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Utilizing Bayesian Modeling and MCMC for Accurate Characterization of Naturally Occurring Radionuclides Reference Background Levels in Mining Areas

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Abstract

Statistical biases may be introduced by imprecisely quantifying background radiation reference levels. It is, therefore, imperative to devise a simple, adaptable approach for precisely describing the reference background levels of naturally occurring radionuclides (NOR) in mining sites. As a substitute statistical method, we suggest using Bayesian modeling in this work to examine the spatial distribution of NOR. For naturally occurring gamma-induced radionuclides like ^{232}Th, ^{40}K, and ^{238}U, statistical parameters are inferred using the Markov Chain Monte Carlo (MCMC) method. After obtaining an accurate subsample using bootstrapping, we exclude any possible outliers that fall outside of the Highest Density Interval (HDI). We use MCMC to build a Bayesian model with the resampled data and make predictions about the posterior distribution of radionuclides produced by gamma irradiation. This method offers a strong and dependable way to describe NOR reference background values, which is important for managing and evaluating radiation risks in mining contexts.

Keywords

Radionuclides, Bayesian Modeling, MCMC, HDI, ^{40}K, ^{232}Th, ^{238}U

1. Introduction

Rich in heavy minerals, building materials, and precious metals such as gold, the southeast of Senegal is known for its vast mineral riches [1]. Mining for gold, both legal and illicit, has become a major source of income for the communities where it occurs since the early 2000s. Unfortunately, there have been negative social and environmental effects of this economic growth as well, such as land erosion and water pollution from mercury contamination. In order to improve the assessment of possible environmental dangers and guarantee the safety and security of the local population, it is essential to quantify background levels of natural radionuclides. Regulation authorities and policymakers continue to have serious concerns about the risk assessment of high-energy ionizing radiation. The main sources of exposure are decay daughters of ^{40}K, ^{232}Th, and ^{238}U, specifically radon and radium. IAEA-2013 study [1] states that of the 60 nGy/h global terrestrial gamma exposure, ^{40}K provides 13.8%, ^{232}Th 14%, and ^{238}U 55% on average. Globally, numerous countries have provided substantial documentation on reference background levels of ^{238}U, ^{232}Th, and ^{40}K [2]-[14]. Important scientific insights are provided by research on the distribution of natural radioactivity and related radiological hazard assessments, which are vital for radiation protection, radiological safety investigations, and setting reference background values. These days, a number of environmental research fields have come to embrace the use of portable handheld gamma-ray spectrometry for mapping radioelement concentrations. This adaptable instrument is used in geotechnical research, mining site assessment, and groundwater quality monitoring. Even with its increasing ubiquity, there is still a significant vacuum in the research and development of data processing techniques targeted at creating a reliable way for establishing reference background levels. This work uses Markov Chain Monte Carlo (MCMC) methods to propose a novel and reliable statistical approach for calculating background reference values. In contrast to traditional methods, our approach provides a comprehensive picture of the radionuclides' distributional properties, including their means and standard deviations. Importantly, our approach sheds light on the relative veracity of different effect sizes, standard deviations, and averages. By utilizing MCMC, we are able to go beyond the constraints of conventional statistical inference techniques and gain a more profound comprehension of the geographical distribution of gamma-induced radionuclides.

2. Materials and Methods

By employing MCMC, we were able to perform field measurements with a large (103 cm^3) high-density Bismuth Germanate crystal detector, which can detect gamma rays in the energy range of 30 KeV to 3000 KeV, and a high-resolution, portable gamma spectrometer with 1024 channels. An approximate 5-minute measurement period was applied to each sampling site after a pseudo-random sampling process. By linking the spectrometer with a Bluetooth GPS device, precise geographic coordinates were recorded. The gathered gamma-ray spectra were examined in further detail, with an emphasis on transit connected to distinct photopeaks that came from naturally occurring radioisotopes such as ^{40}K, ^{232}Th, and

