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Human and Environmental Bias Affecting Risk Perception in Military Radiological and Nuclear Operations

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ABSTRACT

The urban military operating environment may offer favorable conditions for combat involving asymmetric actions or 4th generation warfare which may include chemical, biological, radiological / nuclear (CBRN) events. The CBRN context is characterized by threats capable of producing future detriment. The harm may be produced by intentional release of hazardous materials into the operational environment. This study deals with an environment deliberately contaminated by radioactive materials because of the activation of a radiological dispersive device (RDD). A computer simulation of the radioactive scenario was performed in order to produce useful information which in turn may be used both to support decision-making and training. The main goal was to assess the risk of developing radioinduced solid cancer considering the interaction between local environmental variables and cognitive biases, represented by the Dunning-Kruger specific coefficient. The findings highlight intuitive correlations between local atmospheric stability and cognitive bias affecting decisions. The findings also show that, especially in the military-operational context, the methodology proposed for the assessment of environment-human interactions may be decisive for correctly direct available resources, both human and material, in the way of reducing the operational risk.

Keywords: Radiological risk; Military operations; Cognitive bias; Decision

1. INTRODUCTION

The urban military operating environment may offer favorable conditions for combat involving asymmetric actions or 4th generation warfare[1]. It may be expected that extremist groups will resort to improvised artifacts to cause harm. These devices are not necessarily intended to cause physical damage, although that is also possible[2]. In this study, the device of interest is a Radiological Dispersive Device (RDD). An RDD is considered as a simplified mechanical system that couples radioactive and conventional explosive material[2]. Although physical damage may occur in the process of triggering an RDD, the incapacitation of inhabited areas by increasing radioactive contamination, and consequently radiological risk[3], may be appointed as the target situation. The environment contaminated by an RDD is an object of interest in the fields of Chemical, Biological, Radiological and Nuclear (CBRN) defense[4] in which complex decisions are ordinarily demanded. Therefore, this study intends to verify possible relationships between environmental variables and human cognitive biases capable of affecting the risk perception overlapping the real-time decision-making.

Cognitive biases and their effects in the field of psychology and economics raised a set of questions about influences on human decision processes. Detailed work can be found in Janser[5], who develops the concept of cognitive biases on a heuristic basis applied to military decision-making. In his work, Janser compares the human brain to a computer and its processing limitations, which to improve its performance makes use of cognitive devices that work as shortcuts to access key information. These shortcuts and specific connections produce a context called heuristics[6]. Failures in the heuristic base may represent failures in the response provided by shortcuts and consequent failures in the results, impacting the human decision process. However, the randomization of errors in the heuristic basis may lead to the opposite effect, producing a situation of overconfidence[5] in military decision-making. This state of overconfidence may lead to a state of consciousness governed by a suppressed heuristic basis, generating what is known as the Dunning-Kruger[7-8] effect. Combat can be considered fundamentally as a human activity full of conscious or unconscious decisions, either rational or not. This condition can make the decision-making process susceptible to cognitive biases expressed in heuristics, intuitive choices that can make rational decision-making less effective. Based on these arguments, Shay Shabtai[8] develops a study in which he considers Perception Management, in which cognitive biases are the object of the manipulation of the perception of objective reality. In an interesting essay, kaI[9] explores different types of military decision-making and how each may affect contextual assessments and consequently decisions from a rationality-based evaluation. The study concludes by highlighting that combined with contextual factors, cognitive biases appear to

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result in compromised assessments of accuracy at both strategic and operational levels.

The cognitive bias treated in this study comes from the Dunning-Kruger (DK) effect which is derived from a concept initially presented by researchers Dunning and Kruger[7]. In there the skills associated with competence in a given field of knowledge are often the same skills needed to assess an individual's competence[7]. Based on these ideas, the specific coefficient related to the (DK) effect is built and applied. The DK specific coefficient is then considered to support the assessment of possible impacts of the subjective competences of decision-makers on the decision itself. The study is limited to trying to establish an evaluation method in which the skills of those assessed are scored in a non-parametric way over an arbitrary DK scale. Quantifying the skills is outside the scope of this study.

In the study, an urban combat condition in which a complex decision environment has local variations as boundary conditions that directly impact the dispersion of the radiological agent (immediate threat) is considered. This influence of environmental conditions on the threat alters the radiological exposure profiles of a team operating in the contaminated zone. Once the radiological exposure profiles are altered, so are the inherent risks to which team members are subjected to. The choice of a specific risk can be a convenient option to establish a method of perception and qualification of the radiological risk, representing an alternative decision support.

From this perspective, individuals considered incompetent do not have enough information to identify or evaluate disruptive scenarios with the expected effectiveness[10]. However, the concept of competence is taken in a broad sense, and a formal professional definition that may vary from one field of activity to another is outside the scope of this work. The application of a table of DK coefficients to numerical results on radiological risks may suggest directions on how decision-making may be affected by cognitive biases.

