fill_brewer(name = NULL,
                      labels = c("Population\nProportion", "Risk\nProportion")) +
```

```
    ylim(0,1)
  plot_name <- paste0(country, "_demo_risk.png")
  ggsave(plot_name, plot = country_demo_risk, width = 5, height = 4)

  return(country_demo_risk)
}
```

Appendix 1C – Data File beir_vii_cancers.txt

The data file beir_vii_cancers.txt is a simple extract of the BEIR VII Table 12D-2, Lifetime Attributable Risk of Cancer Mortality (Committee to Assess Health Risks from Exposure to Low Levels of Ionizing Radiation, 2006), condensed down to the data on all cancers by age and sex. This was directly incorporated into all functions except `demo_risk()`, as noted above.

```
age 0 5 10 15 20 30 40 50 60 70 80
male_incidence 2563 1816 1445 1182 977 686 648 591 489 343 174
female_incidence 4777 3377 2611 2064 1646 1065 886 740 586 409 214
male_mortality 1099 852 712 603 511 381 377 360 319 250 153
female_mortality 1770 1347 1104 914 762 542 507 469 409 317 190
```

Appendix 1D – R Function pop_pyramid()

The function pop_pyramid() generates a waterfall chart that illustrates population sex and age proportions for the user-selected country and year. It depends on the function get_data_secure() and, like that function, has the United States data for 2012 as its default.

This is the complete command line:

```
pop_pyramid(country = "US", year = 2012)
```

Where a variable in the command line is followed by an equals sign, it represents a default value.

This command line will generate a waterfall chart for Japan for 2015:

```
pop_pyramid("JA", 2015)
```

And the output would be a plot, Figure 11

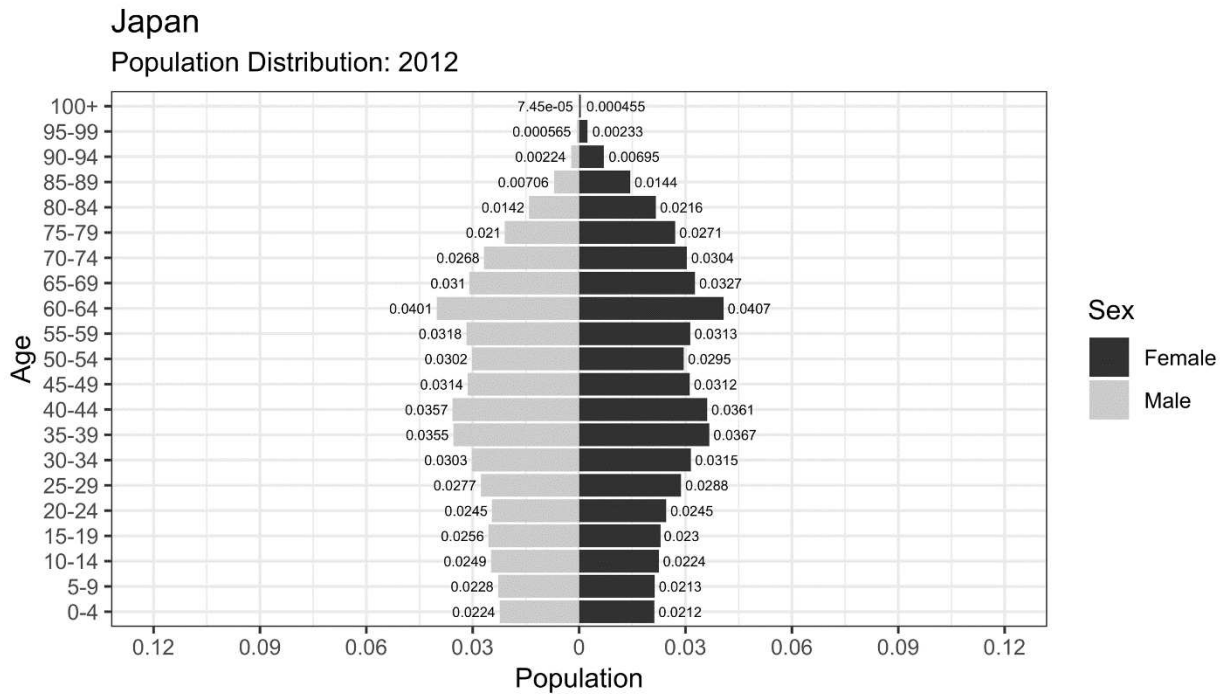


Figure 11 Example plot from the function pop_pyramid()

The code is below:

```
# file pop_pyramid.R
# function pop_pyramid(country="US", year=2012)
#
# edited 28 May 2019 improved comments
```

```
# edited 06 Jan 2019 countrycode() changed its modifiers
# reviewed, tested, comments modified 13 Feb 2018
#
# depends on my custom function get_data_secure(), found in the
# file get_data_secure.R
# default country is US, year is 2012
#
# example call: pop_pyramid("JA", 2010)
#
# generates a waterfall chart to show country demographics
# displays and also saves in the current working directory
# filename is XX_pyramid.png, where XX is the 2-letter country code
#
# uses function get_data_secure, which downloads from census.gov
# and returns a data frame with Age(factor), Sex(factor), Pop
#
# a warning message of "removed # rows" means the scale has been exceeded
# e.g. some population division is greater than 12% of the population
library(gridExtra)
library(jsonlite)
library(ggplot2)
library(countrycode)
library(reshape)

pop_pyramid <- function(country="US", year=2012) {
  demographics <- get_data_secure(country, year)
  # normalizes so as to get proportions
  # comment out if you want actual population numbers
  total_pop <- sum(demographics$Population[22:42])-sum(demographics$Population[1:21])
  demographics$Population <- demographics$Population/total_pop
  country_female <- subset(demographics, Sex == "Female")
  country_male <- subset(demographics, Sex == "Male")

  # A quick conversion of 2-letter (fips) country code to full name
  # tweaked 06 Jan 2019 because of changes to countrycode()
  country_name <- countrycode(country, "fips", "country.name")

  # generate the waterfall diagram
  country_pyramid <- ggplot(demographics, aes(x = Age, y = Population, fill = Sex)) +
    geom_bar(data = country_female, stat = "identity") +
    geom_bar(data = country_male, stat = "identity") +
    scale_y_continuous(breaks = seq(-0.12, 0.12, 0.03),
                       labels = as.character(c(seq(0.12, 0, -0.03),
                                               seq(0.03, 0.12, 0.03))),
                       limits = c(-0.12, 0.12)) +
    coord_flip() +
  # this sets to b&w
  # use scale_fill_brewer(palette="Set1") for nice red and blue
    scale_fill_grey() +
    geom_text(data = country_female, aes(label = signif(abs(Population), digits = 3)),
              size = 2, hjust = -0.1) +
    geom_text(data = country_male, aes(label = signif(abs(Population), digits = 3)),
              size = 2, hjust = 1.1) +
  # uncomment to include individual titles
    ggtitle(country_name, subtitle = paste0("Population Distribution: ", year)) +
  # plain theme_bw() for the full plot, blanks for no y-labels
    theme_bw()
  #  theme(axis.text.y = element_blank(), axis.title.y = element_blank())

  # change file extension to change output type
  plot_name <- paste0(country, "_pyramid.png")
  ggsave(plot_name, plot = country_pyramid, width = 7, height = 4, dpi=600)

return(country_pyramid)
}
```

Appendix 1E – R Function side_by_side2()

The function `side_by_side2()` uses `pop_pyramid()` to generate three population waterfall diagrams in a single plot, with a shared legend. It depends on the function `get_data_secure()`.

This is the complete command line:

```
side_by_side2(country1, country2, country3, year = 2012, out_file_name = "side_by_side.pdf)
```

Where a variable in the command line is followed by an equals sign, it represents a default value.

This command line will generate plots for the United States, Nigeria, and Japan in 2012, saved as "US_NI_JA_2012.pdf":

```
side_by_side2("US", "NI", "JA", "US_NI_JA_2012.pdf")
```

The code is below:

```
# file side_by_side2.R
# function side_by_side2(country1, country2, country3, year=2012,
#                        out_file_name = "side_by_side.pdf")
# takes 3 country names (2-letter FIPS codes)
# and a year, generates waterfall plots of the populations,
# sets them side by side with common legends
#
# year defaults to 2012, output file to "side_by_side.pdf"
# example call: side_by_side2("US", "NI", JA", 2010, "comparison.pdf")
#
# uses pop_pyramid() which in turn uses get_data_secure()
# and grid_arrange_shared_legend()
library(lemon)
library(tidyverse)
library(gridExtra)
library(ggplot2)
```

```
library(countrycode)
library(reshape2)
library(plyr)
library(jsonlite)
library(grid)


side_by_side2 <- function(country1, country2, country3, year=2012,
                          out_file_name = "side_by_side.pdf"){
  plot1 <- pop_pyramid(country1, year)
  plot1
  plot2 <- pop_pyramid(country2, year)
  plot2
  plot3 <- pop_pyramid(country3, year)
  plot3
  #  setEPS()
  pdf(out_file_name, width = 16, height = 5, onefile = FALSE)
poster_plot <-
  grid_arrange_shared_legend(plot1, plot2, plot3)
dev.off()
return()
}
```

APPENDIX 2 – RISK COMPARISON CODES

This work uses, as its core, a risk comparison model developed in the R programming language(R Core Team, 2017). As noted above, two versions of the risk comparison codes were developed, a *strict* and an *extrapolated* version. Both are reproduced here, though they are very similar. See the section Model Description for more details on the inputs and algorithm.

Appendix 2A – risk_comparison_strict()

This function represents the strict version of the code, as described above. It requires, as part of its input, a data frame generated by `get_data_secure()`. It takes a number of variables as inputs, and generates DALYs for radiation, diabetes milletus, and PTSD. The output is a summary table.

The complete command line is:

```
risk_comparison_strict(raw_population, fips_code="US", year = 2012, starting_exposure_rate =
0.04, effective_half_life = 5, duration = 20, pop_size = 100000)
```

Where a variable in the command line is followed by an equals sign, it represents a default value.

This command line will generate DALYs for a Nigerian-proportioned population with a starting exposure rate of 20 mSv per year, an effective half-life of 10 years, and a duration of 50 years under consideration:

```
risk_comparison_strict(raw_population, "NI", 2012, 0.02, 10, 50)
```

The code is below:

```
# Created 07 Jan 2019
# Last Modified 28 May 2019 - removed AUD,
#           moved call to get_data_secure() outside function,
#           other minor tweaks

# Comparative Risk Model (Strict)
# The "strict" version - no extrapolation
# PTSD only age 20+
# Diabetes 40-75

# This code gathers age and sex *proportions* for a given population
# (e.g. the national-level US population), normalizes to 100000 (this
# can be changed in the call).  It also takes radiation exposure info
# and creates simple dose estimate (EPA and Govt of Japan), then
# calculates a DALY for radiation and separate DALYs for
# two clinical outcomes related to displacement.

# uses 2-letter fips codes for country information

# function risk_comparison_strict()
# inputs:
# raw_population: dataframe generated by get_data_secure()
# fips_code: 2-letter fips code, default is "US"
# year: 4-digit year, default is 2012
# starting_exposure_rate: starting exposure rate in Gy/year, default 0.04
# effective_half_life: eff. half-life of contamination, years, default 5
# pop_size: size of the population of interest, default 100,000
# relies on get_data_secure(), found in get_pop_data secure.R for
# data on the population of interest

risk_comparison_strict <- function(raw_population,
                           fips_code="US",
                           year=2012,
                           starting_exposure_rate=0.04,
                           effective_half_life=5,
                           duration=20,
                           pop_size = 100000)  {

# obtain country-level population proportions using get_data_secure()
# raw_population is a df with columns age, sex, and population
# male numbers are negative (a trick for plotting later)

# need to do some combining of age bands to match the BEIR table
# the census data was in 5-year blocks; see beir_ages below for the
# desired breakdown
# brute force methodologies have the advantage of being straightforward
```

