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RESEARCH ARTICLE

RF-EMF Exposure Assessments in Greek Schools to Support Ubiquitous IoT-Based Monitoring in Smart Cities

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ABSTRACT Everyday living environments concentrate a growing amount of wireless communications leading to increased public concern for radiofrequency (RF) electromagnetic fields (EMF) exposure. Recent technological advances are turning the focus on Internet of Things (IoT) systems that enable automated and continuous real-time EMF monitoring, facing however several challenges mainly stemming from infrastructural costs. This paper seeks to provide a comprehensive view of RF-EMF levels in Greece and evidence-based decision support for a spatially prioritized deployment of an IoT RF-EMF monitoring system. We applied the stratified sampling method to estimate Electric Field Strength (EFS) in the 27MHz-3GHz range in 661 schools. Three different residential areas were considered, i.e. urban, semi-urban and rural. Results showed that the 95% confidence interval for the EFS is (0.40, 0.44) with central value equal to the sample mean 0.42 V/m. We obtained strong evidence that the mean EFS value for all Greek schools is 0.42, which is 52 times lower than the Greek safety limit and equal to 1% of international limits. Mean EFS values of individual residential areas were also significantly below safety limits. Rural areas displayed the highest EFS peaks comprising the strongest candidate to start the deployment of an IoT RF-EMF monitoring system from.

INDEX TERMS Radiofrequency electromagnetic fields (RF-EMF), RF-EMF exposure in schools, Internet of Things, RF-EMF monitoring, smart cities.

I. INTRODUCTION

Technological developments have infiltrated every aspect of our lives. Many of our daily activities depend on smart phones and a range of technology-enhanced everyday devices, which utilize sensors and wireless networking to offer a rich variety of novel pervasive services, such as building automation [1], ambulatory health and wellbeing monitoring [2], [3] and location-based services [4]. At the same time, cities experience the digital transformation of major urban infrastructures and systems aiming to deliver on the promise of optimized resource usage, economic growth, environmental sustainability and better quality of living for their citizens [5], [6], [7]. A key technological advancement for realizing smart cities is Internet of Things (IoT), which comprises the backbone of digital urban infrastructures [8]. Billions of interconnected IoT devices weaved into the urban fabric generate huge streams of data for well-informed decision making and improved urban governance [9].

The ever growing need for interconnectedness and rise in cooperation between people and machines shape a future that depends on connectivity and has led to a steep growth in the use of wireless communication technologies that provide short-range and urban-wide coverage [10],

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with an emphasis on mobile networks and particularly 5G [11]. As a result, human living environments have been concentrating a growing amount of environmental radiofrequency (RF) electromagnetic fields (EMF) increasing inhabitants' everyday exposure to RF-EMF radiation. Smart city systems and services, home monitoring and automation, mobile applications, industrial cyber-physical systems and consumer electronics relying on wireless communications are burgeoning worldwide and contribute to increased EMF levels, while emerging technologies, such as autonomous vehicles are expected to worsen this situation.

Due to these developments, in recent years, people have become increasingly concerned about potential health hazards posed by wireless and especially mobile networks [12]. The proximity of base stations to populated areas is of particular concern, as it has been claimed to pose particular health risks to the population. These concerns are reasonable since the majority of citizens do not have the proper scientific background to counter the constant misinformation on the issue of RF-EMF exposure. [13], [14], [15], [16].

In response to social concern and uncertainty, it is important to continuously monitor the RF-EMF radiation to inform citizens and scientists of respective exposure levels [17]. Towards this direction, two main approaches have been implemented. First, monitoring systems based on environmental dosimeters operated by regulatory agencies have been used to measure RF-EMF exposure levels near base stations [18], [19], [20]. These systems consist of a number of remote measurement stations managed, via the mobile network, by a data control center. The stations are stationary and are not placed in public places, or 'places of interest', such as schools, working spaces etc. [21]. Aiming to assess personal exposure to RF-EMF at such points, scientists have utilized environmental and mainly personal dosimeters (or exposimeters) in schools [22], [23], [24], [25], [26], [27], universities [28], hospitals [29], playgrounds, offices and malls [30], [31], [32]. However, this approach requires manual measurements, often cumbersome and costly equipment, while it doesn't support continuous and large-scale monitoring.