2. METHODOLOGY

2.1 Source Term and Computer Simulation

HotSpot Health Physics Codes 3.1.2 package uses the gaussian model to simulate the atmospheric dispersion of radioactive material[11]. The software conservatively evaluates the contamination of an area of interest and estimates the Total Effective Dose Equivalent (TEDE) on individuals from environmental exposure. The radioactive material producing the equivalent dose may be external, internal, or both. The TEDE is thus a reasonable expression of the combined dose (internal and external pathways)[11] to which an individual may be subjected in a radiation field. Hotspot has been chosen since it is fast (by solving analytical equations) and provides a set of results that may support the very first decisions. For this study, the initial timeframe for decisions, regularly called initial phase, is within the first 100 hours (≈ 4 days) after the initial event. In this scope, no compensation for possible delays in identifying the problem is computed. As the source term is Cs-137, whose half-life is around 30 years, delays comparable to the time of 100h may be neglected.

In general, it may be understood that the size of a fine particle in monodisperse suspension (solid or liquid) in the atmosphere can be reasonably characterized by its diameter. Dispersion models applied to Hotspot are oriented to solve the particle size distribution with respect to radioactivity. HotSpot then assumes in its calculations that the mean aerodynamic diameter of the particle is 1 micrometer. This definition contributes to a significant reduction in ballistic effects of any order for the suspended particles.

The hypothetical radioactive release was simulated considering the dispersion of 4.44E+14 Bq (1.20E+3 Ci) of Cs-137 in an urban environment. The radiation dose field provides the TEDE[12], which is considered to be the primary variable for risk estimation.

The source-term is typically used for the irradiation of human blood components[13]. The dispersion of Cs-137 in the environment was calculated by applying the HotSpot[11] which uses Gaussian modeling (Eqn. 1) to assess the presence of the contaminant in 3D space. Developers recommend that simulations consider distances no further than 10 km in order to reduce the associated uncertainties[11]. Table 1 presents the main input data applied to HotSpot.

$$C(x,y,z,H) = \left(\frac{Q}{(2\pi\sigma_y\sigma_z u)}\right) exp\left[-0.5\left(\frac{y}{\sigma_y}\right)^2\right]\left\{\left(exp\left[-0.5\left(\frac{(z-H)}{\sigma_z}\right)^2\right]\right.\right. \\ \left.\left.+exp\left[-0.5\left(\frac{(z+H)}{\sigma_z}\right)^2\right)\right]\right\} exp\left(-\frac{\lambda x}{u}\right) DF(x) \quad (1)$$

Table 1. Main input data for simulation in HotSpot

Input (HotSpot)	Value
source material	Cs-137 (blood components irradiation)
mode and high explosive	General Explosion, ≈ 4.54 kg (TNT)
Material-at-Risk (MAR)	4.44E+14 Bq (1.20E+3 Ci)
Damage Ratio (DR), Airborne Fraction (ARF), Respirable Fraction (RF), and Leakpath Factor (LPF)	1.0
wind speed (h=10 m) and sample time	3.0 m/s and 10 min
effective release height	0.0 (Ground Surface)
stability Class (City)	A to F
respirable and non-respirable deposition velocity	0.30 cm/s and 8.0 cm/s respectively
receptor height, breathing rate	1.5 m and 3.33E-04 m^3/s (conservative)
distance coordinates	All distances are on the plume's centerline

where, C, Q, H and λ represent, respectively, the atmospheric concentration of the radioactive material (Ci-s)/(m^3), the source-term activity (Ci), the effective release height of the material (m) and the constant of decay of the radioactive element (s^{-1}). The cartesian coordinates x, y and z represent the distances (m) downwind, crosswind and on the vertical axis respectively. The standard deviation of the concentration distribution in the transverse and vertical directions of the wind is represented by σ_y and σ_z respectively. The average wind speed at a specific release height is indicated by the variable u (m/s), and DF(x) is the dimensionless plume depletion factor.

2.2 Analytical Approach and the Release Time Frame

The analytical modeling may represent an interesting initial approach for radioactive release events where only little information is available. Previous studies from our group have been considered analytical simulation as a convenient approach at early stages of the response[3, 4, 14-15]. Analytical modeling has advantages such as processing speed in an ordinary computing environment. Although it generates unrealistic results, the Gaussian approach may be considered convenient for an initial assessment as it is conservative. At first sight results allowing overestimations may provide safer guidance to decision-makers by improving risk perception.