```
pop_proportions <- tibble(Age = "0", Sex = "0", Population = 0)
pop_proportions[1,] <- c("0-4", "Male", raw_population[1,3])
pop_proportions[2,] <- c("5-9", "Male", raw_population[2,3])
pop_proportions[3,] <- c("10-14", "Male", raw_population[3,3])
pop_proportions[4,] <- c("15-19", "Male", raw_population[4,3])
pop_proportions[5,] <- c("20-29", "Male",
                         raw_population[5,3] + raw_population[6,3])
pop_proportions[6,] <- c("30-39", "Male",
                         raw_population[7,3] + raw_population[8,3])
pop_proportions[7,] <- c("40-49", "Male",
                         raw_population[9,3] + raw_population[10,3])
pop_proportions[8,] <- c("50-59", "Male",
                         raw_population[11,3] + raw_population[12,3])
pop_proportions[9,] <- c("60-69", "Male",
                         raw_population[13,3] + raw_population[14,3])
pop_proportions[10,] <- c("70-79", "Male",
                          raw_population[15,3] + raw_population[16,3])
pop_proportions[11,] <- c("80+", "Male",
                          raw_population[17,3] + raw_population[18,3] +
                            raw_population[19,3] + raw_population[20,3] +
                            raw_population[21,3])
pop_proportions[12,] <- c("0-4", "Female", raw_population[22,3])
pop_proportions[13,] <- c("5-9", "Female", raw_population[23,3])
pop_proportions[14,] <- c("10-14", "Female", raw_population[24,3])
pop_proportions[15,] <- c("15-19", "Female", raw_population[25,3])
pop_proportions[16,] <- c("20-29", "Female",
                          raw_population[26,3] + raw_population[27,3])
pop_proportions[17,] <- c("30-39", "Female",
                          raw_population[28,3] + raw_population[29,3])
pop_proportions[18,] <- c("40-49", "Female",
                          raw_population[30,3] + raw_population[31,3])
pop_proportions[19,] <- c("50-59", "Female",
                          raw_population[32,3] + raw_population[33,3])
pop_proportions[20,] <- c("60-69", "Female",
                          raw_population[34,3] + raw_population[35,3])
pop_proportions[21,] <- c("70-79", "Female",
                          raw_population[36,3] + raw_population[37,3])
pop_proportions[22,] <- c("80+", "Female",
                          raw_population[38,3] + raw_population[39,3] +
                            raw_population[40,3] + raw_population[41,3] +
                            raw_population[42,3])
pop_proportions$Population <- as.numeric(pop_proportions$Population)
raw_pop_size <- sum(abs(pop_proportions$Population))
pop_proportions$Population <- pop_proportions$Population/raw_pop_size

###################################
# Radiation Risk
###################################

# default to BEIR VII age/sex values; others can be used
# BEIR VII Table 12D-1 and 12D-2 (includes DDREF 1.5), All cancers LAR
# number of cases and mortalities per 100,000
# exposed to a single dose of 0.1 Gy
# may add ICRP values in the future
# BEIR VII values for radiation risk
# (incidence not used any further, just included for possible future use)
beir_ages <- c("0-4", "5-9", "10-14", "15-19", "20-29", "30-39",
               "40-49", "50-59", "60-69", "70-79", "80+")
beir_male_incidence <- c(2563, 1816, 1445, 1182, 977, 686,
                         648, 591, 489, 343, 174)
beir_female_incidence <- c(4777, 3377, 2611, 2064, 1646,
                           1065, 886, 740, 586, 409, 214)
beir_male_mortality <- c(1099, 852, 712, 603, 511, 381, 377,
                         360, 319, 250, 153)
beir_female_mortality <- c(1770, 1347, 1104, 914, 762, 542,
                           507, 469, 409, 317, 190)
age_vector <- c(beir_ages, beir_ages)
sex_vector <- c(rep(c("Male"), times=11), rep(c("Female"), times=11))
beir_mortality <- c(beir_male_mortality, beir_female_mortality)
beir_risk <- tibble("Age" = age_vector, "Sex" = sex_vector,
                    "BEIR Mortality" = beir_mortality)
```

```
# Because the BEIR risk values are mortalities per 100,000 pop,
# divide by 100,000 to represent the risk per person
# note that there is no statistical validity to this per-person risk
# these are aggregate population-level risk values
beir_risk$`BEIR Mortality` <- beir_risk$`BEIR Mortality`/100000

# apply cancer risks to the population of interest
# this is excess cases per age group per 0.1 Gy in a single dose
# assuming a DDREF of 1.5 per BEIR VII
pop_cancer_risk <- pop_proportions
# un-negative the male population values
pop_cancer_risk$Population <- abs(pop_cancer_risk$Population*pop_size)
pop_cancer_risk$'Cancer Risk' <-
  abs(pop_cancer_risk$Population*beir_risk$`BEIR Mortality`)

# Modified 29 Mar 19 to split male/female yll
# NIH figures for US were M=14.7, F=16.6
# Pham et al. figures for JP were M=13.6, F=17.5
# selected values of M=14, F=17
male_cancer_yll <- 14
female_cancer_yll <- 17

# so total excess cancer mortalities expected per 0.1 Gy is:
pop_male_cancers <- sum(pop_cancer_risk$`Cancer Risk`[1:11])
pop_female_cancers <- sum(pop_cancer_risk$`Cancer Risk`[12:22])
# and the total DALY per 0.1 Gy applied in a single dose (conservative)
pop_cancer_daly <- pop_male_cancers*male_cancer_yll +
  pop_female_cancers*female_cancer_yll

# finally, convert basis from per 0.1 Gy to per 1 Gy
# this is a table of cancer DALY for each population block per Gy
pop_cancer_daly <- pop_cancer_daly*10
#
# **********************
# Dose of interest
# **********************
# variables are:
# starting_exposure_rate in Gy or Sv per year
# effective_half_life in years (weathering, decay)
# duration_of_exposure in years

# there are two models calculated, only the second is actually used
# the first, here, applies the *entire* dose in one shot
# this is a very simple and conservative model
# assumes low LET (e.g. photons)

lambda <- 0.693/effective_half_life
duration <- 20
cumulative_exposure <- starting_exposure_rate*(1/lambda)*
  (1-exp(-lambda*duration))

# hyperconservative to assume all dose arrives at once, at time=0
# e.g. effects on youngest age groups very exaggerated
# epa says crude exposure = dose
# govt of japan says cut this down a bit, to 60%
epa_dose <- cumulative_exposure
goj_dose <- 0.6*cumulative_exposure

# finally, multiply dose by per-Gy DALY
epa_daly <- epa_dose*pop_cancer_daly
goj_daly <- goj_dose*pop_cancer_daly

# this is the second case (actually used in the paper)
# each 5-year block is calculated and
# applied - still conservative but much less so
# assumes entire pop stays stable, same age groups
# all dose delivered at start of 5 year period
# block_epa_daly and block_gov_daly are the outputs

num_blocks <- (duration %/% 5) + 1
```

```
val <- 1
cum_epa_daly <- 0
cum_goj_daly <- 0
block_time <- 0
block_starting_exposure_rate <- starting_exposure_rate
block_pop_cancer_risk <- pop_cancer_risk
block_epa_daly <- 0
block_goj_daly <- 0
while (val <= num_blocks)
  {
  ifelse (val == num_blocks,
          temp_duration <- (duration %% 5), temp_duration <- 5)
  block_exposure <- block_starting_exposure_rate*(1/lambda)*
    (1-exp(-lambda*5))
  block_time <- (ifelse (val == num_blocks,
                         duration, val*5))
  block_epa_dose <- block_exposure
  block_goj_dose <- 0.6*block_exposure
  block_pop_cancer_risk$`Cancer Risk` <-
    block_pop_cancer_risk$Population*beir_risk$`BEIR Mortality`
  block_pop_male_cancers <- sum(block_pop_cancer_risk$`Cancer Risk`[1:11])
  block_pop_female_cancers <- sum(block_pop_cancer_risk$`Cancer Risk`[12:22])
  # and the total DALY per 0.1 Gy applied in a single dose (conservative)
  block_pop_cancer_daly <- block_pop_male_cancers*male_cancer_yll +
    block_pop_female_cancers*female_cancer_yll
  block_epa_daly <- block_pop_cancer_daly*10*block_epa_dose + block_epa_daly
  block_goj_daly <- block_pop_cancer_daly*10*block_goj_dose + block_goj_daly
  # reset values for next iteration
  val <- val + 1
  block_starting_exposure_rate <-
    block_starting_exposure_rate*exp(-lambda*temp_duration*block_time)
}

#####################################
# Non-Radiation Risks
#####################################

# PTSD
# No clear info on age so apply evenly to all ages over 20
# Oe et al. identified excess PTSD incidence among evacuees
# fairly steady over 3 years post-incident M=+7%, F=+8%
# Mean duration of PTSD is 41.3 Months = 3.44 Years
pop_ptsd_risk <- pop_proportions
# un-negative the male population values and bring up to the pop
# of interest (remember, pop_proportion is just fractions)
pop_ptsd_risk$Population <- abs(pop_ptsd_risk$Population)*pop_size
pop_ptsd_male_incidence = 0.07
pop_ptsd_female_incidence = 0.08
pop_ptsd_duration = 3.44
pop_male_ptsd <-
  pop_ptsd_male_incidence*sum(pop_ptsd_risk$Population[5:11])
pop_female_ptsd <-
  pop_ptsd_female_incidence*sum(pop_ptsd_risk$Population[16:22])

# PTSD has no associated YLL
# PTSD DALY has multiple weights depending on severity; the literature does
# not cover degrees of PTSD after disasters so use the value for
# "moderate" PTSD, 0.133
ptsd_daly_wt <- 0.133
# and the total DALY for the pop of interest for PTSD
pop_ptsd_daly <- (pop_male_ptsd + pop_female_ptsd)*ptsd_daly_wt

# Diabetes
# age-based using Murakami et al 2017
# also Satoh et al. 2015 and Nomura et al. 2016
# only assessed people 40-75 YO at time of disaster
#
# excess diabetes set to 2.4%
pop_dia_excess <- 0.024

# duration: remainder of life
```

```
# disability weight: use least-severe value: 0.104
# for YLL extract from Narayan et al.
# since data only collected for 40-75 ignore other ages
# Age 40 M=11.6, F=14.3
# Age 50 M=9.2, F=12.1
# Age 60 M=7.3, F=9.5
# Age 70 M=5.3, F=6.5
# Age 80 M=3.8, F=4.1
dia_yll <- c(0,0,0,0,0,0,11.6,9.2,7.3,5.3,3.8,0,
             0,0,0,0,0,14.3,12.1,9.5,6.5,4.1)
dia_wt <- 0.104

pop_dia_risk <- pop_proportions
# un-negative the male population values and bring up to the pop
# of interest (remember, pop_proportion is just fractions)
pop_dia_risk$Population <- abs(pop_dia_risk$Population)*pop_size
# setting up remaining life based on YLLs above
# values in age categories outside 40-79 are not used and so are set
# to zero; remaining life is only used for diabetes cases
# WHO max age assumed to be 91.9 years
ages <- c(0,5,10,15,20,30,40,50,60,70,80,0,5,10,15,20,30,40,50,60,70,80)
remaining_life_dia <- 91.9 - ages - dia_yll
pop_dia_risk$Remaining <- remaining_life_dia

# excess cases = population*prev
pop_dia_risk$excess <- 0
pop_dia_risk$yld <-0
pop_dia_risk$yll <- 0
pop_dia_risk$excess[7:11] <-
  pop_dia_risk$Population[7:11]*pop_dia_excess
pop_dia_risk$excess[18:21] <-
  pop_dia_risk$Population[18:21]*pop_dia_excess

# yld = excess*duration*wt
pop_dia_risk$yld <- pop_dia_risk$excess*pop_dia_risk$Remaining*dia_wt
# yll
pop_dia_risk$yll <- pop_dia_risk$excess*dia_yll

# sum up for DALY
pop_dia_daly <- sum(pop_dia_risk$yld, pop_dia_risk$yll)

# output of interest:
# pop_ptsd_risk
# pop_dia_risk
# make a table of results
daly_output <- tibble(
  Country = fips_code,
  Pop_Size = pop_size,
  Start_Exp = starting_exposure_rate,
  Eff_Half = effective_half_life,
  Duration = duration,
  EPA_DALY = epa_daly,
  GOJ_DALY = goj_daly,
  BLOCK_EPA_DALY = block_epa_daly,
  BLOCK_GOJ_DALY = block_goj_daly,
  PTSD = pop_ptsd_daly,
  Diabetes = pop_dia_daly,
  Displaced_DALY = sum(pop_ptsd_daly, pop_dia_daly)
)
return(daly_output)
}
```

Appendix 2B – risk_comparison_extrapolated()

This function represents the extrapolated version of the code, as described above. It requires, as part of its input, a data frame generated by `get_data_secure()`. It takes a number of variables as inputs, and generates DALYs for radiation, diabetes milletus, and PTSD. The output is a summary table.

The complete command line is:

```
risk_comparison_extrapolated(raw_population, fips_code="US", year = 2012, starting_exposure_rate
= 0.04, effective_half_life = 5, duration = 20, pop_size = 100000)
```

Where a variable in the command line is followed by an equals sign, it represents a default value.

This command line will generate DALYs for a Japanese-proportioned population with a starting exposure rate of 40 mSv per year, an effective half-life of 7 years, and a duration of 20 years under consideration:

```
risk_comparison_extrapolated(raw_population, "JA", 2012, 0.04, 7, 20)
```

The code is below:

```
# Created 07 Jan 2019
# Last Modified 28 May 2019 - removed AUD,
#           moved call to get_data_secure() outside function,
```

```
#           other minor tweaks

# Comparative Risk Model (Extrapolated)
# The "extrapolated" version - assume that the PTSD affects
# all ages, and that diabetes affects both younger and older
# persons to a lesser extent.  No quantitative data supports this.
# PTSD all ages
# Diabetes 40-70 half value age 30-40 and 70+

# This code gathers age and sex *proportions* for a given population
# (e.g. the national-level US population), normalizes to 100000 (this
# can be changed in the call).  It also takes radiation exposure info
# and creates simple dose estimate (EPA and Govt of Japan), then
# calculates a DALY for radiation and separate DALYs for
# two clinical outcomes related to displacement.