More recently, to address these challenges, scholars have started to experiment on smart city systems that employ IoT technologies for spatiotemporal RF-EMF monitoring [33], [34], [35], [36]. These systems have generated significant attention amongst policy makers, academia and technology firms as they automate EMF exposure assessment and enable continuous real-time data collection through autonomous, lightweight, low-complexity and interconnected sensing devices. Nonetheless, the application of dense and extended RF-EMF sensing infrastructures is substantially hindered by high installation and maintenance costs leading to localized monitoring solutions [33], [37]. Attempts to address this issue have focused on fabricating low cost sensor nodes and examining the trade-off between sensor density and RF-EMF measurements' accuracy [38]. The use of statistical and machine learning methods to increase the spatiotemporal EMF monitoring coverage and accuracy using data from a limited amount of sensors has been also explored [37].

Framed in this context, this paper aims to estimate RF-EMF exposures in different residential environments, in order to simultaneously build a comprehensive view of the electromagnetic radiation levels throughout Greece and draw conclusions on the spatial prioritization of a gradual deployment of a large-scale IoT-based RF-EMF monitoring system. Focusing on assessing the RF-EMF radiation distribution in urban, semi-urban and rural areas, we took measurements in schools located at such areas in Greece through environmental dosimeters. Contrary to existing methodological approaches that adopted the convenience sampling method, we applied a probabilistic method, named stratified sampling, to support a multi-parameter estimation of the Electric Field Strength (EFS) in the 27MHz-3GHz range in a total of 661 schools. To the best of our knowledge, this is the first time this sampling method is used for RF-EMF exposure estimation contributing to improved validity and confidence of the results.

The contributions of this work are the following:

- systematically examines RF-EMF exposure in diverse residential areas on a country-wide level
- considers a uniquely large amount of measurement sites reinforcing the reliability of the obtained results
- provides insights on how probabilistic sampling methods can be applied in RF-EMF exposure estimation
- supports evidence-based decision making on IoT systems for ubiquitous RF-EMF monitoring deployment in residential environments
- creates a reference point for comparison with exposures including 5G and beyond technologies

II. TOOLS AND METHODS

A. RESEARCH CONTEXT AND PROCEDURE

The basic objectives of our study were to estimate the total and per stratum EFS distribution parameters. We structured this study in three stages:

1) Development and implementation of the measurement plan;
2) definition of a protocol for measuring RF-EMF exposure values;
3) analysis of collected data to determine EFS distributions;

The measurement plan's objective was to determine the electromagnetic radiation's distribution parameters in urban, semi-urban and rural areas. This classification was based on the population density (persons/km^2 or p/km^2) of all municipalities in Greece. More specifically we used 3 strata ($L = 3$): urban areas (U), with municipalities having a population density of more than 500 p/km^2, semi-urban areas (S), with municipalities having a population density of 50 p/km^2 to 500 p/km^2, and finally rural areas (R), with municipalities having a population density of less of 50 p/km^2.