2.3 TEDE Limits, Expected Effects, and Relative Risk (RR) Calculation

This study considers a radioactive plume traveling across an urban zone. From the HotSpot simulation, the main TEDE contour considered is that representative of the zone of 700 mSv isodose, which may be addressed to deterministic effects in the early stage such as acute radiation syndrome (ARS)[16]. A critical parameter considered was the local atmospheric stability conditions represented by the Pasquill-Gifford (PG) classes. Variations of PG classes range from extremely unstable (class A) to moderately stable (class F)[17], and may impact on the contamination plume dynamics and so the radiological risk levels.

The Radiation Effects Research Foundation (RERF) has developed a model designed to provide an estimate of the risk of developing radioinduced cancer in humans[18]. The model is based on data on exposed humans who survived the bombings of Hiroshima and Nagasaki, the Life Span Study (LSS)[19]. For this study, the RERF model is applied in order to provide an estimate of the relative risk of solid cancer (RR) considering full immersion in the contamination plume for the time of evaluation (100 h). Alternative radiopepidemiological models for the development of solid cancer can be found in the main health and environmental protection official agencies. In this study, the main objective was not testing or defining the risk from a specific model, but instead drawing attention to the possibility of using such models as part of risk evaluation.

The RR is usually considered as a relationship between the risk of developing the disease in the exposed and unexposed population[18]. Sex and age were considered as input parameters in the calculations. For solid cancers, the RERF model requires that RR be expressed as in Eqn. (2).

$$RR = r_0(a,s)[1+\alpha_s D\exp(\beta(e-25))] \quad (2)$$

where $r_0(a,s)$ is the basic incidence rate of morbidity in the potentially affected population in the absence of irradiation, α_S is the age specific linear excess relative risk per Gy being considered 0.45 (Gy^{-1}) and 0.77 (Gy^{-1}) for male and female, respectively, D is the dose (Gy), e is the age (years) at exposure and β is the coefficient determining the modifying effect of age at exposure being considered as -0.026 (y^{-1}) for males and females [18]. Parameter estimates were based on models fitted to the Life Span Study (LSS) incidence data for the period 1958-1998[19].

2.4 Dunning-Kruger (DK) Coefficient and the Application to a Sample Scenario

In this study the DK effect, after conversion into competence, generates a specific coefficient (DK) taken as the center of the arbitrated interval for valuing the combinations presented in Table 2. This is aimed at quantifying the level of performance that may be expected, although subject to a certain

Table 2. Qualifications considering competence, vulnerability, and intentionality. Consider: C (competent), NC (non-competent), I (intentional), V (vulnerable) and NV (non-vulnerable).

Competence, vulnerability, and intentionality	Combinations	Coefficient (DK)	Specific coefficient DK (middle term for each interval)
NC / NC - V/I	High / High	DK = -1	-1
NC / NC - NV / I	High / Low	- 1 < DK ≤- 0.66	-0.830
NC / C - V/I	Moderate / High	- 0.66 < DK ≤ -0.33	-0.490
NC / C - NV / I	Moderate / Low	- 0.33 < DK < 0	-0.150
	NEUTRAL	0	0
C / NC – V / I	Low / High	0 < DK ≤ 0.33	0.150
C / NC - NV / I	Low / Low	0.33 < DK ≤0.66	0.490
C / C - NV / I	Very low / Low	0.66 < DK < 1	0.830
C / C – V / I	Very low / High	DK = 1	1

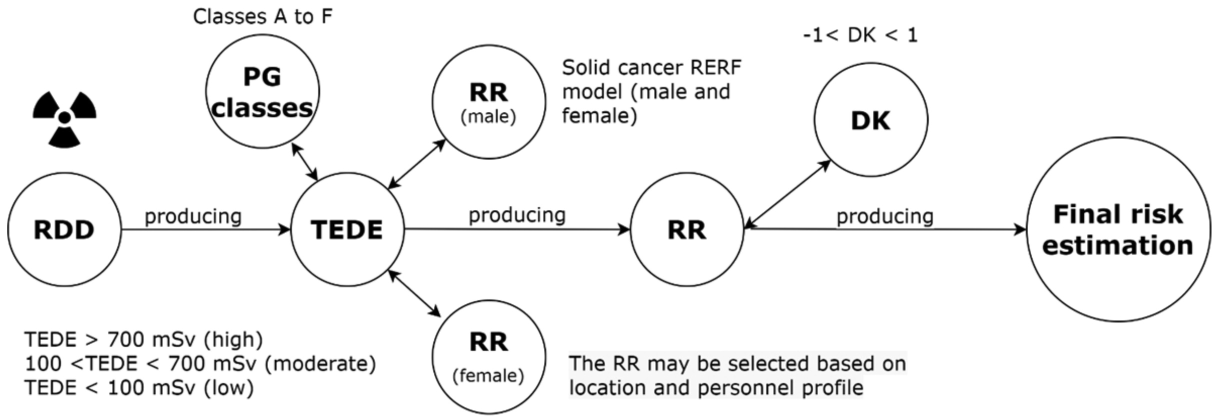

Figure 1. Schematic summary of the applied methodology.