# uses 2-letter fips codes for country information

# function risk_comparison_extrapolated()
# inputs:
# raw_population: dataframe generated by get_data_secure()
# fips_code: 2-letter fips code, default is "US"
# year: 4-digit year, default is 2012
# starting_exposure_rate: starting exposure rate in Gy/year, default 0.04
# effective_half_life: eff. half-life of contamination, years, default 5
# pop_size: size of the population of interest, default 100,000
# relies on get_data_secure(), found in get_pop_data secure.R for
# data on the population of interest

risk_comparison_extrapolated <- function(raw_population,
                            fips_code="US",
                            year=2012,
                            starting_exposure_rate=0.04,
                            effective_half_life=5,
                            duration=20,
                            pop_size = 100000)  {

# obtain country-level population proportions using get_data_secure()
# raw_population is a df with columns age, sex, and population
# male numbers are negative (a trick for plotting later)
raw_population <- get_data_secure(fips_code, year)

# need to do some combining of age bands to match the BEIR table
# the census data was in 5-year blocks; see beir_ages below for the
# desired breakdown
# brute force methodologies have the advantage of being straightforward
pop_proportions <- tibble(Age = "0", Sex = "0", Population = 0)
pop_proportions[1,] <- c("0-4", "Male", raw_population[1,3])
pop_proportions[2,] <- c("5-9", "Male", raw_population[2,3])
pop_proportions[3,] <- c("10-14", "Male", raw_population[3,3])
pop_proportions[4,] <- c("15-19", "Male", raw_population[4,3])
pop_proportions[5,] <- c("20-29", "Male",
                         raw_population[5,3] + raw_population[6,3])
pop_proportions[6,] <- c("30-39", "Male",
                         raw_population[7,3] + raw_population[8,3])
pop_proportions[7,] <- c("40-49", "Male",
                         raw_population[9,3] + raw_population[10,3])
pop_proportions[8,] <- c("50-59", "Male",
                         raw_population[11,3] + raw_population[12,3])
pop_proportions[9,] <- c("60-69", "Male",
                         raw_population[13,3] + raw_population[14,3])
pop_proportions[10,] <- c("70-79", "Male",
                          raw_population[15,3] + raw_population[16,3])
pop_proportions[11,] <- c("80+", "Male",
                          raw_population[17,3] + raw_population[18,3] +
                            raw_population[19,3] + raw_population[20,3] +
                            raw_population[21,3])
pop_proportions[12,] <- c("0-4", "Female", raw_population[22,3])
pop_proportions[13,] <- c("5-9", "Female", raw_population[23,3])
pop_proportions[14,] <- c("10-14", "Female", raw_population[24,3])
pop_proportions[15,] <- c("15-19", "Female", raw_population[25,3])
```

```
pop_proportions[16,] <- c("20-29", "Female",
                          raw_population[26,3] + raw_population[27,3])
pop_proportions[17,] <- c("30-39", "Female",
                          raw_population[28,3] + raw_population[29,3])
pop_proportions[18,] <- c("40-49", "Female",
                          raw_population[30,3] + raw_population[31,3])
pop_proportions[19,] <- c("50-59", "Female",
                          raw_population[32,3] + raw_population[33,3])
pop_proportions[20,] <- c("60-69", "Female",
                          raw_population[34,3] + raw_population[35,3])
pop_proportions[21,] <- c("70-79", "Female",
                          raw_population[36,3] + raw_population[37,3])
pop_proportions[22,] <- c("80+", "Female",
                          raw_population[38,3] + raw_population[39,3] +
                            raw_population[40,3] + raw_population[41,3] +
                            raw_population[42,3])
pop_proportions$Population <- as.numeric(pop_proportions$Population)
raw_pop_size <- sum(abs(pop_proportions$Population))
pop_proportions$Population <- pop_proportions$Population/raw_pop_size

###################################
# Radiation Risk
###################################

# default to BEIR VII age/sex values; others can be used
# BEIR VII Table 12D-1 and 12D-2 (includes DDREF 1.5), All cancers LAR
# number of cases and mortalities per 100,000
# exposed to a single dose of 0.1 Gy
# may add ICRP values in the future
# BEIR VII values for radiation risk
# (incidence not used any further, just included for possible future use)
beir_ages <- c("0-4", "5-9", "10-14", "15-19", "20-29", "30-39",
               "40-49", "50-59", "60-69", "70-79", "80+")
beir_male_incidence <- c(2563, 1816, 1445, 1182, 977, 686,
                         648, 591, 489, 343, 174)
beir_female_incidence <- c(4777, 3377, 2611, 2064, 1646,
                           1065, 886, 740, 586, 409, 214)
beir_male_mortality <- c(1099, 852, 712, 603, 511, 381, 377,
                         360, 319, 250, 153)
beir_female_mortality <- c(1770, 1347, 1104, 914, 762, 542,
                           507, 469, 409, 317, 190)
age_vector <- c(beir_ages, beir_ages)
sex_vector <- c(rep(c("Male"), times=11), rep(c("Female"), times=11))
beir_mortality <- c(beir_male_mortality, beir_female_mortality)
beir_risk <- tibble("Age" = age_vector, "Sex" = sex_vector,
                    "BEIR Mortality" = beir_mortality)

# Because the BEIR risk values are mortalities per 100,000 pop,
# divide by 100,000 to represent the risk per person
# note that there is no statistical validity to this per-person risk
# these are aggregate population-level risk values
beir_risk$`BEIR Mortality` <- beir_risk$`BEIR Mortality`/100000

# apply cancer risks to the population of interest
# this is excess cases per age group per 0.1 Gy in a single dose
# assuming a DDREF of 1.5 per BEIR VII
pop_cancer_risk <- pop_proportions
# un-negative the male population values
pop_cancer_risk$Population <- abs(pop_cancer_risk$Population*pop_size)
pop_cancer_risk$'Cancer Risk' <-
  abs(pop_cancer_risk$Population*beir_risk$`BEIR Mortality`)

# Modified 29 Mar 19 to split male/female yll
# NIH figures for US were M=14.7, F=16.6
# Pham et al. figures for JP were M=13.6, F=17.5
# selected values of M=14, F=17
male_cancer_yll <- 14
female_cancer_yll <- 17

# so total excess cancer mortalities expected per 0.1 Gy is:
pop_male_cancers <- sum(pop_cancer_risk$`Cancer Risk`[1:11])
```

```
pop_female_cancers <- sum(pop_cancer_risk$`Cancer Risk`[12:22])
# and the total DALY per 0.1 Gy applied in a single dose (conservative)
pop_cancer_daly <- pop_male_cancers*male_cancer_yll +
  pop_female_cancers*female_cancer_yll

# finally, convert basis from per 0.1 Gy to per 1 Gy
# this is a table of cancer DALY for each population block per Gy
pop_cancer_daly <- pop_cancer_daly*10

# **********************
# Dose of interest
# **********************
# variables are:
# starting_exposure_rate in Gy or Sv per year
# effective_half_life in years (weathering, decay)
# duration_of_exposure in years

# there are two models calculated, only the second is actually used
# the first, here, applies the *entire* dose in one shot
# this is a very simple and conservative model
# assumes low LET (e.g. photons)

lambda <- 0.693/effective_half_life
duration <- 20
cumulative_exposure <- starting_exposure_rate*(1/lambda)*
  (1-exp(-lambda*duration))

# hyperconservative to assume all dose arrives at once, at time=0
# e.g. effects on youngest age groups very exaggerated
# epa says crude exposure = dose
# govt of japan says cut this down a bit, to 60%
epa_dose <- cumulative_exposure
goj_dose <- 0.6*cumulative_exposure

# finally, multiply dose by per-Gy DALY
epa_daly <- epa_dose*pop_cancer_daly
goj_daly <- goj_dose*pop_cancer_daly

# this is the second case (actually used in the paper)
# each 5-year block is calculated and
# applied - still conservative but much less so
# assumes entire pop stays stable, same age groups
# all dose delivered at start of 5 year period
# block_epa_daly and block_gov_daly are the outputs

num_blocks <- (duration %/% 5) + 1
val <- 1
cum_epa_daly <- 0
cum_goj_daly <- 0
block_time <- 0
block_starting_exposure_rate <- starting_exposure_rate
block_pop_cancer_risk <- pop_cancer_risk
block_epa_daly <- 0
block_goj_daly <- 0
while (val <= num_blocks)
  {
  ifelse (val == num_blocks,
          temp_duration <- (duration %% 5), temp_duration <- 5)
  block_exposure <- block_starting_exposure_rate*(1/lambda)*
    (1-exp(-lambda*5))
  block_time <- (ifelse (val == num_blocks,
                         duration, val*5))
  block_epa_dose <- block_exposure
  block_goj_dose <- 0.6*block_exposure
  block_pop_cancer_risk$`Cancer Risk` <-
    block_pop_cancer_risk$Population*beir_risk$`BEIR Mortality`
  block_pop_male_cancers <- sum(block_pop_cancer_risk$`Cancer Risk`[1:11])
  block_pop_female_cancers <- sum(block_pop_cancer_risk$`Cancer Risk`[12:22])
  # and the total DALY per 0.1 Gy applied in a single dose (conservative)
  block_pop_cancer_daly <- block_pop_male_cancers*male_cancer_yll +
    block_pop_female_cancers*female_cancer_yll
```

```
  block_epa_daly <- block_pop_cancer_daly*10*block_epa_dose + block_epa_daly
  block_goj_daly <- block_pop_cancer_daly*10*block_goj_dose + block_goj_daly
  # reset values for next iteration
  val <- val + 1
  block_starting_exposure_rate <-
    block_starting_exposure_rate*exp(-lambda*temp_duration*block_time)
}

#####################################
# Non-Radiation Risks
#####################################

# PTSD
# Extrapolated version - apply to all ages (not just 20+)
# Oe et al. identified excess PTSD incidence among evacuees
# fairly steady over 3 years post-incident M=+7%, F=+8%
# Mean duration of PTSD is 41.3 Months = 3.44 Years
pop_ptsd_risk <- pop_proportions
# un-negative the male population values and bring up to the pop
# of interest (remember, pop_proportion is just fractions)
pop_ptsd_risk$Population <- abs(pop_ptsd_risk$Population)*pop_size
pop_ptsd_male_incidence = 0.07
pop_ptsd_female_incidence = 0.08
pop_ptsd_duration = 3.44
pop_male_ptsd <-
  pop_ptsd_male_incidence*sum(pop_ptsd_risk$Population)
pop_female_ptsd <-
  pop_ptsd_female_incidence*sum(pop_ptsd_risk$Population)

# PTSD has no associated YLL
# PTSD DALY has multiple weights depending on severity; the literature does
# not cover degrees of PTSD after disasters so use the value for
# "moderate" PTSD, 0.133
ptsd_daly_wt <- 0.133
# and the total DALY for the pop of interest for PTSD
pop_ptsd_daly <- (pop_male_ptsd + pop_female_ptsd)*ptsd_daly_wt

# Diabetes
# age-based using Murakami et al 2017
# also Satoh et al. 2015 and Nomura et al. 2016
# only assessed people 40-75 YO at time of disaster
#
# excess diabetes set to 2.4%
pop_dia_excess <- 0.024

# duration: remainder of life
# disability weight: use least-severe value: 0.104
# for YLL extract from Narayan et al.
# since data only collected for 40-75 ignore other ages
# Age 30 M=14.5, F=16.5
# Age 40 M=11.6, F=14.3
# Age 50 M=9.2, F=12.1
# Age 60 M=7.3, F=9.5
# Age 70 M=5.3, F=6.5
# Age 80 M=3.8, F=4.1
dia_yll <- c(0,0,0,0,0,14.5,11.6,9.2,7.3,5.3,3.8,
             0,0,0,0,0,16.5,14.3,12.1,9.5,6.5,4.1)
dia_wt <- 0.104

pop_dia_risk <- pop_proportions
# un-negative the male population values and bring up to the pop
# of interest (remember, pop_proportion is just fractions)
pop_dia_risk$Population <- abs(pop_dia_risk$Population)*pop_size
# setting up remaining life based on YLLs above
# values in age categories outside 40-70 are not used and so are set
# to zero; remaining life is only used for diabetes cases
# WHO max age assumed to be 91.9 years
ages <- c(0,5,10,15,20,30,40,50,60,70,80,0,5,10,15,20,30,40,50,60,70,80)
remaining_life_dia <- 91.9 - ages - dia_yll
pop_dia_risk$Remaining <- remaining_life_dia
```

```
# excess cases = population*prev
# extrapolated version
pop_dia_risk$excess <- 0
pop_dia_risk$yld <-0
pop_dia_risk$yll <- 0
pop_dia_risk$excess[6] <- pop_dia_risk$Population[6]*pop_dia_excess*0.5
pop_dia_risk$excess[17] <- pop_dia_risk$Population[17]*pop_dia_excess*0.5
pop_dia_risk$excess[7:11] <-
  pop_dia_risk$Population[7:11]*pop_dia_excess
pop_dia_risk$excess[18:21] <-
  pop_dia_risk$Population[18:21]*pop_dia_excess