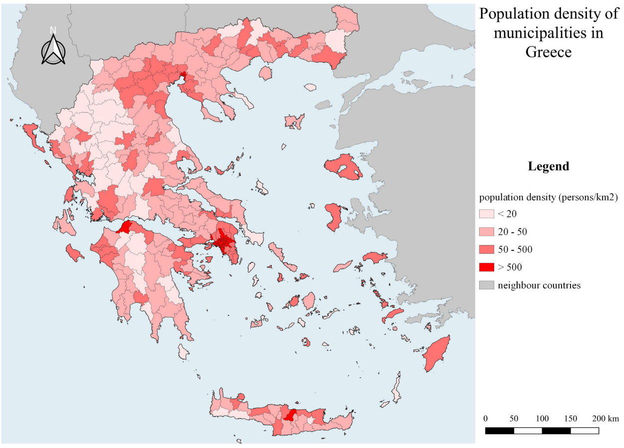

FIGURE 1. **Population density of municipalities in Greece.**

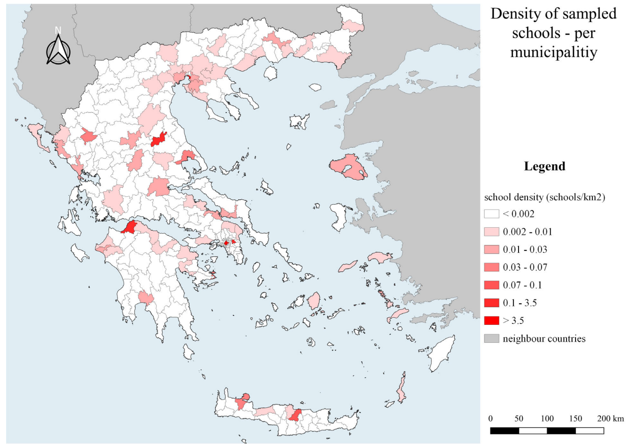

FIGURE 2. **Density of sampled schools – per municipality.**

Fig. 1 is a choropleth map representing the population density of each municipality in Greece (326 in total), according to the most recent data (2011 census). Municipalities rendered with greater (red) color intensity are more densely populated. Municipalities around the capital city of Athens, and around the two other greater cities in Greece, Thessaloniki and Patra, are the most densely populated ones (typically > 500 persons/km^2). These regions are mostly lowland. Crete is an island which is also characterized by medium or great (municipality of the Heraklion city) population density. On the contrary, municipalities that lie in the mountain range of Pindus present the lowest population density values (<20 persons/km^2).

The next step was to determine the type of measurement sites. We opted for taking measurements at school environments for two main reasons. They are related to sensitive population groups (i.e. children) and they constitute a very dense network of places of interest. Due to the above, they comprise very popular RF-EMF measurement sites in the literature, as they are able to provide adequate coverage for outdoor environments [39].

In order to meet the goals of our research, it was necessary to have the best possible approximation of the electromagnetic radiation's distribution parameters in Greek schools. The optimal solution would include taking measurements at all 15,000 schools in Greece. Because such a solution is very expensive and incredibly time-consuming, we decided to use the probabilistic sampling method of stratified sampling, that is, to randomly collect data from a large sample of schools located at the three examined strata.

This particular sampling methodology offers more accurate estimates of the various parameters of the population (mean, standard deviation, etc.) than other sampling methods. It allows us to obtain more accurate results for specific subpopulations of interest, since each stratum can be studied as an individual (sub)population. Moreover, by dividing the population into strata our sample becomes more representative. In addition, knowing the categories and the percentages of each category allows for more efficient sampling than if the categories were not known and finally allows us to select the sample within the categories in different ways and with different percentages [40]. Stratified sampling requires the standard deviation of the distribution to be known for each stratum. Since no such research has been done before in Greece, this information remained unknown.

Thus, our study had to initially estimate the standard deviation of the electromagnetic radiation. Thus, we conducted a pilot study, which would provide this estimation and indicate the minimum number of schools that our main study should include, using a pre-specified estimation error [41], [42], [43]. We eventually included 661 schools as measurements' sites in the main study, which comprised an optimal sample for the needs of our research, minimizing the error, while giving a short confidence interval. In order to specify which schools would participate in the sample of every stratum, we used a random number generator implemented in R based on pseudo-random number algorithms.

Aiming to cartographically visualize the number of sampled schools for each municipality, we calculated the density of schools in which the RF-EMF exposure measurements took place – per municipality. In this choropleth map (Fig. 2), the density of sampled schools in each municipality of Greece is portrayed, harnessing the same visual variable (color intensity) also used in Fig. 1. As it can be clearly noticed, the municipalities with the highest density of sampled schools lie around the greater cities of: Athens, Thessaloniki, Patra, Heraklion, Larissa, Volos, Ioannina, etc. – which also constitute low lying municipalities.