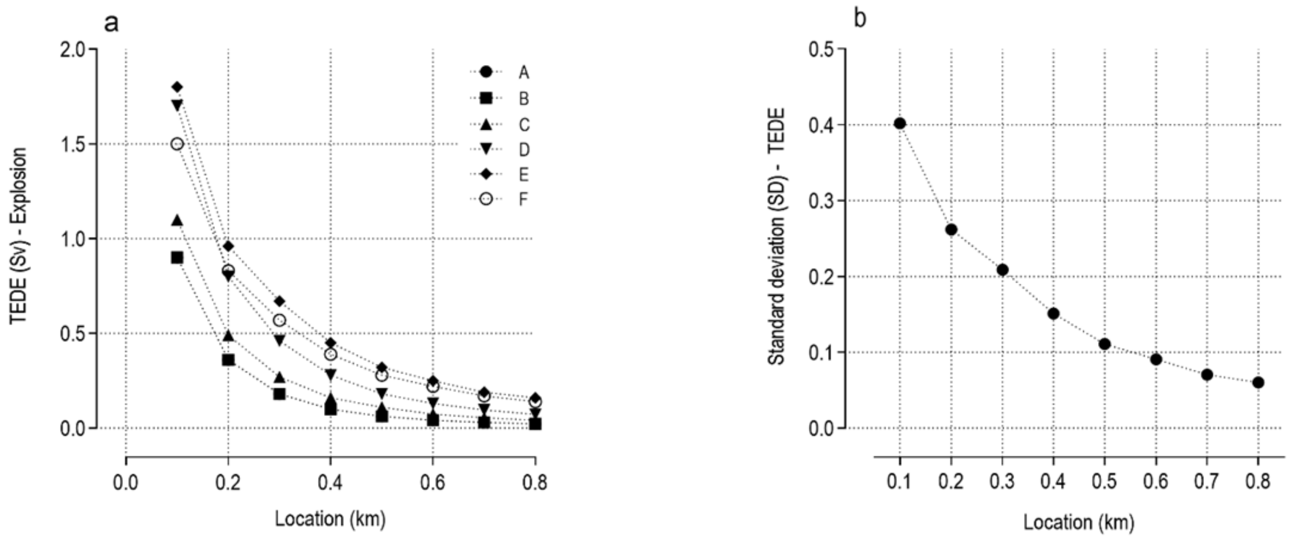

Figure 2. TEDE estimated for each location and PG class (2a – subplots indicating each PG class - A to F), and the local estimation of TEDE dispersion (SD) in regard to each PG class for each location (2b).

degree of subjectivity. To apply the specific DK coefficients, a possible radiological scenario was proposed. In that 15 team members are progressing through a contaminated urban zone counting with 2 in charge of leading the decision-process. The following variables are considered in the scenario's design: (*a*) age and sex of each team member, (*b*) local atmospheric stability class (PG), (c) the radiation dose (TEDE) and (*d*) the relative risk (RR) based on everyone's location (and exposure).

Table 2 presents the boundary conditions considered for generating specific DK coefficients. These conditions are (*a*) the competence of the person responsible, (*b*) the vulnerability (location dependent), and (*c*) intentionality. The combinations sweep a domain ranging from -1 to +1 ($-1 < DK < 1$), divided equally into the nine intervals corresponding to the combinations of the variables. The central value of each interval is the reference for applying the specific DK coefficient on the RR values calculation.

In the scenario used as an example, two team members leading the decision-making are chosen so that they are classified as NC / NC and C / NC respectively (Table 2). The CBRN event is intentional (I) and the location is considered non-vulnerable (NV), values also shown in Table 2. For each decision-maker's competence classification, a value is assigned for the specific coefficient DK (middle term for each interval). Thus, the values (-0.830) and (0.490) refer respectively to the classifications (NC / NC) and (C / NC) being applied to the Relative Risk (RR) values for each atmospheric stability class (Fig. 3). The RR values corrected by the specific coefficient DK represent the human-environment interaction by the interaction between environmental and cognitive variables. Basically, the interaction between Tables 2 and 3. Figure 1 summarizes the central paradigm developed in this study.

3. RESULTS

Figure 2 shows the calculations for the TEDE considering all the PG classes. Figure 2a shows the expected TEDE as a function of the distance from the release point. Figure 2b presents the standard deviation of the TEDE for each location and all PG classes. These SD values provide a quantitative approach for the influence of the PG classes changes on RR at a specific location.

Figure 3 shows the estimated RR. Figures 3a to 3f refers to each PG class respectively. They contain the sex-dependent RR for those aged between 20 and 50 years. The RR are also presented as a function of the distances to the release point.