^{238}U. In particular, the 1460 KeV gamma-ray emission linked to the decay process of primordial potassium ^{40}K was detected in soil to confirm its occurrence. The estimate of thorium radioisotope concentrations was based on the observation of the 2615 KeV gamma-ray energy emitted by 208TI, using the secular equilibrium assumption of naturally occurring radioisotopes within the ^{232}Th and ^{238}U primordial series. Similarly, 214Bi's 1765 KeV gamma-ray energy was detected in order to estimate ^{238}U. Primordial radionuclides are frequently found in rocks, and the ^{232}Th series is frequently thought to be in equilibrium in the majority of geological settings [15]. The relationship given by the IAEA-2003 recommendations was then used to translate the activity concentration of radioisotopes into particular concentrations. The research area's geographic location is shown in **Figure 1**, where the cumulative rainfall for the years 2015 to 2016 ranged from 1100 to 1500 mm. The temperature in the area varies significantly, ranging from 19˚C to 45˚C. Six separate fields were used for the measurements at the Saraya location.

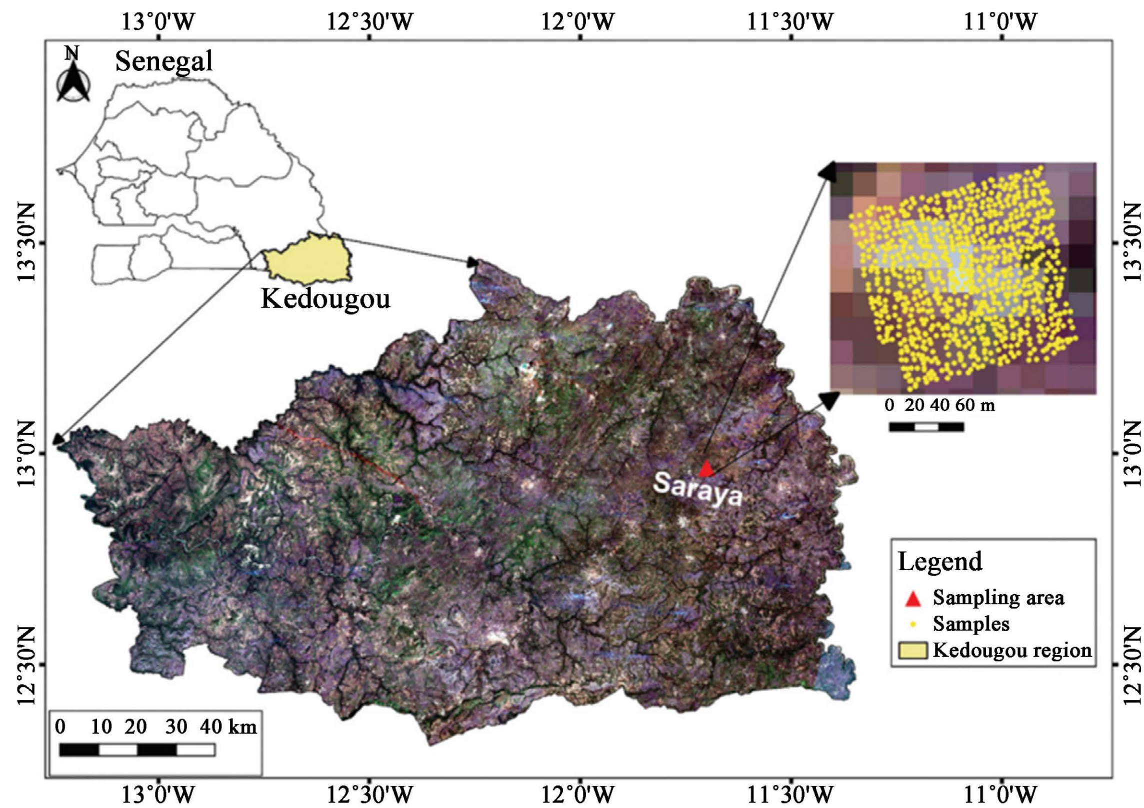

Figure 1. The study site is situated in southeast Senegal, which is acknowledged as the nation's principal mining sector.