Another means to geovisualize the schools in which the RF-EMF exposure measurements took place is via heatmaps (Fig. 3). To this end, we computed the centroid point of each municipality, while the number of the sampled schools of each municipality was attributed to this point. For each point, the density of the sampled schools was represented by circles symbolized with radially varying (color) hues of the visible spectrum. Colors that are near the red hues portray

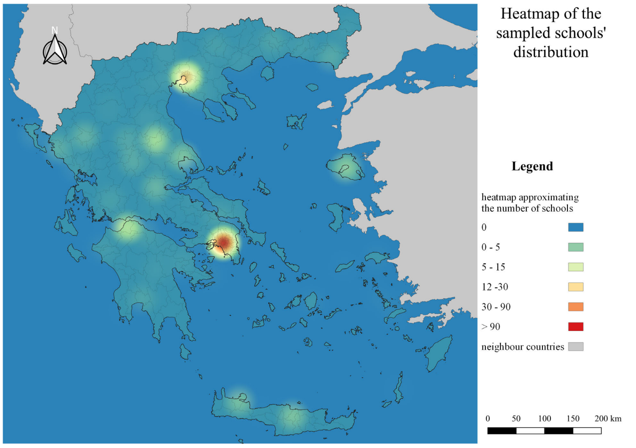

FIGURE 3. Heatmap of sampled schools' distribution.

FIGURE 4. Research group leader with SRM-3006, used during the measurement process.

high density or number of sampled schools, while colors approximating blue hues portray low density or number of sampled schools. Fig. 3 depicts the distribution and the number of sampled schools, as in Fig. 2, but in a different, complementary means.

The measurement protocol we implemented complied with the following: (a) All measurement points were located outdoor, at the perimeter of the schools; (b) The worst-case scenario was selected. This means that an initial broadband survey was performed at each measurement site, indicating the spot with the highest power density. According to the Greek Atomic Energy Commission (Decision No 2300 / 3-3-2008), analytical, narrow-band measurements were performed at this spot; (c) Clear sky and normal weather conditions were met: $15 - 20^{o}$C / 45-55% humidity; (d) Measurements were carried out in a time interval of 6 minutes with a sampling frequency of 5 seconds and the average value of the EFS was calculated. Moreover, a spatial average of the three heights (1.1 m, 1.5 m, and 1.7 m) proposed by the Electronic Communications Committee Recommendation (02)04 [44] was taken into consideration (measurement time of 6 minutes with one sample per 5 seconds for each height).

Measurements were performed at high-traffic hours (mid-day) to acquire a conservative estimation of the EFS. The unit device and the antenna system were kept 1m from reflecting objects and the human body to avoid interactions or overestimations [45]. The measurement method was based on the Greek Governmental Decision No 2300 published in March 2008. The obtained data set contained 2 variables: Area and EFS. Area is a categorical variable with 3 groups (U = urban areas, S = semi-urban areas and R = rural areas); EFS is a continuous variable in V/m.

The equipment used to conduct EMF radiation measurements consists of the following:

- an SRM 3006 field strength analyzer by NARDA Safety Test Solutions, and
- an E, B – Field 3–Axis – Antenna EHP 1Hz – 400Hz probe by NARDA Safety Test Solutions.

TABLE 1. Greek safety exposure limits.

Frequency range	E (V/m) Electric field strength	H (A/m)Magnetic field strength
1 – 3 kHz	$150 / f$	3
3 – 188 kHz	52.2	3
0.188 – 1.66 MHz	52.2	$0.565 / f$
1.66 – 10 MHz	$67.3 / f$	$0.565 / f$
10 – 400 MHz	21.7	0.0565
400 – 2000 MHz	$1.065 \cdot f$	$0{,}00287 \cdot f$
2 – 300 GHz	47.2	0.124

The SRM-3006 [46] selective radiation meter has been developed specifically for environmental and safety measurements of EMF. Equipped with isotropic measurement antennas, this device covers the whole frequency range from 9 kHz to 6 GHz.