# yld = excess*duration*wt
pop_dia_risk$yld <- pop_dia_risk$excess*pop_dia_risk$Remaining*dia_wt
# yll
pop_dia_risk$yll <- pop_dia_risk$excess*dia_yll

# sum up for DALY
pop_dia_daly <- sum(pop_dia_risk$yld, pop_dia_risk$yll)

# output of interest:
# pop_ptsd_risk
# pop_dia_risk
# make a table of results
daly_output <- tibble(
  Country = fips_code,
  Pop_Size = pop_size,
  Start_Exp = starting_exposure_rate,
  Eff_Half = effective_half_life,
  Duration = duration,
  EPA_DALY = epa_daly,
  GOJ_DALY = goj_daly,
  BLOCK_EPA_DALY = block_epa_daly,
  BLOCK_GOJ_DALY = block_goj_daly,
  PTSD = pop_ptsd_daly,
  Diabetes = pop_dia_daly,
  Displaced_DALY = sum(pop_ptsd_daly, pop_dia_daly)
)
return(daly_output)
}
```

APPENDIX 3 – SUPPORTING SCRIPTS

Four supporting scripts were developed in the R programming language (R Core Team, 2017)to automate certain plots specifically for this work. These were not generalized, though a user could adapt them with relative ease. They include custom labels and tailored positions for graphic elements that might not be suited to other uses. Three scripts were developed to generate plots specific to each country; only one is reproduced here as the others are very similar. They are `us_batch_risk2.R`, `ni_batch_risk2.R`, and `ja_batch_risk2.R`. One additional script, `combo_plot.R`, generates a plot combining elements of the various data generated by the other three scripts, and requires that they have been run successfully. These scripts do not have command lines; rather they are invoked by running the code directly from the R console.

Appendix 3A - us_batch_risk2.R

This script generates a series of plots for differing radiation dose rates and half-lives for a US-proportioned population. The other scripts, `ni_batch_risk2.R`, and `ja_batch_risk2.R`, mirror this one, with adjustments to graphical element positions and other minor tweaks. Figure 4 is an example of the output of this script. The code is below:

```
# us_batch_risk2.R
# created 21 May 2019
# heavily modified 28 May 2019
#
# this is a custom script generating images specific to my own work
# I did not attempt to generalize this
#
# batch script for testing multiple runs of code
# generates plot of DALYs for 3 different half-lifes
# and a range of starting exposure rates set by the user
# common values
run_count <- 12
```

```
dose_increment <- 0.01
year <- "2012"
pop_size <- 1
duration <- 20
country <- "US"
half_life_range <- c(3,5,7)
us_population <- get_data_secure("US", 2012)

# individual plots
for(half_life in half_life_range) {
#strict
starting_dose <- 0.01
xlower <- starting_dose
for (i in 1:run_count) {
    temp_risk <- risk_comparison_strict(us_population,
                                country,
                                year,
                                starting_dose,
                                half_life,
                                duration,
                                pop_size)
    ifelse(i == 1,
    us_s_summary <- tibble("Dose" = starting_dose,
                           "EPA_DALY" = temp_risk$BLOCK_EPA_DALY,
                           "GOJ_DALY" = temp_risk$BLOCK_GOJ_DALY),
    us_s_summary <- add_row(us_s_summary,
                            "Dose" = starting_dose,
                            "EPA_DALY" = temp_risk$BLOCK_EPA_DALY,
                            "GOJ_DALY" = temp_risk$BLOCK_GOJ_DALY))
  starting_dose <- starting_dose + dose_increment

    if(i == run_count)
     us_s_info <- tibble("country" = country,
                         "year" = year,
                         "half_life" = half_life,
                         "pop_size" = pop_size,
                         "ptsd_daly" = temp_risk$PTSD,
                         "diabetes_daly" = temp_risk$Diabetes)
}

# error checking - comment out when working
#  print(paste0("half-life= ", half_life))
#  print(us_s_summary)

# extrapolated
# only run once to get extrapolated displacement DALYs
# radiation DALYs are the same as strict
temp_risk <- risk_comparison_extrapolated(us_population,
                                          country,
                                          year,
                                          starting_dose,
                                          half_life,
                                          duration,
                                          pop_size)
us_e_info <- tibble("country" = country,
                    "year" = year,
                    "half_life" = half_life,
                    "pop_size" = pop_size,
                    "ptsd_daly" = temp_risk$PTSD,
                    "diabetes_daly" = temp_risk$Diabetes)
disp_daly_strict <-sum(us_s_info$ptsd_daly,
                       us_s_info$diabetes_daly)
disp_daly_extrapolated <- sum(us_e_info$ptsd_daly,
                              us_e_info$diabetes_daly)
# doing some math only to set the plot boundaries
# deleted in favor of a consistent xupper across all plots
#test_model <- lm(GOJ_DALY ~ Dose, data = us_s_summary)
#raw_xlim <- disp_daly_extrapolated/coef(test_model)[2]
#xupper <-floor(raw_xlim*100)/100 +.01
xupper <- us_s_summary$Dose[run_count]
```

```
us_risk_plot <- ggplot(us_s_summary, aes(x=Dose)) +
  geom_line(linetype= "twodash", aes(y=us_s_summary$GOJ_DALY)) +
  geom_text(aes(us_s_summary$Dose[5],
                us_s_summary$GOJ_DALY[5],
                label="GOJ DALY",
                vjust = 3),
            size = 2) +
  geom_line(linetype= "dashed", color = "red", aes(y=us_s_summary$EPA_DALY)) +
  geom_text(aes(us_s_summary$Dose[3],
                us_s_summary$EPA_DALY[3],
                label="EPA DALY",
                hjust = -.4),
            size = 2) +
  geom_hline(color = "royalblue",aes(yintercept = disp_daly_strict)) +
  geom_text(aes(us_s_summary$Dose[1],
                disp_daly_strict,
                label = paste0("Displacement DALY (strict) = ",
                          signif(disp_daly_strict,3)),
                vjust = -1,
                hjust = -.05),
            size = 2) +
  geom_hline(color = "green", aes(yintercept = disp_daly_extrapolated)) +
  geom_text(aes(us_s_summary$Dose[1],
                disp_daly_extrapolated,
                label = paste0("Displacement DALY (extrapolated) = ",
                               signif(disp_daly_extrapolated,3)),
                vjust = -1,
                hjust = -.05),
            size = 2) +
  geom_text(aes(x = 0.02,
                y = 0.3,
                label = paste0("Country Profile = ", country)),
            size = 2) +
  geom_text(aes(x = 0.0205,
                y = 0.29,
                label = paste0("Effective half-life = ", half_life, " years")),
            size = 2) +
  geom_text(aes(x = 0.02,
                y = 0.28,
                label = paste0("Duration = ", duration, " years")),
            size = 2) +
  theme_bw() +
  labs(x = "Starting Dose Rate (mSv/y)",
       y = "DALY (years)") +
  scale_x_continuous(limits = c(xlower, xupper),
                     expand = c(0,0),
                     breaks = seq(xlower, xupper, dose_increment),
                     labels = seq(xlower*1000,
                                  xupper*1000, dose_increment*1000)) +
  scale_y_continuous(limits = c(0,0.3))

file_save_name <- paste0("./", country, "_risk_", trunc(half_life),"_yr_half_life.pdf")
ggsave(file_save_name, plot=us_risk_plot,
       device = "pdf", width = 6, height = 4, units = "in")

}

# ********************
# overlay plots
# ********************
for(half_life in half_life_range) {
  #strict
  starting_dose <- 0.01
  xlower <- starting_dose
  line_name_GOJ <- paste0(half_life,"_year_line_GOJ")
  line_name_EPA <- paste0(half_life,"_year_line_EPA")
  for (i in 1:run_count) {
    temp_risk <- risk_comparison_strict(us_population,
                                        country,
                                        year,
                                        starting_dose,
```

```
                                        half_life,
                                        duration,
                                        pop_size)
    ifelse(((half_life == half_life_range[1]) & (i == 1)),
           us_s_summary <- tibble("Half_Life" = half_life,
                                  "Dose" = starting_dose,
                                  "EPA_DALY" = temp_risk$BLOCK_EPA_DALY,
                                  "GOJ_DALY" = temp_risk$BLOCK_GOJ_DALY),
           us_s_summary <- add_row(us_s_summary,
                                   "Half_Life" = half_life,
                                   "Dose" = starting_dose,
                                   "EPA_DALY" = temp_risk$BLOCK_EPA_DALY,
                                   "GOJ_DALY" = temp_risk$BLOCK_GOJ_DALY))
    starting_dose <- starting_dose + dose_increment

    if(i == run_count)
      us_s_info <- tibble("country" = country,
                          "year" = year,
                          "half_life" = half_life,
                          "pop_size" = pop_size,
                          "ptsd_daly" = temp_risk$PTSD,
                          "diabetes_daly" = temp_risk$Diabetes)

  # doing some math only to set the plot boundaries
# deleted in favor of a consistent xupper across plots
#if((half_life == half_life_range[1]) & (i == run_count)) {
#  test_model <- lm(GOJ_DALY ~ Dose, data = us_s_summary)
#  raw_xlim <- disp_daly_extrapolated/coef(test_model)[2]
#  xupper <-floor(raw_xlim*100)/100 +.01
#  print(paste(half_life, i, " xupper= ", xupper))
#  }
xupper <- us_s_summary$Dose[run_count]

}

  # extrapolated
  # only run once to get extrapolated displacement DALYs
  # radiation DALYs are the same as strict
  temp_risk <- risk_comparison_extrapolated(us_population,
                                            country,
                                            year,
                                            starting_dose,
                                            half_life,
                                            duration,
                                            pop_size)
  us_e_info <- tibble("country" = country,
                      "year" = year,
                      "half_life" = half_life,
                      "pop_size" = pop_size,
                      "ptsd_daly" = temp_risk$PTSD,
                      "diabetes_daly" = temp_risk$Diabetes)
  disp_daly_strict <-sum(us_s_info$ptsd_daly,
                         us_s_info$diabetes_daly)
  disp_daly_extrapolated <- sum(us_e_info$ptsd_daly,
                                us_e_info$diabetes_daly)
}

# break out each run for plotting
GOJ_DALY_1 <- us_s_summary[1:run_count, c(2,4)]
GOJ_DALY_2 <- us_s_summary[(run_count+1):(2*run_count), c(2,4)]
GOJ_DALY_3 <- us_s_summary[(2*run_count+1):(3*run_count), c(2,4)]
EPA_DALY_1 <- us_s_summary[1:run_count, c(2,3)]
EPA_DALY_2 <- us_s_summary[(run_count+1):(2*run_count), c(2,3)]
EPA_DALY_3 <- us_s_summary[(2*run_count+1):(3*run_count), c(2,3)]

# scale factor just a visual trait for plotting
scale_factor <- 0.244
# find slope angle of each line to align text
angle_gd1 <- as.numeric(atan(scale_factor*coef(lm(GOJ_DALY ~ Dose,
                                                  GOJ_DALY_1))[2]))*180/pi
angle_gd2 <- as.numeric(atan(scale_factor*coef(lm(GOJ_DALY ~ Dose,
```