3. Results and Discussion

The foundation of Bayesian statistics is the Bayes theorem, which describes how to determine a hypothesis's probability given observed data. The sample data may not always have a normal distribution with zero variance, it is vital to remember this [16].

$$p(\theta_\epsilon / x) = \frac{p(\theta_\epsilon) p(x/\theta_\epsilon)}{p(\theta_\epsilon) p(x/\theta_\epsilon)}$$

In this case, the likelihood of the measured data is indicated by $p(x/\theta_\epsilon)$, while the prior distribution of the radioisotope ϵ is represented by $p(\theta_\epsilon)$. The statistical parameter of naturally occurring radionuclides (which includes variables like mean, variance, standard deviation, and uncertainty) is denoted by the symbol θ_ϵ. We will use R [17] for computing Bayesian inference combined with JAGS, an MCMC sampling language available via the rjags package [18] [19]. As an alternative, stan can be used to carry out comparable analysis [20]. The rjags or BEST package environments can be used for any statistical analyses and model implementations. The goal of this work is to use the Bayes rule to thoroughly characterize naturally occurring radioisotopes and to determine the distribution of coefficients of variation within the highest density probability. Without requiring the marginal posterior distribution to be numerically resolved, MCMC will be utilized to estimate the whole distribution of interest. A non-informative previous distribution will be used. Furthermore, previous distributions in upcoming field sampling can be fed into the computed posterior distribution. The posterior distribution of the concentrations of ^{238}U, ^{40}K, and ^{232}Th in soil, vegetation, and rock samples is depicted by the histogram in **Figure 2**. The largest posterior density intervals for ^{40}K, within a 95% confidence interval (HDI), are 385 - 460 Bq·kg^{-1} in rocks and 1020 - 1090 Bq·kg^{-1} in plants.

As a result of the similarity in thorium concentration between rock and vegetation, a Bayesian analysis of variance was performed, which involved estimating the mean difference (null hypothesis), the difference in standard deviation, and the effect size between thorium measured in rock and vegetation. Robust Bayesian estimation provides detailed insights into the differences between radionuclide classes. The results show that there is no possible overlap between the concentrations of ^{238}U and ^{40}K among different sample types. Conversely, there is a potential statistical overlap in the case of thorium between rock and vegetation samples. Given the data, the Markov Chain Monte Carlo (MCMC) approach generates a huge number of plausible parameter choices with high efficiency. The posterior probability of the mean difference at a 95% HDI is shown in **Figure 3**. There is a 99% chance that the concentration of ^{232}Th in rock will be higher than that in plants. There is a mean difference of about 2.54 Bq·kg^{-3}. The posterior distribution is represented by these combinations of parameters. In addition, **Figure 3** shows the posterior distribution of the difference in standard deviation (($\sigma_1 - \sigma_2$), which suggests that vegetation samples have greater measurement variability for thorium concentrations.

4. Assessment of Radiological Risks

4.1. Radium Equivalent Activity

When evaluating the consistency of radiation exposure in materials with different concentrations of Uranium-238 (^{238}U), Thorium-232 (^{232}Th), and Potassium-40