Consequently, it can be effectively deployed to: (a) assess safety at the vicinity of radio-frequency emissions, (b) measure radio and TV signal emissions, and (c) to determine the levels of exposure caused by the latest generation of mobile telecommunication services. This device can receive signals from individual channels and assess each channel's contribution to the total field emission. In the same manner, the value can be incorporated to the frequency band, and the total value displayed will be the absolute value or a percentage of the allowed limit.

The safety limits of RF-EMF exposure of the general public described by Greek legislation have been based on the Council of the European Union's Recommendation L 199/59. They are set to 70% of those recommended by the EU [47], as shown in table 1. In particular, in the case of Base Transceiver Station (BTS) antenna installations within 300 metres of building facilities, kindergartens, schools, care homes and hospitals, a provision is made for further lowering safety limitations of exposure of the general public to 60% of the EU standard.

B. STATISTICAL UNCERTAINTIES

A measurement procedure is considered complete when accompanied by documentation of calculation of the associated uncertainty, because all measurements are subject to uncertainty. Furthermore, it is important that the calculation of uncertainty is carried out during the data interpretation process where the levels of compliance with the regulations, as with the RF-EMF exposure limits, are determined. The relevant standards [48], [49] provide guidance on how the sources of uncertainty in equipment calibration and measurements should be combined to determine the overall measurement uncertainty. Based on these guidelines and the mathematical methodologies described in [50] we formed the uncertainty model of our EFS measurements as detailed below.

In our case we have two types of uncertainties. Type A is assessed using statistical analysis of observations, while Type B is calculated using available information on the variability of the measured quantity, such as equipment specifications etc. Based on the regulatory authority's official guidelines, our aim is that the final reading of the measurement in each school is of the form

$$T_m \pm U_T \tag{1}$$

where T_m is the measured value, and the range $\pm U_T$ is the measurement's uncertainty.

The measured value T_m essentially represents the total exposure ratio Λ and $U_T = U_\Lambda(U_A, U_B)$ will be the aggregation of the two types of uncertainties.

The total exposure ratio Λ in each measurement site is calculated as the sum of the exposure ratios λ_f in the frequency range f

$$\Lambda = \sum_f \lambda_f = \sum_f \sum_i^3 \lambda_{i,f} \tag{2}$$

where the exposure ratios $\lambda_{i,f}$ recorded at each point i (i.e. the three different heights of EFS measurements at each site) and frequency range f are calculated from equation 3.

$$\lambda_{i,f} = \left(\frac{E_{i,f}}{E_{L,f}}\right)^2 \tag{3}$$

where $E_{i,f}$ is the EFS at height i for frequency band f, and $E_{L,f}$ the reference EFS at frequency band f.

1) STATISTICAL UNCERTAINTY TYPE A

The calculation of the uncertainty type A involves some statistical processes. From the results of n values for the exposure ratio $\lambda_{i,f}$, the mean value $\lambda_f = \sum_{i=1}^{n} \frac{\lambda_{i,f}}{i}$ and the standard deviation s_f are calculated.

$$s_f = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}\left(\lambda_{i,f} - \lambda_f\right)^2} \tag{4}$$

Because each frequency component varies differently in space, and the effect of the instrument's anisotropy and the observer's proximity is different for each point and frequency band, it could be assumed that the values of the exposure ratios are statistically independent, so that the developed type A, statistical uncertainty for the total exposure ratio $U_A(\Lambda)$ is calculated as:

$$U_A(\Lambda) = \frac{A_2}{\sqrt{3}}\sigma_\Lambda \tag{5}$$

where $\sigma_\Lambda = \sqrt{\sum_f f(s_f)^2}$ and A_2 is the value of the Student distribution with $2 = 3 - 1$ (number of measurements-1) degrees of freedom, for which P applies $(-A_2 < t < A_2) = 95\%$. This value is equal to 4.303.