```
                                                GOJ_DALY_2))[2]))*180/pi
angle_gd3 <- as.numeric(atan(scale_factor*coef(lm(GOJ_DALY ~ Dose,
                                                GOJ_DALY_3))[2]))*180/pi
angle_ed1 <- as.numeric(atan(scale_factor*coef(lm(EPA_DALY ~ Dose,
                                                EPA_DALY_1))[2]))*180/pi
angle_ed2 <- as.numeric(atan(scale_factor*coef(lm(EPA_DALY ~ Dose,
                                                EPA_DALY_2))[2]))*180/pi
angle_ed3 <- as.numeric(atan(scale_factor*coef(lm(EPA_DALY ~ Dose,
                                                EPA_DALY_3))[2]))*180/pi

us_overlay_risk_plot<- ggplot(GOJ_DALY_1, aes(x=Dose)) +
  geom_path(data=GOJ_DALY_1,
            linetype= "twodash", aes(x=Dose, y=GOJ_DALY)) +
  geom_text(aes(GOJ_DALY_1$Dose[10],
                GOJ_DALY_1$GOJ_DALY[10],
                label="GOJ DALY 3-Yr Half-Life",
                vjust = -.4,
                angle = angle_gd1),
            size = 2) +
  geom_path(data=GOJ_DALY_2,
            linetype= "twodash", aes(x=Dose, y=GOJ_DALY)) +
  geom_text(aes(GOJ_DALY_2$Dose[10],
                GOJ_DALY_2$GOJ_DALY[10],
                label="GOJ DALY 5-Yr Half-Life",
                vjust = -.4,
                angle = angle_gd2),
            size = 2) +
  geom_path(data=GOJ_DALY_3,
            linetype= "twodash", aes(x=Dose, y=GOJ_DALY)) +
  geom_text(aes(GOJ_DALY_3$Dose[10],
                GOJ_DALY_3$GOJ_DALY[10],
                label="GOJ DALY 7-Yr Half-Life",
                vjust = -.4,
                angle = angle_gd3),
            size = 2) +
  geom_path(data=EPA_DALY_1, linetype= "dashed",
            color = "red", aes(x=Dose, y=EPA_DALY)) +
  geom_text(aes(EPA_DALY_1$Dose[8],
                EPA_DALY_1$EPA_DALY[8],
                label="EPA DALY 3-Yr Half-Life",
                vjust = -.4,
                angle = angle_ed1),
            size = 2) +
  geom_path(data=EPA_DALY_2, linetype= "dashed",
            color = "red", aes(x=Dose, y=EPA_DALY)) +
  geom_text(aes(EPA_DALY_2$Dose[7],
                EPA_DALY_2$EPA_DALY[7],
                label="EPA DALY 5-Yr Half-Life",
                vjust = -.4,
                angle = angle_ed2),
            size = 2) +
  geom_path(data=EPA_DALY_3, linetype= "dashed",
            color = "red", aes(x=Dose, y=EPA_DALY)) +
  geom_text(aes(EPA_DALY_3$Dose[6],
                EPA_DALY_3$EPA_DALY[6],
                label="EPA DALY 7-Yr Half-Life",
                vjust = -.4,
                angle = angle_ed3),
            size = 2) +
  geom_hline(color = "royalblue",aes(yintercept = disp_daly_strict)) +
  geom_text(aes(us_s_summary$Dose[1],
                disp_daly_strict,
                label = paste0("Displacement DALY (strict) = ",
                               signif(disp_daly_strict,3)),
                vjust = -1,
                hjust = -.05),
            size = 2) +
  geom_hline(color = "green", aes(yintercept = disp_daly_extrapolated)) +
  geom_text(aes(us_s_summary$Dose[1],
                disp_daly_extrapolated,
                label = paste0("Displacement DALY (extrapolated) = ",
```

```
                                signif(disp_daly_extrapolated,3)),
                vjust = -1,
                hjust = -.05),
            size = 2) +
  geom_text(aes(x = 0.02,
                y = 0.3,
                label = paste0("Country Profile = ", country)),
            size = 2) +
  geom_text(aes(x = 0.02,
                y = 0.29,
                label = paste0("Duration = ", duration, " years")),
            size = 2) +
  theme_bw() +
  labs(x = "Starting Dose Rate (mSv/y)",
       y = "DALY (years)") +
  scale_x_continuous(limits = c(xlower, xupper),
                     expand = c(0,0),
                     breaks = seq(xlower, xupper, dose_increment),
                     labels = seq(xlower*1000,
                                  xupper*1000, dose_increment*1000)) +
  scale_y_continuous(limits = c(0,0.3)) +
    coord_fixed(scale_factor)

file_save_name <- paste0("./", country, "_risk_overlay.pdf")
ggsave(file_save_name, plot=us_overlay_risk_plot,
       device = "pdf", width = 6, height = 4, units = "in")
```

Appendix 3B – combo_risk.R

The script `combo_plot.R` generates a plot combining elements of the various data generated by the other three scripts, and requires that they have been run successfully. Figure 7 is an example of the output of this code. The code is below:

```
# combo_plot.R
# created 21 May 2019
# last modified 28 May 2019 minor tweaks
#
# batch script for plotting from multiple runs of code
#
# this is a custom script generating images specific to my own work
# I did not attempt to generalize this
#
# depends on the output of: us_batch_risk2.R
#                           ja_batch_risk2.R
#                           ni_batch_risk2.R
#
# generates plot of DALYs
# varying starting dose rate, keeping pop and half-life constant
# common values must match the other batch files
run_count <- 12
starting_dose <- 0.01
dose_increment <- 0.01
year <- "2012"
```

```
duration <- 20

disp_daly_extrapolated_us <- sum(us_e_info$ptsd_daly,
                                 us_e_info$diabetes_daly)
disp_daly_extrapolated_ja <- sum(ja_e_info$ptsd_daly,
                                 ja_e_info$diabetes_daly)
disp_daly_extrapolated_ni <- sum(ni_e_info$ptsd_daly,
                                 ni_e_info$diabetes_daly)
us_epa_daly1 <- us_s_summary[1:12,c(2,3)]
us_epa_daly2 <- us_s_summary[13:24,c(2,3)]
us_epa_daly3 <- us_s_summary[25:36,c(2,3)]
us_goj_daly1 <- us_s_summary[1:12,c(2,4)]
us_goj_daly2 <- us_s_summary[13:24,c(2,4)]
us_goj_daly3 <- us_s_summary[25:36,c(2,4)]

ja_epa_daly1 <- ja_s_summary[1:12,c(2,3)]
ja_epa_daly2 <- ja_s_summary[13:24,c(2,3)]
ja_epa_daly3 <- ja_s_summary[25:36,c(2,3)]
ja_goj_daly1 <- ja_s_summary[1:12,c(2,4)]
ja_goj_daly2 <- ja_s_summary[13:24,c(2,4)]
ja_goj_daly3 <- ja_s_summary[25:36,c(2,4)]

ni_epa_daly1 <- ni_s_summary[1:12,c(2,3)]
ni_epa_daly2 <- ni_s_summary[13:24,c(2,3)]
ni_epa_daly3 <- ni_s_summary[25:36,c(2,3)]
ni_goj_daly1 <- ni_s_summary[1:12,c(2,4)]
ni_goj_daly2 <- ni_s_summary[13:24,c(2,4)]
ni_goj_daly3 <- ni_s_summary[25:36,c(2,4)]

# ******************
# plot 1, half-life = 3 years
# ******************
half_life <- 3
combo_plot1 <- ggplot(ni_s_summary, aes(x=Dose)) +
  geom_line(data=us_epa_daly1, color = "green",
            linetype= "twodash", aes(y=EPA_DALY)) +
  geom_text(aes(us_s_summary$Dose[8],
                us_epa_daly1$EPA_DALY[8],
                label="EPA DALY (US)",
                vjust = -3.5),
            size = 2) +
  geom_line(data=ja_epa_daly1, color = "royalblue",
            linetype= "dotdash", aes(y=EPA_DALY)) +
  geom_text(aes(ja_s_summary$Dose[3],
                ja_epa_daly1$EPA_DALY[3],
                label="EPA DALY (JA)",
                hjust = -.2),
            size = 2) +
  geom_line(data=ni_epa_daly1, color="red",
            linetype= "dotted", aes(y=EPA_DALY)) +
  geom_text(aes(ni_s_summary$Dose[6],
                ni_epa_daly1$EPA_DALY[6],
                label="EPA DALY (NI)",
                hjust = 1.2),
            size = 2) +
    geom_hline(color = "green", aes(yintercept = disp_daly_extrapolated_us)) +
  geom_text(aes(us_s_summary$Dose[1],
                disp_daly_extrapolated_us,
                label = paste0("US Displacement DALY (extrapolated) = ",
                               signif(disp_daly_extrapolated_us,3), " Y"),
                vjust = -1,
                hjust = -.05),
            size = 2) +
  geom_hline(color = "royalblue", aes(yintercept = disp_daly_extrapolated_ja)) +
  geom_text(aes(ja_s_summary$Dose[1],
                disp_daly_extrapolated_ja,
                label = paste0("JA Displacement DALY (extrapolated) = ",
                               signif(disp_daly_extrapolated_ja,3), " Y"),
                vjust = -1,
                hjust = -.05),
            size = 2) +
```

```
  geom_hline(color = "red", aes(yintercept = disp_daly_extrapolated_ni)) +
  geom_text(aes(ni_s_summary$Dose[1],
                disp_daly_extrapolated_ni,
                label = paste0("NI Displacement DALY (extrapolated) = ",
                               signif(disp_daly_extrapolated_ni,3), " Y"),
                vjust = -1,
                hjust = -.05),
            size = 2) +
  geom_text(aes(x = 0.07,
                y = 0.01,
                label = paste0("Effective half-life = ", half_life, " years")),
            size = 2) +
  geom_text(aes(x = 0.07,
                y = 0,
                label = paste0("Duration = ", duration, " years")),
            size = 2) +
  theme_bw() +
  labs(x = "Starting Dose Rate (mSv/y)",
       y = "DALY (years)") +
  scale_x_continuous(limits = c(xlower, xupper),
                     expand = c(0,0),
                     breaks = seq(xlower, xupper, dose_increment),
                     labels = seq(xlower*1000, xupper*1000,
                                  dose_increment*1000)) +
  scale_y_continuous(limits = c(0,0.3))

file_save_name <- paste0("./", "combo_risk_",
                         trunc(half_life),"_yr_half_life.pdf")
ggsave(file_save_name, plot = combo_plot1,
       device = "pdf", width = 6, height = 4, units = "in")

# ******************
# plot 2, half-life = 5 years
# ******************
half_life <- 5
combo_plot2 <- ggplot(ni_s_summary, aes(x=Dose)) +
  geom_line(data=us_epa_daly2, color = "green",
            linetype= "twodash", aes(y=EPA_DALY)) +
  geom_text(aes(us_s_summary$Dose[9],
                us_epa_daly2$EPA_DALY[9],
                label="EPA DALY (US)",
                vjust = -3.5),
            size = 2) +
  geom_line(data=ja_epa_daly2, color = "royalblue",
            linetype= "dotdash", aes(y=EPA_DALY)) +
  geom_text(aes(ja_s_summary$Dose[3],
                ja_epa_daly2$EPA_DALY[3],
                label="EPA DALY (JA)",
                hjust = -.2),
            size = 2) +
  geom_line(data=ni_epa_daly2, color="red",
            linetype= "dotted", aes(y=EPA_DALY)) +
  geom_text(aes(ni_s_summary$Dose[7],
                ni_epa_daly2$EPA_DALY[7],
                label="EPA DALY (NI)",
                hjust = 1.2),
            size = 2) +
  geom_hline(color = "green", aes(yintercept = disp_daly_extrapolated_us)) +
  geom_text(aes(us_s_summary$Dose[1],
                disp_daly_extrapolated_us,
                label = paste0("US Displacement DALY (extrapolated) = ",
                               signif(disp_daly_extrapolated_us,3), " Y"),
                vjust = -1,
                hjust = -.05),
            size = 2) +
  geom_hline(color = "royalblue", aes(yintercept = disp_daly_extrapolated_ja)) +
  geom_text(aes(ja_s_summary$Dose[1],
                disp_daly_extrapolated_ja,
                label = paste0("JA Displacement DALY (extrapolated) = ",
                               signif(disp_daly_extrapolated_ja,3), " Y"),
                vjust = -1,
```

```
                hjust = -.05),
            size = 2) +
  geom_hline(color = "red", aes(yintercept = disp_daly_extrapolated_ni)) +
  geom_text(aes(ni_s_summary$Dose[1],
                disp_daly_extrapolated_ni,
                label = paste0("NI Displacement DALY (extrapolated) = ",
                               signif(disp_daly_extrapolated_ni,3), " Y"),
                vjust = -1,
                hjust = -.05),
            size = 2) +
  geom_text(aes(x = 0.07,
                y = 0.01,
                label = paste0("Effective half-life = ", half_life, " years")),
            size = 2) +
  geom_text(aes(x = 0.07,
                y = 0,
                label = paste0("Duration = ", duration, " years")),
            size = 2) +
  theme_bw() +
  labs(x = "Starting Dose Rate (mSv/y)",
       y = "DALY (years)") +
  scale_x_continuous(limits = c(xlower, xupper),
                     expand = c(0,0),
                     breaks = seq(xlower, xupper, dose_increment),
                     labels = seq(xlower*1000, xupper*1000,
                                  dose_increment*1000)) +
  scale_y_continuous(limits = c(0,0.3))

file_save_name <- paste0("./", "combo_risk_",
                         trunc(half_life),"_yr_half_life.pdf")
ggsave(file_save_name, plot = combo_plot1,
       device = "pdf", width = 6, height = 4, units = "in")

# *****************
# plot 3, half-life = 7 years
# *****************
half_life <- 7
combo_plot3 <- ggplot(ni_s_summary, aes(x=Dose)) +
  geom_line(data=us_epa_daly3, color = "green",
            linetype= "twodash", aes(y=EPA_DALY)) +
  geom_text(aes(us_s_summary$Dose[6],
                us_epa_daly3$EPA_DALY[6],
                label="EPA DALY (US)",
                vjust = -3.5),
            size = 2) +
  geom_line(data=ja_epa_daly3, color = "royalblue",
            linetype= "dotdash", aes(y=EPA_DALY)) +
  geom_text(aes(ja_s_summary$Dose[2],
                ja_epa_daly3$EPA_DALY[2],
                label="EPA DALY (JA)",
                hjust = -.2),
            size = 2) +
  geom_line(data=ni_epa_daly3, color="red",
            linetype= "dotted", aes(y=EPA_DALY)) +
  geom_text(aes(ni_s_summary$Dose[5],
                ni_epa_daly3$EPA_DALY[5],
                label="EPA DALY (NI)",
                hjust = 1.2),
            size = 2) +
  geom_hline(color = "green", aes(yintercept = disp_daly_extrapolated_us)) +
  geom_text(aes(us_s_summary$Dose[1],
                disp_daly_extrapolated_us,
                label = paste0("US Displacement DALY (extrapolated) = ",
                               signif(disp_daly_extrapolated_us,3), " Y"),
                vjust = -1,
                hjust = -.05),
            size = 2) +
  geom_hline(color = "royalblue", aes(yintercept = disp_daly_extrapolated_ja)) +
  geom_text(aes(ja_s_summary$Dose[1],
                disp_daly_extrapolated_ja,
                label = paste0("JA Displacement DALY (extrapolated) = ",
```