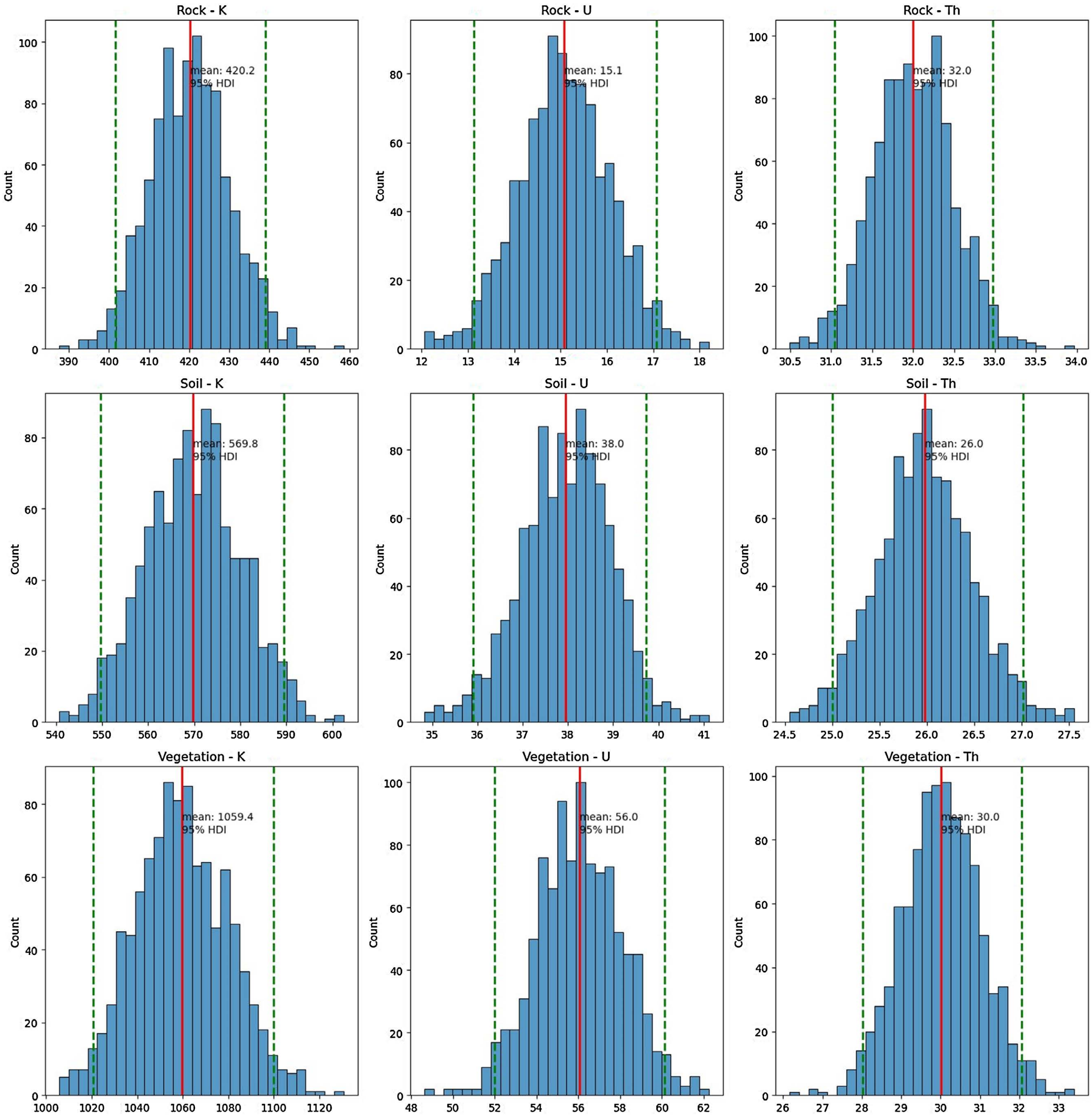

Figure 2. Displays the posterior distribution of the true parameters estimated for the mean (θ) within a 95% Highest Density Interval (HDI) for the three gamma-emitting radionuclides using Markov Chain Monte Carlo (MCMC) in soil, vegetation, and rock samples.