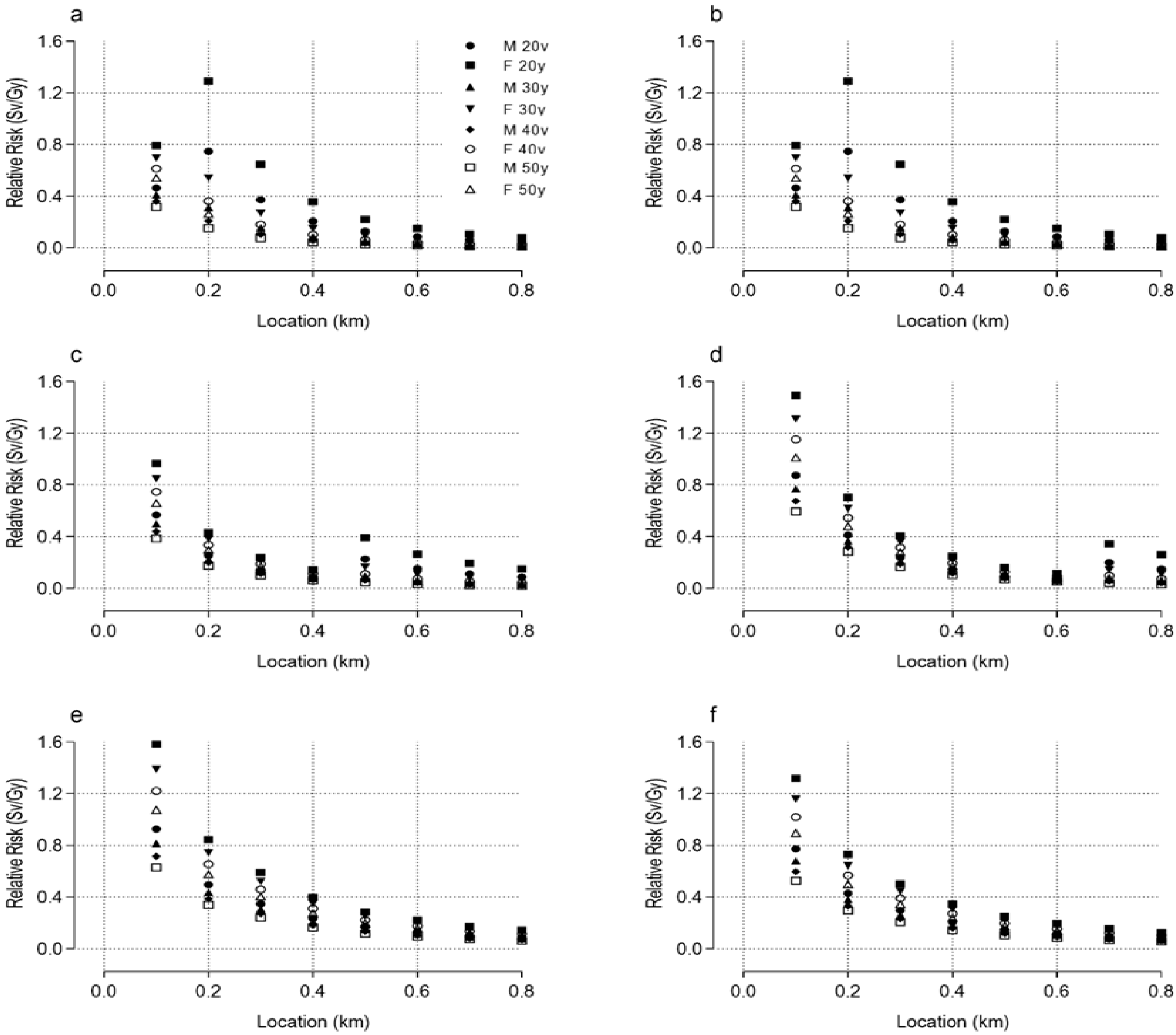

Figure 3. RR estimation dependent on sex and age for each distance and PG class (subplots indicating each PG class - A to F).

Figure 4 shows the estimation of the variability for RR. As shown by Fig. 3, this variability is represented by the calculation of the standard deviation (SD) of the results for each location and PG class.

The results presented in Table 3 are the estimated RR calculated according the RERF model. The RR are classified as High (H), Moderate (M) and Low (L) in regard to the TEDE values, 700, 100 and 50 mSv respectively. The data in Table 3 is the set of information that allows characterizing the risk of a specific team. The specific DK coefficients are applied to selected data from Table 3, generating the results shown in Fig. 5.

Figure 5 shows the result after the specific DK coefficient (Table 2) be applied on the RR (Table 3). Since the DK intervals vary in the range of $-1 \leq DK \leq +1$, it is expected that an asymmetric mirroring effect occurs in relation to the *x*-axis.