```
                                signif(disp_daly_extrapolated_ja,3), " Y"),
                vjust = -1,
                hjust = -.05),
            size = 2) +
  geom_hline(color = "red", aes(yintercept = disp_daly_extrapolated_ni)) +
  geom_text(aes(ni_s_summary$Dose[1],
                disp_daly_extrapolated_ni,
                label = paste0("NI Displacement DALY (extrapolated) = ",
                                signif(disp_daly_extrapolated_ni,3), " Y"),
                vjust = -1,
                hjust = -.05),
            size = 2) +
  geom_text(aes(x = 0.07,
                y = 0.01,
                label = paste0("Effective half-life = ", half_life, " years")),
            size = 2) +
  geom_text(aes(x = 0.07,
                y = 0,
                label = paste0("Duration = ", duration, " years")),
            size = 2) +
  theme_bw() +
  labs(x = "Starting Dose Rate (mSv/y)",
       y = "DALY (years)") +
  scale_x_continuous(limits = c(xlower, xupper),
                     expand = c(0,0),
                     breaks = seq(xlower, xupper, dose_increment),
                     labels = seq(xlower*1000, xupper*1000,
                                  dose_increment*1000)) +
  scale_y_continuous(limits = c(0,0.3))

file_save_name <- paste0("./", "combo_risk_",
                         trunc(half_life),"_yr_half_life.pdf")
ggsave(file_save_name, plot = combo_plot3,
       device = "pdf", width = 6, height = 4, units = "in")
```

APPENDIX 4: RADIATION DOSE DEFINITIONS

Dose, as stated in 10 CFR §20.1003, is "… a generic term that means absorbed dose, dose equivalent, effective dose equivalent, committed dose equivalent, committed effective dose equivalent, or total effective dose equivalent [.]" (U.S. Nuclear Regulatory Commission, 2015) In this paper, the term "dose," without further elaboration, will refer only to the total effective dose equivalent, as described below.

The most basic measure of radiation energy deposition is *absorbed dose*. The SI unit of absorbed dose is the *gray*, calculated in joules per kilogram (Bureau International des Poids et Mesures, 2006).

The gray is the most general unit of measure for radiation dose, but does not account for differences between types of radiation and their effects on biological systems. To account for these differences, other measures have been developed, the *dose equivalent* (absorbed dose multiplied by weighting factors accounting for radiation type) and the *effective dose equivalent* (the sum of dose equivalents for the entire body with weighting factors for the sensitivity of each tissue or organ). The unit of dose equivalent and effective dose equivalent is the *sievert* (U.S. Nuclear Regulatory Commission, 2015).

To account for radioactive material deposited in the body, a further nuanced definition is utilized, the *committed effective dose equivalent*. This dose measure accounts for the effective

dose equivalent integrated over 50 years, and applies to exposures from internally incorporated radionuclides. The unit remains the sievert (U.S. Nuclear Regulatory Commission, 2015).