(^{40}K), one term utilized is the radium equivalent activity ($R_{a_{eq}}$). According to the definition provided by the International Atomic Energy Agency (IAEA) in 2003, it is computed using the following relation:

$$R_{a_{eq}} = C_U + 1.43C_{Th} + 0.07C_K$$

where:

C_U is the activity concentration of Uranium-238 (^{238}U) in Bq·kg^{-1}, C_{Th} is the activity concentration of Thorium-232 (^{232}Th) in Bq·kg^{-1}, C_K is the activity

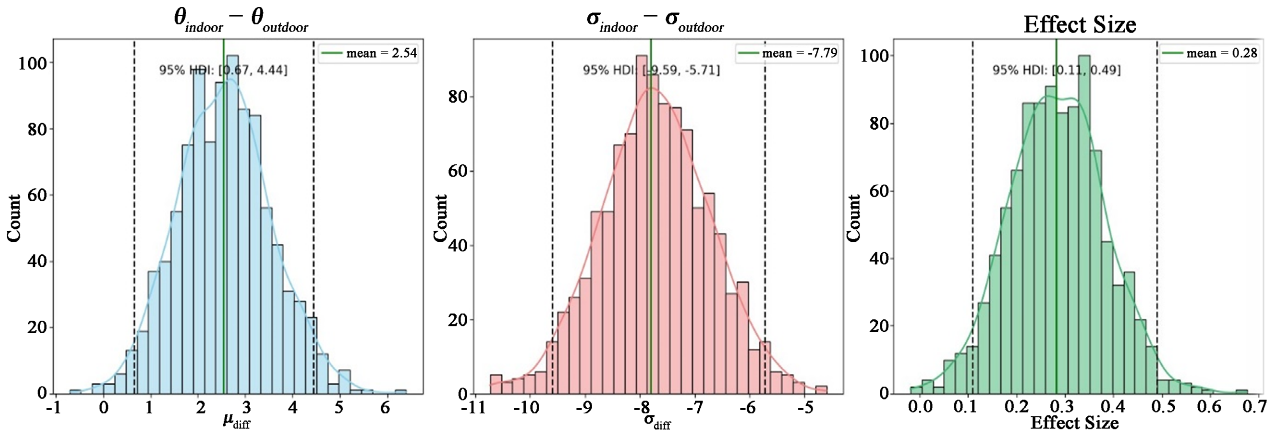

Figure 3. A Bayesian MCMC t-test between ^{232}Th in rock and vegetation.

concentration of Potassium-40 (^{40}K) in Bq·kg^{-1}. The radium equivalent activity (Raeq) is defined on the assumption that the gamma dose rate is the same for specific activity levels of 370 Bq·kg^{-1} of Uranium-238 (^{238}U), 259 Bq·kg^{-1} of Thorium-232 (^{232}Th), or 4810 Bq·kg^{-1} of Potassium-40 (^{40}K). The posterior probability distribution of $R_{a_{eq}}$ is shown in **Figure 4** (left). The projected range of $R_{a_{eq}}$'s mean value, within a 95% Highest Density Interval (HDI), is 175-186 Bq·kg^{-1}. Significantly, this mean value is between 47 and 50 percent below the highest suggested value. This implies that $R_{a_{eq}}$'s representation of the real radiation dose is far lower than the upper advised limit. This result can point to a lower radiation risk rating for the materials under evaluation.

4.2. Calculation of Air-Absorbed Dose Rate

With the conversion factors for each radionuclide provided, the air-absorbed dose rate (D) at a height of approximately one meter above the ground can be calculated. According to the IAEA (2003), the conversion factor for ^{40}K is 0.0414 nGy.h^{-1}/Bq·kg^{-1}, for ^{238}U, it is 0.461 nGy·h^{-1}/Bq·kg^{-1}, and for ^{232}Th, it is 0.623 nGy.h^{-1}/Bq·kg^{-1}. The air-absorbed dose rate computation was provided by:

$$D\left(\text{nGy}\cdot\text{h}^{-1}\right) = 0.461C_U + 0.623C_{Th} + 0.0414C_K$$