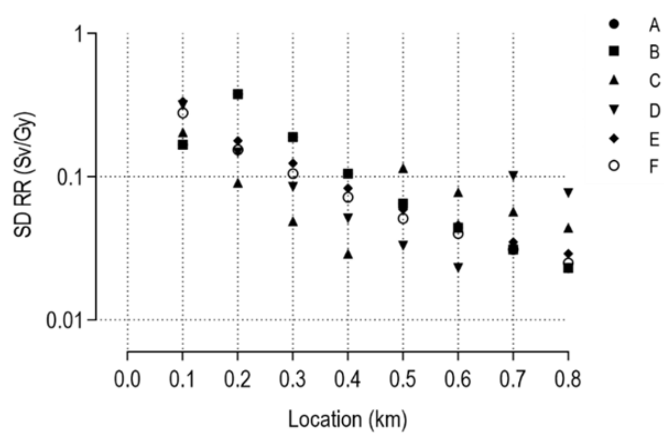

Figure 4. RR variability for each distance with respect to each PG class (subplots indicating each PG class - A to F).

Table 3. Sex and age-dependent radiological risk levels for solid tumor development (RERF model) considering PG classes and specific RR levels (High, Moderate and Low).

	Male (RR)											
	Age 20			Age 30			Age 40			Age 50		
PG	H	M	L	H	M	L	H	M	L	H	M	L
A	0.747	0.465	0.087	0.409	0.314	0.037	0.361	0.210	0.024	0.318	0.153	0.018
B	0.747	0.465	0.087	0.409	0.314	0.037	0.361	0.210	0.024	0.318	0.153	0.018
C	0.568	0.142	0.153	0.499	0.126	0.064	0.440	0.113	0.043	0.387	0.100	0.032
D	0.414	0.147	0.199	0.365	0.131	0.084	0.321	0.116	0.056	0.284	0.104	0.041
E	0.347	0.168	NA	0.306	0.149	NA	0.270	0.132	NA	0.239	0.118	NA
F	0.429	0.147	NA	0.378	0.131	NA	0.333	0.116	NA	0.294	0.104	NA

	Female (RR)											
	Age 20			Age 30			Age 40			Age 50		
PG	H	M	L	H	M	L	H	M	L	H	M	L
A	1.290	0.792	0.150	0.697	0.542	0.063	0.613	0.362	0.042	0.540	0.265	0.031
B	1.290	0.792	0.150	0.697	0.542	0.063	0.613	0.362	0.042	0.540	0.265	0.031
C	0.967	0.239	0.265	0.850	0.212	0.111	0.748	0.189	0.074	0.659	0.168	0.054
D	0.704	0.248	0.344	0.620	0.220	0.144	0.546	0.195	0.097	0.481	0.174	0.071
E	0.590	0.283	NA	0.520	0.251	NA	0.458	0.222	NA	0.404	0.197	NA
F	0.730	0.248	NA	0.643	0.220	NA	0.566	0.195	NA	0.499	0.174	NA

*H (High), M (moderate) and L (low)

4. DISCUSSION

Regardless of any situational risk assessment methodology, the main problem is the determination of the TEDE (radiation dose). Figure 2(a) presents dose profile data integrated after 4 days (≈ 100 h). Figure 2(a) shows the computational TEDE simulations result by applying HotSpot code for all local PG classes and locations. A relevant finding is related to the trend followed by the dose curve for each PG class. It is verified that the TEDE decreases its dependence on the PG classes as the location is getting further away from the release point. The markers representing the TEDE for each location evolute from sparsely disperse at 0.1 km to close together at 0.8 km from the release site. This trend is concerned to the relevance that must be given to the local PG classes. This relevance may be roughly provided by measuring the dispersion of the TEDE at the same location and for different PG classes. In this study the TEDE dispersion is represented by the standard deviation (SD). Figure 2(b) shows the SD calculated for TEDE at each location for all PG classes quantifying the decreasing influence of the PG classes on TEDE estimate. This finding may impact decision-making in terms of operational flexibility, since the PG class's influence on the TEDE increases significantly upwind. From an operational perspective and considering access to local weather information, it might be advantageous to wait for more favorable conditions of atmospheric stability to progress. However, this decision may be overshadowed if the evaluation criteria are superficial and consider only immediate factors, such as measures of TEDE values.