Finally, the combination of all radiation doses from all pathways is termed the *total effective dose equivalent*, and is the sum of effective dose equivalent (for external exposures) and the committed effective dose equivalent (for internal exposures) (U.S. Nuclear Regulatory Commission, 2015).

An important note here is that the sievert, built on a combination of physical quantities (energy and mass) and weighting factors is defined only for *stochastic* effects – primarily cancer induction and mutation – as opposed to *non-stochastic* or *deterministic* effects such as Acute Radiation Syndrome (ARS) or cataract induction (U.S. Nuclear Regulatory Commission, 2015).

APPENDIX 5: OUTPUT OF MODEL TEST RUNS

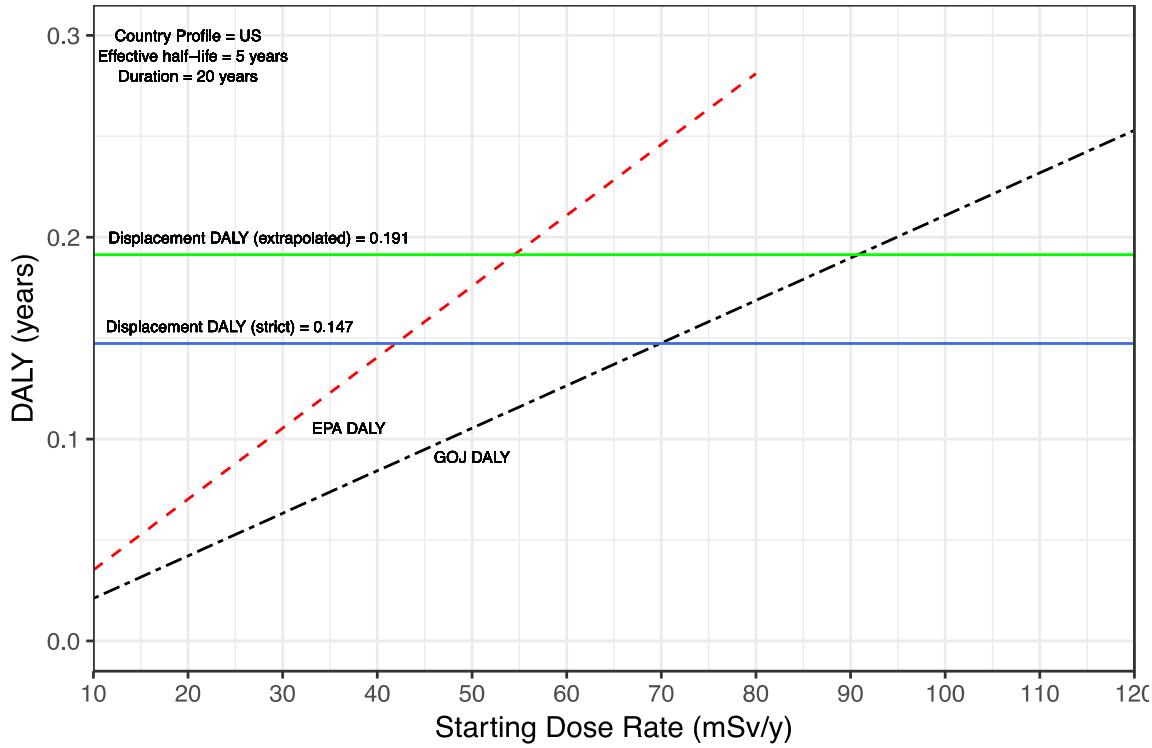
United States

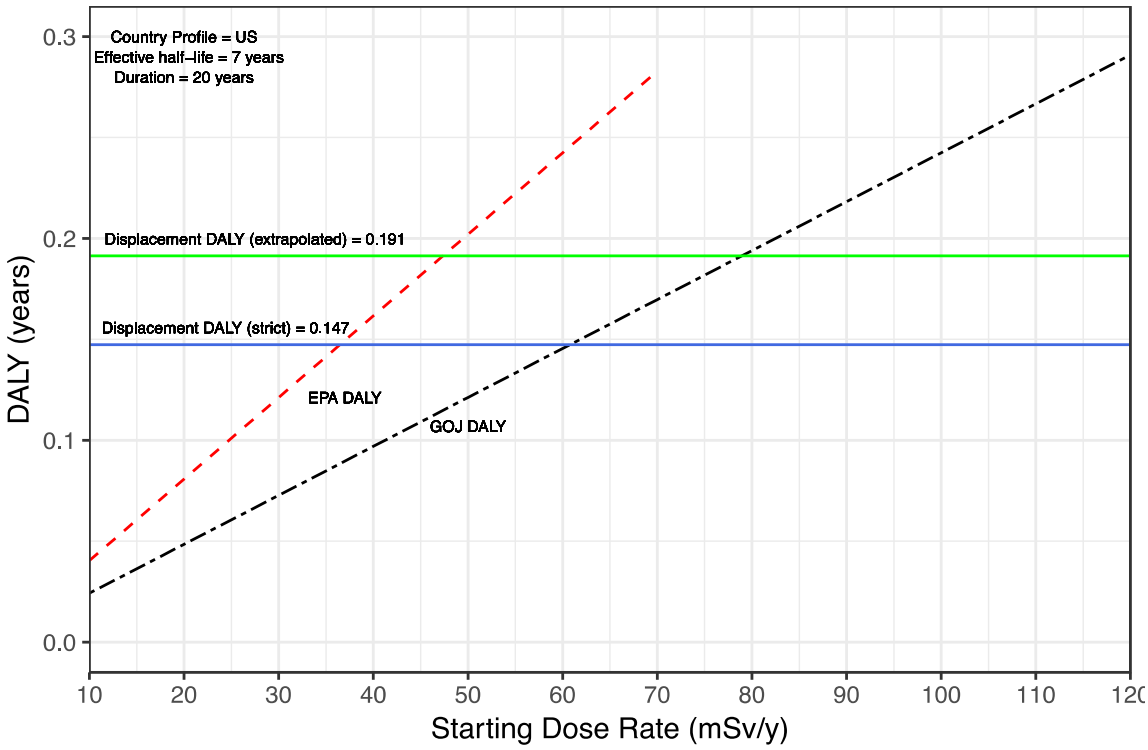
US Radiation

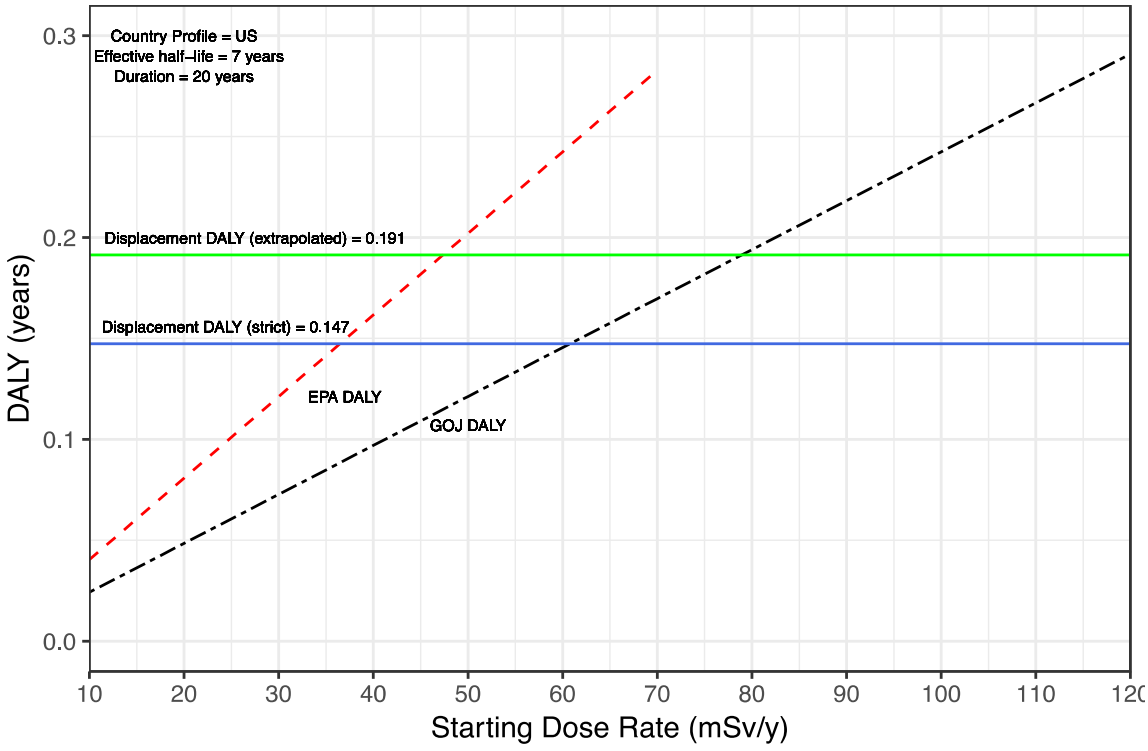
Starting Exposure Rate (Sv/y)	Effective Half-Life (y)	DALY (EPA methodology) (y)	DALY (GOJ methodology) (y)
0.01	3	0.028	0.017
0.02	3	0.056	0.034
0.03	3	0.084	0.051
0.04	3	0.11	0.067
0.05	3	0.14	0.084
0.06	3	0.17	0.10
0.07	3	0.20	0.12
0.08	3	0.22	0.13
0.09	3	0.25	0.15
0.1	3	0.28	0.17
0.11	3	0.31	0.19
0.12	3	0.34	0.20
0.01	5	0.035	0.021
0.02	5	0.070	0.042
0.03	5	0.11	0.063
0.04	5	0.14	0.084
0.05	5	0.18	0.11
0.06	5	0.21	0.13
0.07	5	0.25	0.15
0.08	5	0.28	0.17
0.09	5	0.32	0.19
0.1	5	0.35	0.21
0.11	5	0.39	0.23
0.12	5	0.42	0.25
0.01	7	0.040	0.024
0.02	7	0.081	0.048
0.03	7	0.12	0.073
0.04	7	0.16	0.097
0.05	7	0.20	0.12
0.06	7	0.24	0.15
0.07	7	0.28	0.17
0.08	7	0.32	0.19
0.09	7	0.36	0.22
0.1	7	0.40	0.24
0.11	7	0.44	0.27
0.12	7	0.48	0.29

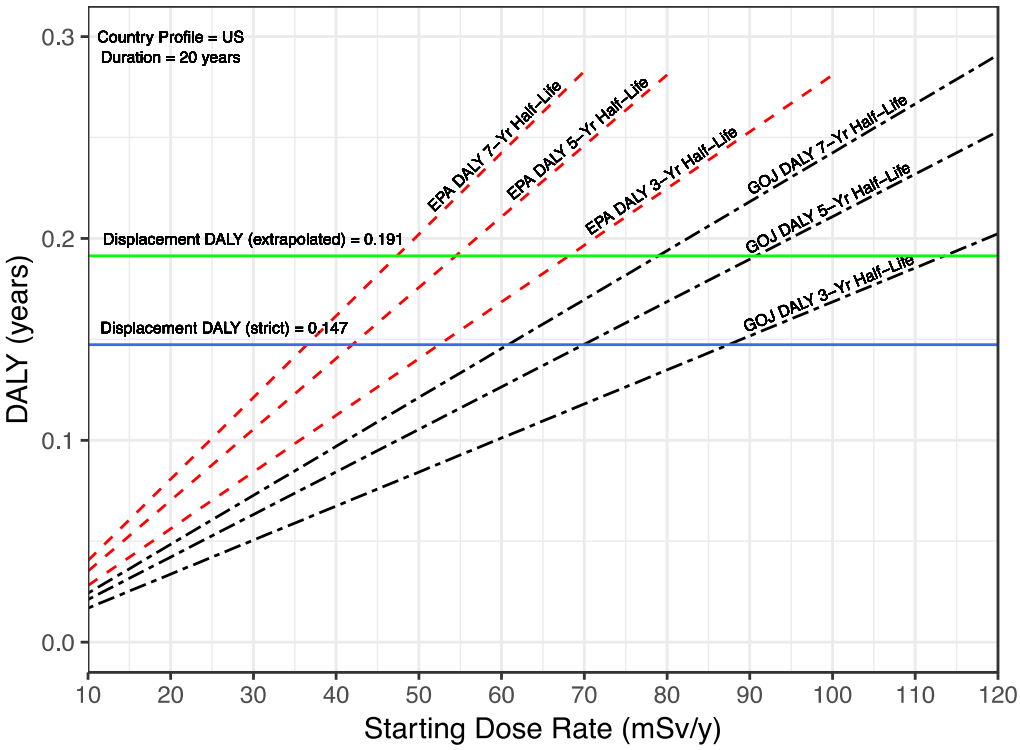
US Displacement

	Strict		Extrapolated	
Data Year	PTSD DALY (y)	Diabetes DALY (y)	PTSD DALY (y)	Diabetes DALY (y)
2012	0.0074	0.14	0.020	0.17




Country Profile = US
Effective half–life = 7 years
Duration = 20 years
Displacement DALY (extrapolated) = 0.191
Displacement DALY (strict) = 0.147
EPA DALY
GOJ DALY
DALY (years)
Starting Dose Rate (mSv/y)
0.0
0.1
0.2
0.3
10
20
30
40
50
60
70
80
90
100
110
120


Country Profile = US
Effective half–life = 7 years
Duration = 20 years
Displacement DALY (extrapolated) = 0.191
Displacement DALY (strict) = 0.147
EPA DALY
GOJ DALY
DALY (years)
Starting Dose Rate (mSv/y)
0.0
0.1
0.2
0.3
10
20
30
40
50
60
70
80
90
100
110
120


Country Profile = US
Duration = 20 years
EPA DALY 7–Yr Half–Life
EPA DALY 5–Yr Half–Life
EPA DALY 3–Yr Half–Life
GOJ DALY 7–Yr Half–Life
GOJ DALY 5–Yr Half–Life
GOJ DALY 3–Yr Half–Life
Displacement DALY (extrapolated) = 0.191
Displacement DALY (strict) = 0.147
DALY (years)
0.0
0.1
0.2
0.3
10
20
30
40
50
60
70
80
90
100
110
120
Starting Dose Rate (mSv/y)

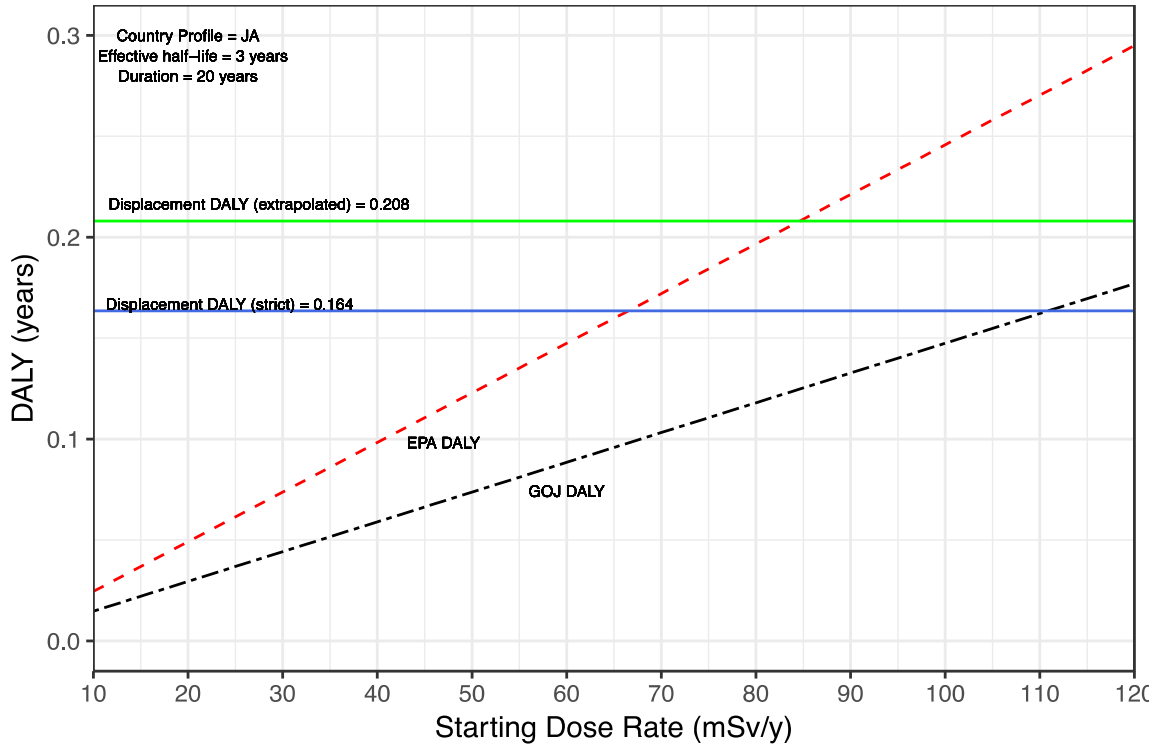
Japan

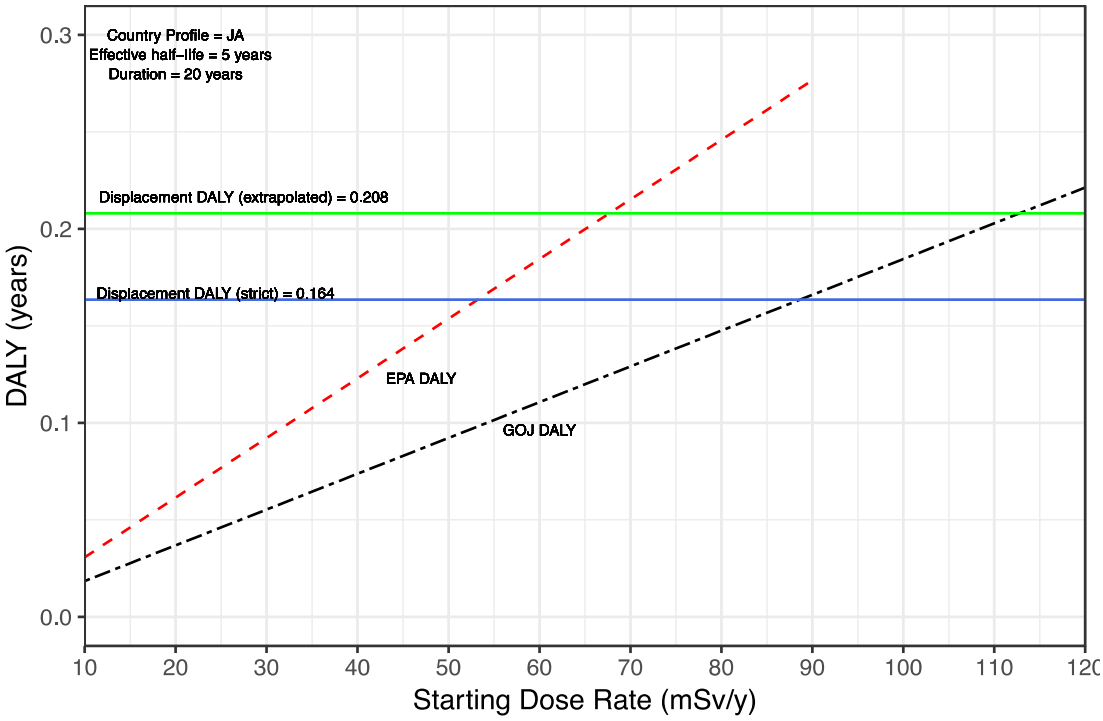
Japan Radiation

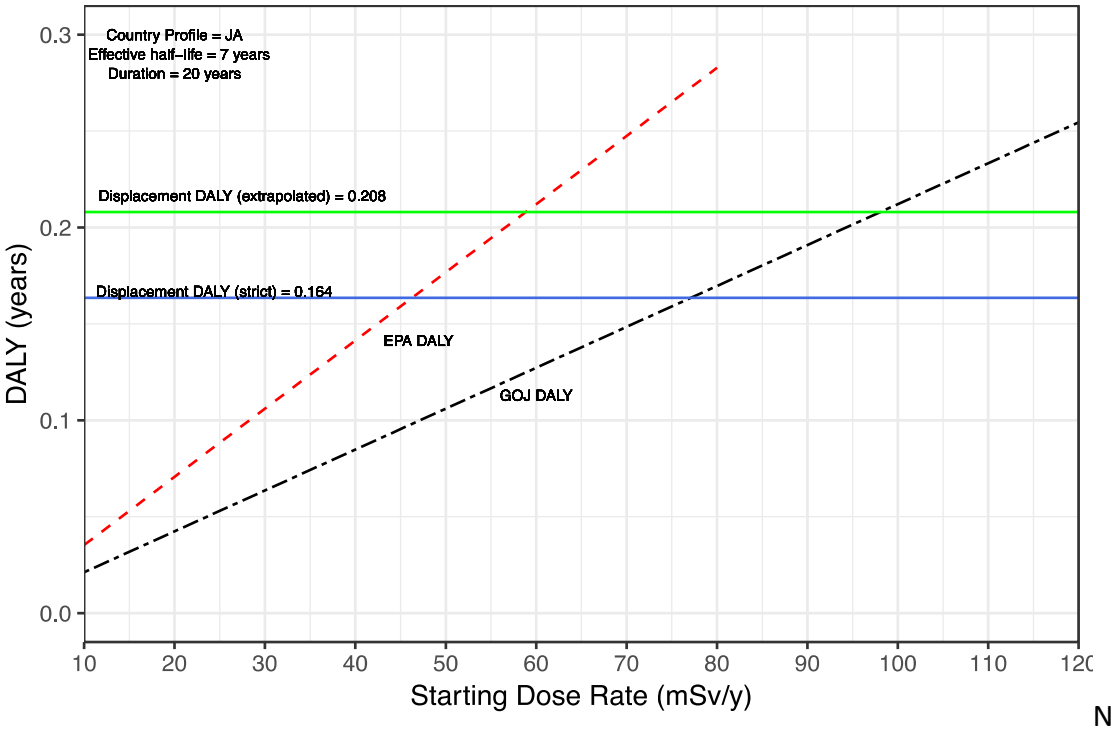
Starting Exposure Rate (Sv/y)	Effective Half-Life (y)	DALY (EPA methodology) (y)	DALY (GOJ methodology) (y)
0.01	3	0.025	0.015
0.02	3	0.049	0.029
0.03	3	0.074	0.044
0.04	3	0.098	0.059