where C_U, C_{Th} and C_K are the activity concentrations (Bq·kg^{-1}) of Uranium, thorium, and potassium in the samples. **Figure 4** (right) shows that the gamma absorbed dose rates, or just dosage, within a 95% Highest Density Interval (HDI) are 83.7 nGy/h and 89 nGy/h based on the posterior probability distribution of the air-absorbed dose rate. The IAEA-2003 study states that, in typical circumstances, the dosage rate from terrestrial gamma rays is about 60 nGy/h. It appears that the predicted dose rates within the 95% HDI (83.7 nGy/h to 89 nGy/h) are greater than the typical value of 60 nGy/h under normal conditions when comparing this value with the posterior probability distribution from **Figure 4** (right). This implies that, in comparison to normal or average conditions, the area under investigation might contain higher amounts of terrestrial gamma radiation.

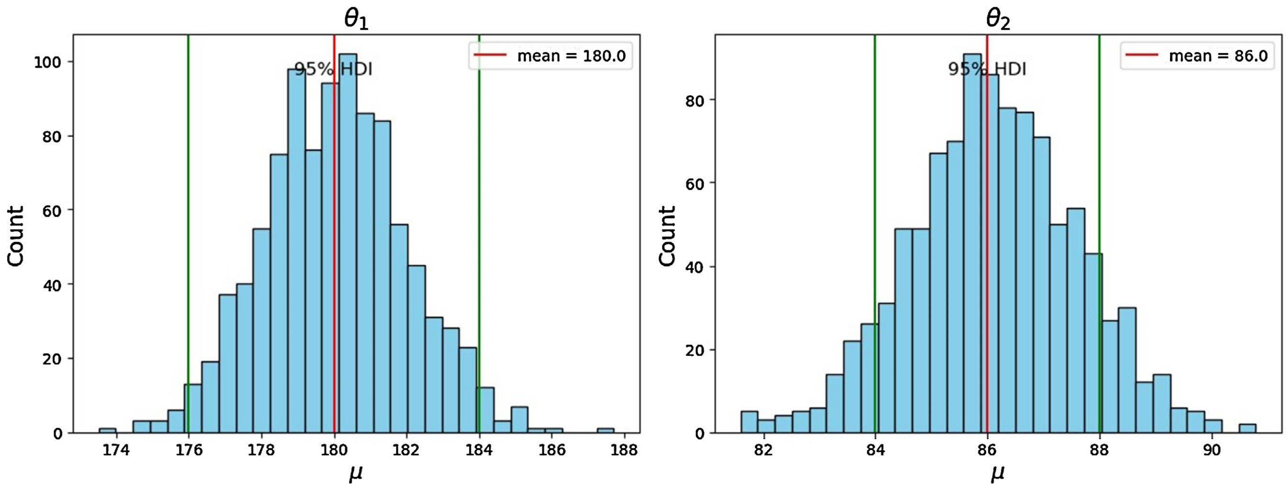

Figure 4. Posterior probability distribution of the radiological hazards index (radium equivalent and air-dose rate).

4.3. Calculation of Annual Effective Dose and External Hazard Index (H_{ex})

In order to calculate annual effective doses, two factors need to be considered: (a) the indoor occupancy factor and (b) the conversion coefficient from absorbed dosage in air to effective dose. We can use the information provided to determine the estimated average effective dosage equivalent that a member receives annually. Conversion factor: 0.7 Sv/Gy (Sieverts per Gray); 20% of the space is occupied outside; 80% of it is occupied within. Here's how the yearly effective dosages are calculated:

$$\text{Indoor}(nSv) = (Absorbed\ Dose)\text{nGy}\cdot\text{h}^{-1} \times 8760\ h \times 0.8 \times 0.7\ Sv\cdot Gy^{-1}$$

$$\text{Outdoor}(nSv) = (Absorbed\ Dose)\text{nGy}\cdot\text{h}^{-1} \times 8760\ h \times 0.2 \times 0.7\ Sv\cdot Gy^{-1}$$