2) STATISTICAL UNCERTAINTY TYPE B

The developed uncertainty type B in the total exposure ratio $U_B(\Lambda)$ is calculated from the corresponding uncertainties of exposure ratios $U_B(\lambda_f)$, which are obtained from the measurement uncertainties of the EFS given by the provider of the RF-EMF measurement equipment.

Due to non-existence of a linear relationship between the exposure ratio λ_f and the measurement of the EFS E_f and because of uncertainties $\delta(E_f)$ being high enough, the linearity is lifted and is separated of uncertainty in the exposure ratio of upward $+U_B(\lambda_f)$ to that of downward $-U_B(\lambda_f)$.

$$+U_B(\lambda_f) = 4\lambda_f[\delta E_f + \delta^2(E_f)] \tag{6}$$

and

$$-U_B(\lambda_f) = -4\lambda_f[\delta E_f - \delta^2(E_f)] \tag{7}$$

Because the measurement uncertainties of the frequency bands are correlated, the developed uncertainties in the total exposure ratio are calculated as:

$$+U_B(\Lambda) \leq \sum_f +U_B(\lambda_f) \tag{8}$$

and

$$-U_B(\Lambda) \geq \sum_f -U_B(\lambda_f) \tag{9}$$

After the calculation of the uncertainties of types A and B, the total developed uncertainty in the total exposure ratio $U(\Lambda)$ is aggregated following the formulas:

$$+U(\Lambda) = \sqrt{U_A^2(\Lambda) + [+U_B(\Lambda)]^2} \tag{10}$$

and

$$-U(\Lambda) = -\sqrt{U_A^2(\Lambda) + [-U_B(\Lambda)]^2} \tag{11}$$

Then, the 95% confidence interval for the total exposure ratio $(\Lambda_{2.5\%})$, $\Lambda_{97.5\%}$ is calculated as:

$$\Lambda_{2.5\%} = \Lambda - U(\Lambda) \text{ and } \Lambda_{97.5\%} = \Lambda + U(\Lambda) \tag{12}$$

In order to declare that an exposure level as measured complies with the Greek safety limits imposed in Greek legislation, the Greek Atomic Energy Commission demands the measured values in addition to the expanded uncertainty to be below the reference values, so for the final decision we use the interval according to 12.

C. DATA ANALYSIS

As described in the previous section, analysis of the data collected during the pilot study aimed at defining the minimum number of schools that should be included in the sample of the main study. After finding the sample standard deviation for each area using the following formula

$$s_k = \sum_{i=1}^{n_k} \sqrt{\frac{\|x_i - \bar{x}\|^2}{n_k - 1}} \tag{13}$$

with $k \in \{U, R, S\}$, where U, S and R refer to urban, semi-urban and rural areas respectively, we need to solve equation 14 knowing the error, which requires the distance between population mean μ and the sample mean $\bar{x}$ to be less than an estimation error, i.e.:

$$P\left(|\bar{x}_{st} - \mu| \leq d\right) = 1 - \alpha \tag{14}$$

Therefore, if we solve the inequality

$$\frac{d}{\sqrt{\mathrm{Var}(\bar{X}_{st})}} \geq z_{\frac{a}{2}} \tag{15}$$

we get

$$n \geq \frac{\left(\sum_{k=1}^{L} W_k s_k\right)^2}{\left(\frac{d}{z_{\frac{a}{2}}}\right)^2 + \frac{1}{N}\sum_{k=1}^{L} W_k s_k^2} \tag{16}$$

where W_k stands for the proportion of school units in each residential area, which, according to the Hellenic statistical authority, follows the distribution

$$W_U = 50\%, W_S = 16\%, W_R = 34\%, \tag{17}$$

with W_U, W_S and W_R refering to the proportion of urban, semi-urban and rural areas respectively.