0.05	3	0.12	0.074
0.06	3	0.15	0.088
0.07	3	0.17	0.10
0.08	3	0.20	0.12
0.09	3	0.22	0.13
0.1	3	0.25	0.15
0.11	3	0.27	0.16
0.12	3	0.29	0.18
0.01	5	0.031	0.018
0.02	5	0.061	0.037
0.03	5	0.092	0.055
0.04	5	0.12	0.074
0.05	5	0.15	0.092
0.06	5	0.18	0.11
0.07	5	0.22	0.13
0.08	5	0.25	0.15
0.09	5	0.28	0.17
0.1	5	0.31	0.18
0.11	5	0.34	0.20
0.12	5	0.37	0.22
0.01	7	0.035	0.021
0.02	7	0.071	0.042
0.03	7	0.11	0.064
0.04	7	0.14	0.085
0.05	7	0.18	0.11
0.06	7	0.21	0.13
0.07	7	0.25	0.15
0.08	7	0.28	0.17
0.09	7	0.32	0.19
0.1	7	0.35	0.21
0.11	7	0.39	0.23
0.12	7	0.42	0.25

Japan Displacement

	Strict		Extrapolated	
Data Year	PTSD DALY (y)	Diabetes DALY (y)	PTSD DALY (y)	Diabetes DALY (y)
2012	0.0082	0.16	0.020	0.19




Country Profile = JA
Effective half–life = 5 years
Duration = 20 years
Displacement DALY (extrapolated) = 0.208
Displacement DALY (strict) = 0.164
EPA DALY
GOJ DALY
DALY (years)
0.0
0.1
0.2
0.3
10
20
30
40
50
60
70
80
90
100
110
120
Starting Dose Rate (mSv/y)


Country Profile = JA
Effective half–life = 7 years
Duration = 20 years
Displacement DALY (extrapolated) = 0.208
Displacement DALY (strict) = 0.164
EPA DALY
GOJ DALY
DALY (years)
0.0
0.1
0.2
0.3
10
20
30
40
50
60
70
80
90
100
110
120
Starting Dose Rate (mSv/y)

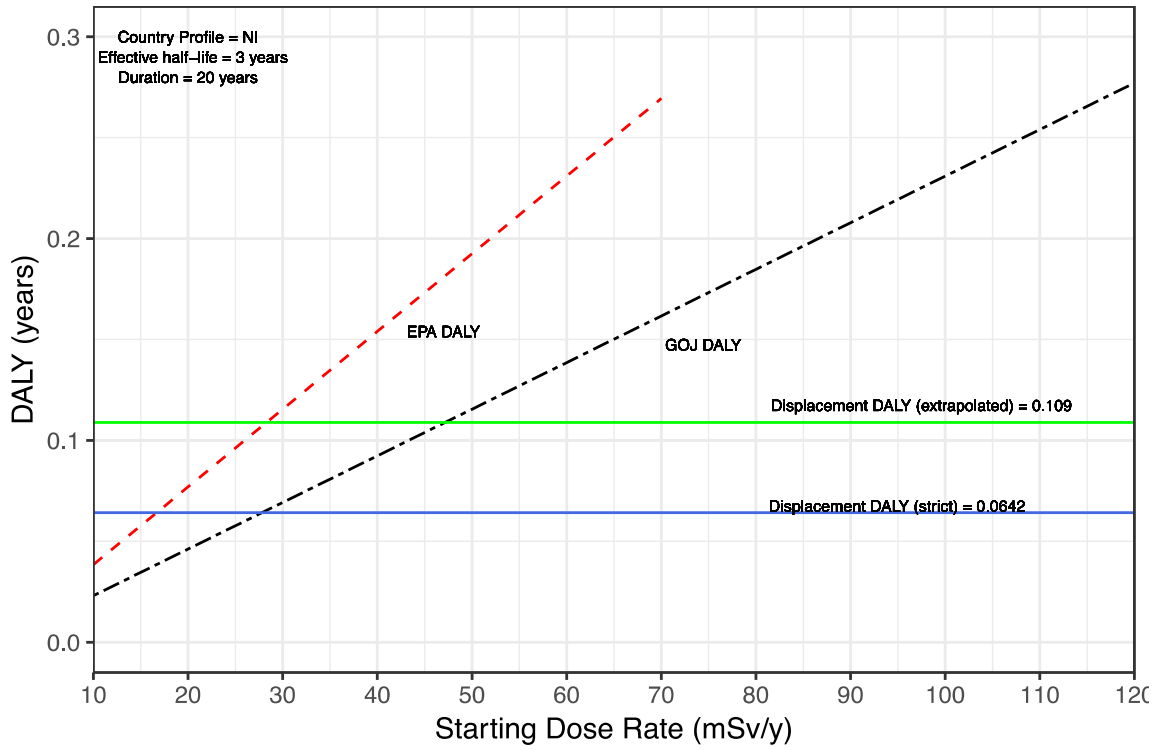
Nigeria

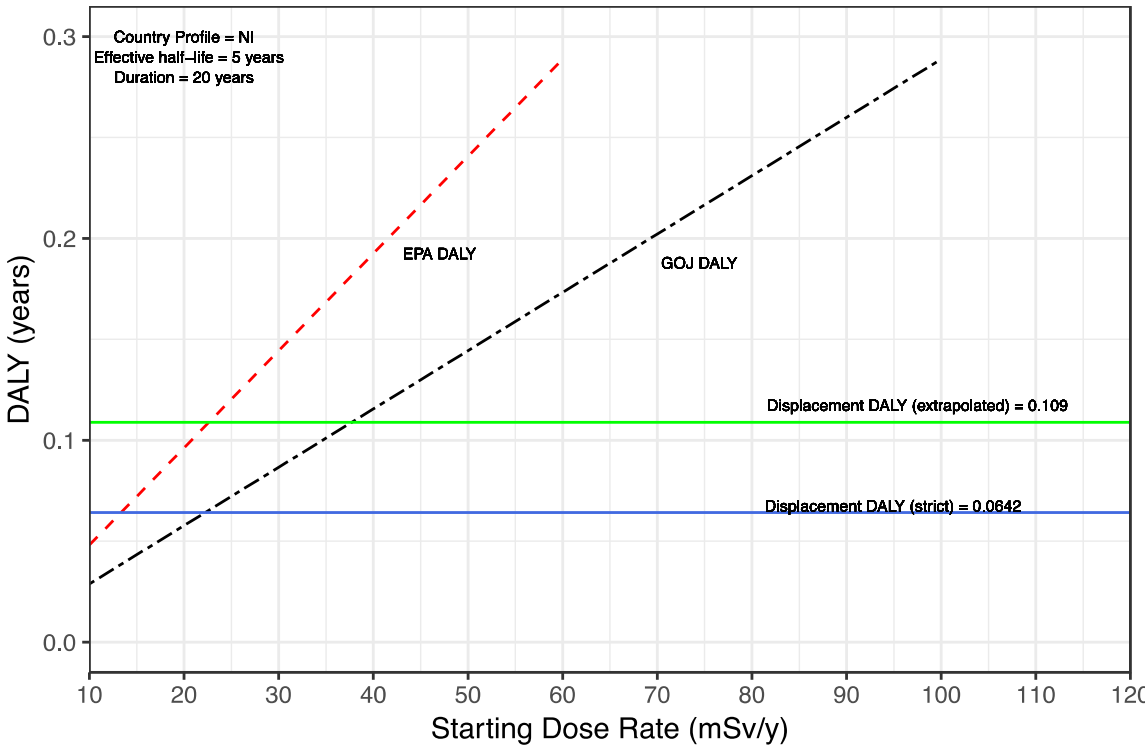
Nigeria Radiation

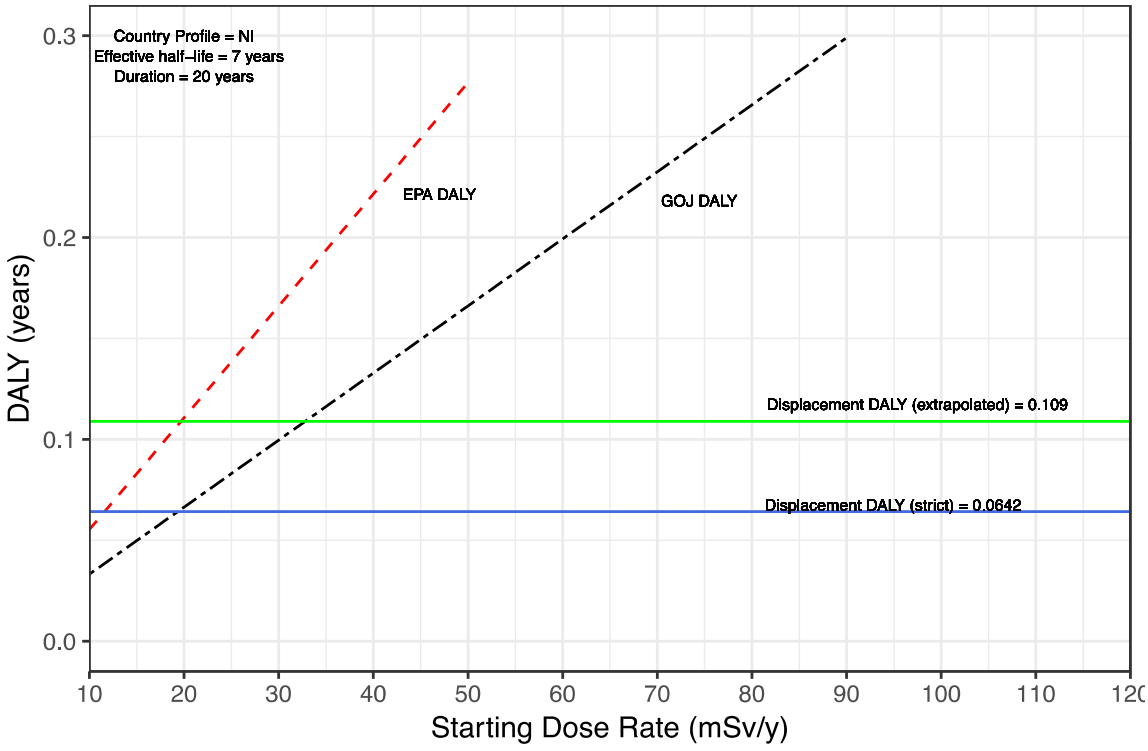
Starting Exposure Rate (Sv/y)	Effective Half-Life (y)	DALY (EPA methodology) (y)	DALY (GOJ methodology) (y)
0.01	3	0.038	0.023
0.02	3	0.077	0.046
0.03	3	0.12	0.069
0.04	3	0.15	0.092
0.05	3	0.19	0.12
0.06	3	0.23	0.14
0.07	3	0.27	0.16
0.08	3	0.31	0.18
0.09	3	0.35	0.21
0.1	3	0.38	0.23
0.11	3	0.42	0.25
0.12	3	0.46	0.28
0.01	5	0.048	0.029
0.02	5	0.096	0.058
0.03	5	0.14	0.087
0.04	5	0.19	0.12
0.05	5	0.24	0.14
0.06	5	0.29	0.17
0.07	5	0.34	0.20
0.08	5	0.39	0.23
0.09	5	0.43	0.26
0.1	5	0.48	0.29
0.11	5	0.53	0.32
0.12	5	0.58	0.35
0.01	7	0.055	0.033
0.02	7	0.11	0.066
0.03	7	0.17	0.10
0.04	7	0.22	0.13
0.05	7	0.28	0.17
0.06	7	0.33	0.2
0.07	7	0.39	0.23
0.08	7	0.44	0.27
0.09	7	0.50	0.30
0.1	7	0.55	0.33
0.11	7	0.61	0.37
0.12	7	0.66	0.40

Nigeria Displacement

	Strict		Extrapolated	
Data Year	PTSD DALY (y)	Diabetes DALY (y)	PTSD DALY (y)	Diabetes DALY (y)
2012	0.0046	0.060	0.020	0.089


Country Profile = NI
Effective half–life = 3 years
Duration = 20 years
EPA DALY
GOJ DALY
Displacement DALY (extrapolated) = 0.109
Displacement DALY (strict) = 0.0642
DALY (years)
0.0
0.1
0.2
0.3
10
20
30
40
50
60
70
80
90
100
110
120
Starting Dose Rate (mSv/y)


Country Profile = NI
Effective half–life = 5 years
Duration = 20 years
EPA DALY
GOJ DALY
Displacement DALY (extrapolated) = 0.109
Displacement DALY (strict) = 0.0642
DALY (years)
0.0
0.1
0.2
0.3
10
20
30
40
50
60
70
80
90
100
110
120
Starting Dose Rate (mSv/y)


Country Profile = NI
Effective half–life = 7 years
Duration = 20 years
EPA DALY
GOJ DALY
Displacement DALY (extrapolated) = 0.109
Displacement DALY (strict) = 0.0642
DALY (years)
0.0
0.1
0.2
0.3
10
20
30
40
50
60
70
80
90
100
110
120
Starting Dose Rate (mSv/y)