Since the TEDE is estimated, the methodology allows to calculate the relative risks (RR) via the chosen RERF model (Eqn. 2) for each location. The latency for solid cancer may reach 20 years, and this may appear as an obstacle to argue about the implementation of an active risk assessment methodology leading up to a practical result. On the other hand, the model is represented by an equation that does not offer mathematical obstacles to its manipulation. A good example of a complicated model is the radioepidemiological equations for estimating radioinduced leukemia[18] morbidity. The radioinduced leukemia presents an average latency period of around 2.5 years[20] becoming an interesting threat model. However, the model presents many equations and involves intricate parameters that may offer difficulties in the evaluation if applied to a group whose epidemiological profile is unknown or not detailed enough. The results on RR presented in Fig. 3 show the sensitivity of the method in the perception of vulnerabilities with respect to the sex and age for each location and atmospheric stability condition (PG class). In general, for the PG classes, the trends seem to be equivalent both in terms of quality and quantity. Variations in the local atmospheric stability conditions seem to produce increased risks for young females. However, the differences in relation to the risks tend to be the same regardless of gender and age variables for locations far from the release point.

Figure 4 introduces a rough quantification of the PG classes' influence on RR. Also, this evaluation is carried out by calculating the standard deviation (SD) of the contributions of the PG classes at each location. Again, this may be considered as a valuable information to verify possible variations in the expected detriment levels due to local weather changing. In Fig. 4, each marker (symbol) represents, for each PG class, the

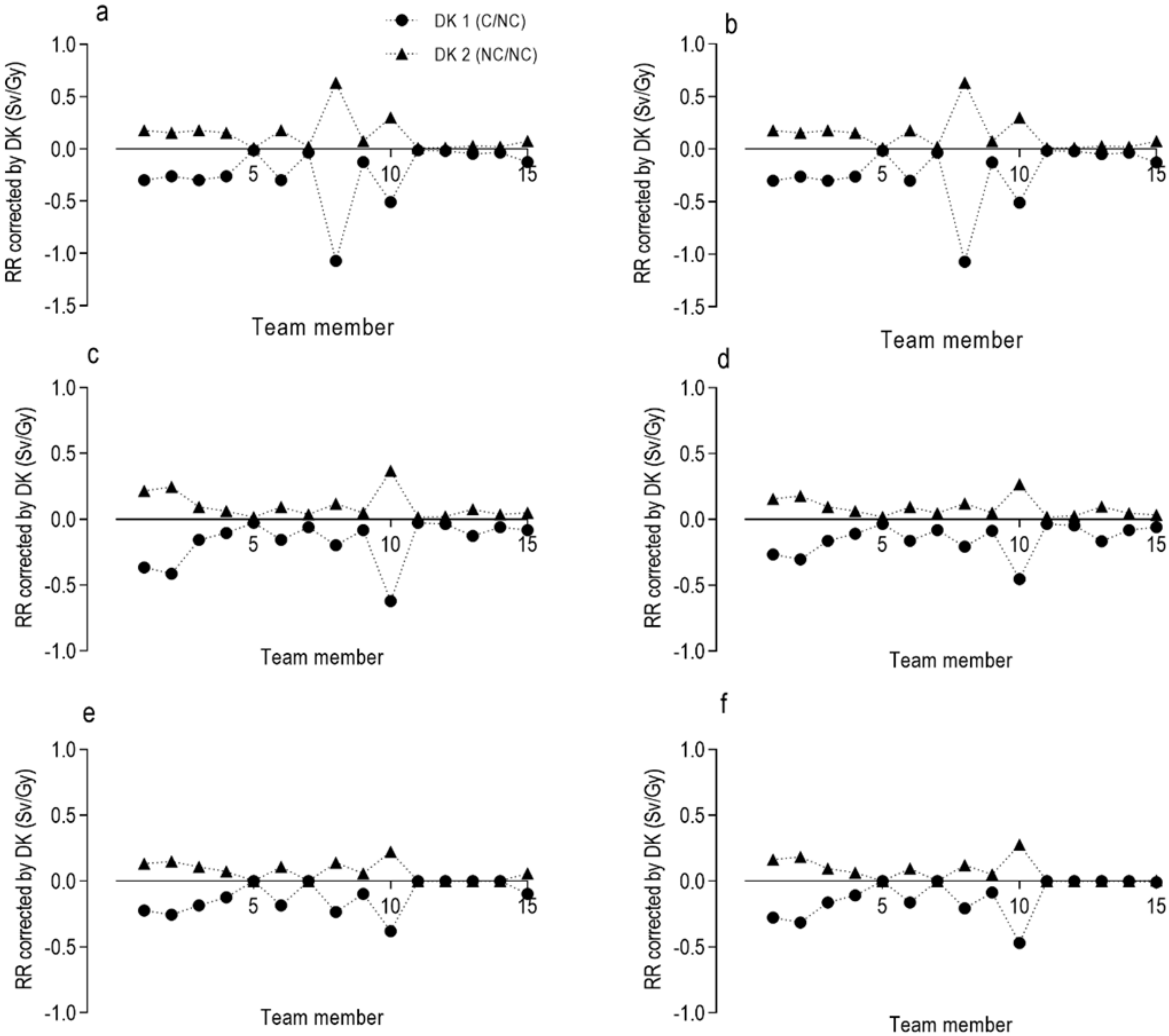

Figure 5. The RR corrected by the specific DK (-0.830 for DK1 and +0.490 for DK2) coefficient for the hypothetical team in all atmospheric conditions (PG classes A to F).