For the needs of the main study we estimated the mean of the distribution of the RF-EMF exposure in the schools of our sample. After that we performed a hypothesis test for the mean value of RF-EMF radiation sources in the 27MHz-3GHz range for all Greek schools, as formally defined below:

H_0 : The null hypothesis assumes that the mean is equal to 0.415 i.e. $\mu = 0.415$

H_1 : The two-tailed alternative hypothesis assumes that the mean is not equal to 0.415 i.e. $\mu \neq 0.415$

Also, we performed a hypothesis test to investigate whether the mean values of RF-EMF radiation sources in the 27MHz-3GHz range differ between urban, semi-urban and rural areas. This is because we wanted to determine whether there are any statistically significant differences between the means of the general populations (i.e. the three residential areas).

TABLE 2. EFS (V/m) for RF-EMF radiation sources in the 27MHz-3GHz range for all three areas in the pilot study.

Urban areas						
Minimum	Q_1	Median	Q_3	Maximum	Mean	SD
0.29	0.31	0.44	0.59	1.87	0.50	0.25
Semi-urban areas						
Minimum	Q_1	Median	Q_3	Maximum	Mean	SD
0.28	0.30	0.31	0.36	1.40	0.39	0.23
Rural areas						
Minimum	Q_1	Median	Q_3	Maximum	Mean	SD
0.29	0.32	0.40	0.47	1.35	0.48	0.27

In the end, we performed hypothesis testing to gain statistical evidence that the order of the three areas in terms of EFS mean value can be generalized to the general populations. Formally, we performed the following three Hypothesis tests:

Semi-urban vs Urban

H_0 : The null hypothesis assumes that the two population means are equal $\mu_S = \mu_U$.

H_1 : The alternative hypothesis assumes that $\mu_S < \mu_U$

Semi-urban vs Rural

H_0 : The null hypothesis assumes that the two population means are equal $\mu_S = \mu_R$.

H_1 : The alternative hypothesis assumes that $\mu_S < \mu_R$

Urban vs Rural

H_0 : The null hypothesis assumes that the two population means are equal $\mu_U = \mu_R$.

H_1 : The alternative hypothesis assumes that $\mu_U > \mu_R$

III. RESULTS

A. PILOT STUDY

During the pilot study we took measurements at 166 schools (64 schools from rural areas, 45 schools from semi-urban areas and 64 schools from urban areas). As we may observe from table 2, the mean and median EFS values for urban areas are $\bar{x} = 0.50$ and $M = 0.44$ respectively, while for semi-urban areas are $\bar{x} = 0.39$ and $M = 0.31$ and for rural areas are $\bar{x} = 0.48$ and $M = 0.40$. The mean and median values diverge significantly both among the three areas and within each individual area. This verifies the skewness illustrated in Figs. 5,6 and 7.

Fig. 5 illustrates the histogram and the boxplot of the EFS values from the urban areas. It is shown that the distribution follows a non-normal pattern and includes outliers. We can observe a similar distribution among all residential areas (Figs. 6 and 7) with the difference that the boxplot of the rural areas has more outliers than the other areas' boxplots. The latter is something we expected because many times in rural areas the antenna network is more sparse than in other areas and this means that we have antennas with a stronger signal. In any case, that similarity of the distributions highlights the need for a more extensive research like the one that follows in the main study of our work. More specifically by calculating

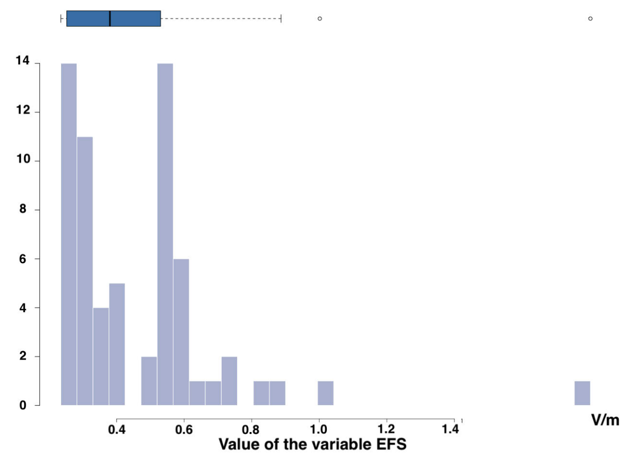

FIGURE 5. Histogram with boxplot of EFS (V/m) for RF-EMF radiation sources in the 27MHz-3GHz range in urban areas.