The external hazard index (H_{ex}) can be calculated using the following equation:

$$H_{ex} = \frac{C_U}{370} + \frac{C_{Th}}{259} + \frac{C_K}{4180} \leq 1$$

where C_U, C_{Th} and C_K are the activity concentrations of ^{238}U, ^{232}Th and ^{40}K in Bq·kg$^{-1,}$ respectively. The values of this index must be less than unity to keep the radiation hazard to be significant. The annual radiation exposure resulting from radioactive materials used in construction is restricted to 1.5 milligamma-rays.

Figure 5: The credible value of the outdoor dosage falls between 0.103 and 0.109 mSv, but the indoor yearly effective dose falls between 0.411 and 0.436 mSv within the 95% HDI. **Figure 5**'s results indicate that the external hazard index is between 0.472 and 0.503 Bq·kg^{-1}.

5. Conclusion

An in-situ gamma-ray spectrometer fitted with a huge high-density Bismuth Germanate detector was used in this work to look at radionuclides that produce radiation on land, namely ^{40}K, ^{232}Th, and ^{238}U. By using this apparatus, it was possible to monitor the gamma radiation that these radionuclides released directly outside in

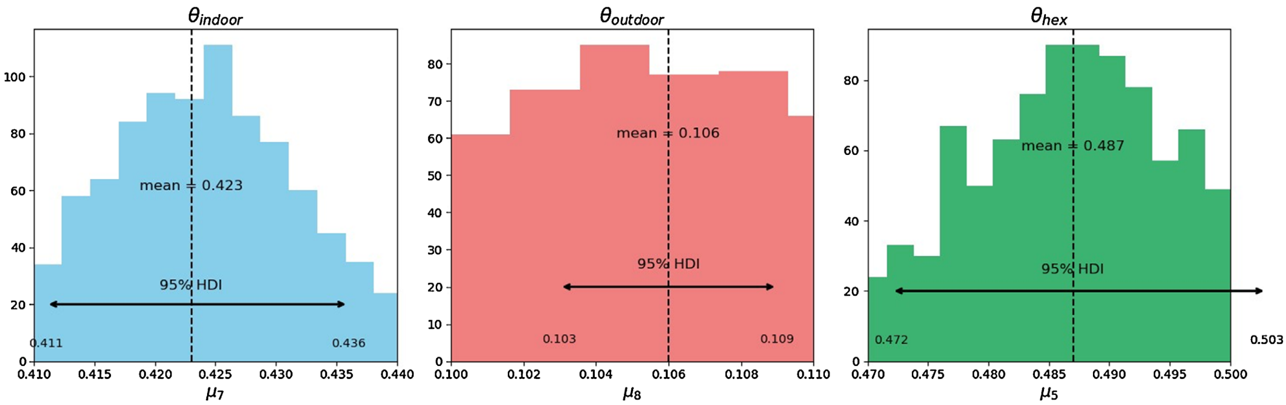

Figure 5. MCMC approach of parameter inference of indoor, outdoor and External Radiation hazards.

the open air. An in-situ gamma-ray spectrometer fitted with a huge high-density Bismuth Germanate detector was used in this work to look at radionuclides that produce radiation on land, namely ^{40}K, ^{232}Th, and ^{238}U. This device made it feasible to observe the gamma radiation that these radionuclides released outdoors in the open. In particular, it made it possible to estimate the mean, uncertainty, and effect size of the radiation levels that were observed. The work improved our knowledge of natural background radiation levels by integrating in-situ gamma-ray spectroscopy with Bayesian MCMC analysis. This allowed for the acquisition of important insights into the distribution and properties of terrestrial gamma-emitting radionuclides in the environment. This thorough statistical method helps to improve the accuracy of risk assessments and the decision-making process related to radiation exposure and environmental safety.

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Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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