dispersion around the average of the RR presented in Fig. 3, in each location. The location at 0.6 km presents increased SD for PG class C. This may suggest that the RR depends more on the age and sex for the PG class C compared to the PG class D. This information may be relevant if a valuable objective is placed in this location. The assignment of a team member to perform the task may run under guidance of this evaluation, ending up to producing radiological risk and detriment reduction.

After simulating the activation of the RDD, estimating the contamination plumes (TEDE profiles) and drawing the radiation isodoses for each PG class (Fig. 2), the relative risks (RR) were calculated (Fig. 3). The RR in turn interacts with the cognitive bias data presented in Table 2. The result of this interaction considering environmental (PG) and cognitive (DK) aspects is presented as the final result in Fig. 5. Each graph represents the application of the methodology to a different PG class for all locations. Two different cognitive conditions were imposed, indicated as DK 1 (C/NC) and DK 2 (NC/NC). By observing each graph in Figure 5, it is possible to verify a mirroring trend between DK 1 and DK 2. However, this mirroring is only apparent. The DK 2 curve is the one that indicates the potentially worst performance due to having two incompetent decision-makers working together. The DK 2 curve is always on the positive side of the graphs (higher risk) and may have different ranges from the corrected RR values. On the other hand, the outputs from DK 1, on the negative side of the graphs (lower risk), have different heights compared to the absolute DK 2 values. The simple exchange of an incompetent decision-maker for a competent one (DK 1 trend) broke mirroring. This mirroring break is a revolution of the RR evaluation from the positive (higher detriment) to the negative (higher protection) zone.

The methodology may be of value both for use in preparation for a field operation, and for training with the purpose of qualifying and/or selecting specialized personnel. However, it is essential to consider that as this is a simulated event, and limitations exist in regard to the estimated TEDE. On the other hand, uncertainties and the assessment of TEDE result in a conservative picture. This approach is welcome as it overestimates threats, leading to a more severe modeling of consequences than may be found in reality. This overestimated severity condition is typical of decision-making environments where time and resources are scarce. The findings allow to infer that an intelligent application of the available resources necessarily involves human management capacity, the competence. It was also shown that environmental variables are especially relevant for threats enhancement prediction. The findings also suggest that deepening knowledge about the interactions between environmental features and human cognitive biases are of value as a way for reducing risks.

Furthermore, administrative obstacles may arise, considering that moving into a field contaminated by radioactive material lacks clear instructions that are not always available. Consequently, a RDD scenario is capable of (*a*) administratively impacting military operations via the necessity for specific instructions. This includes delays which may cause a phenomenon called Clausewitz friction[21]. This concept regards to the temporal difference between the bureaucratic procedure and the real-time unexpected distractions[21]; (*b*) producing immediate psychological instabilities[22]; (*c*) producing immediate and late biological effects depending on the radiation levels faced[23], and (*d*) forcing the teams to undesirable changing in plans.

Although the CBRN environment seems preferred, it is possible to consider applications outside this context. Recently, a study conducted by our research group[24] found that the DK competency table can be applied to non-radiological events such as floods and dam failures. In this case, the radiological risk equations are replaced by equivalent risk assessments, such as those referring to building collapses.

Prospectively, the concept of competence applied in this study may change. Rather than being an individual human characteristic, it may be defined as a characteristic of an information-providing system, such as a real-time event monitoring system. In this approach, the two instances considered for decision-making would then be interactions of the data library at two different times and no longer a comparison of immutable individual characteristics. Therefore, the specific coefficient DK would be being pointed to a system that can be managed by Artificial Intelligence (AI) instead of a human being. This new condition may facilitate the quantification of the DK coefficients, increasing their reliability.

5. CONCLUSION

The study articulated methodological steps seeking to arrive at a model that is applicable to the optimization of human radiological protection in the operational environment. The synergy verified in the interaction between environmental variables and human cognitive biases is relevant and may represent a starting point for further studies aiming to reduce risks in military operations. The findings are also is suggestive that, especially in the CBRN military-operational context, the methodology proposed for the assessment of environment-human interactions may be decisive for correctly direct available resources, both human and material, reducing operational risk. The core novelty for decision-making in the context of CBRN or similar operations is the possibility to quantify, through the application of an arbitrary scale via DK coefficients, the influence of a subjective variable and competence during crisis management.

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