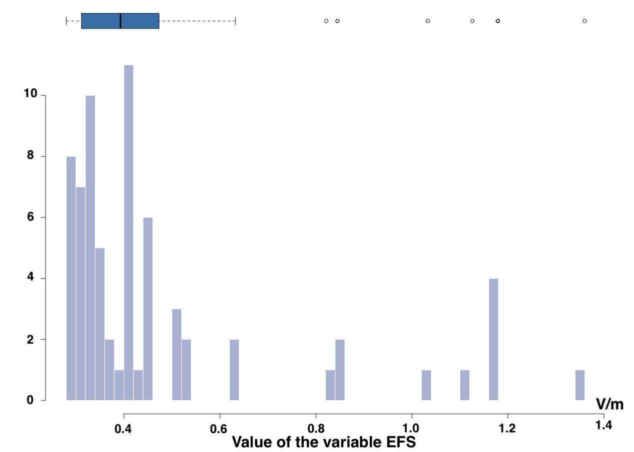

FIGURE 6. Histogram with boxplot of EFS (V/m) for RF-EMF radiation sources in the 27MHz-3GHz range in rural areas.

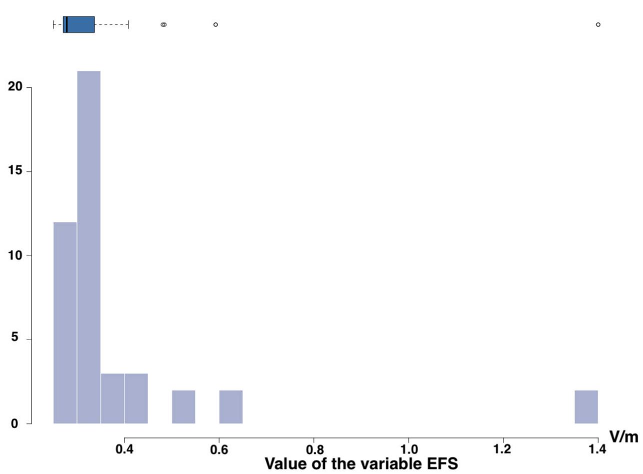

FIGURE 7. Histogram with boxplot of EFS (V/m) for RF-EMF radiation sources in the 27MHz-3GHz range in semi-urban areas.

the samples' standard deviations

$$s_U = 0.25,\ \ s_S = 0.23,\ \ s_R = 0.27 \tag{18}$$

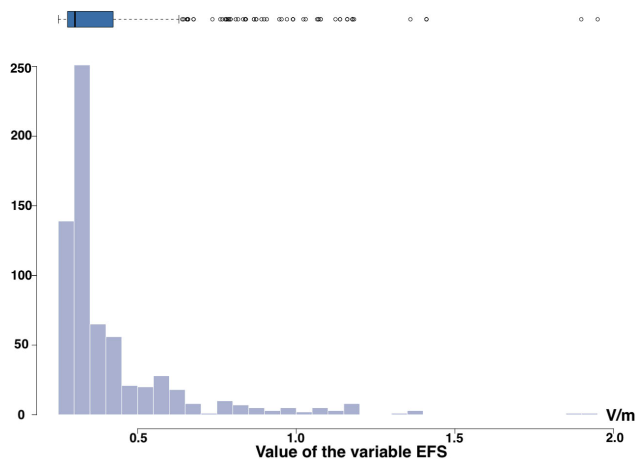

FIGURE 8. Histogram with boxplot of EFS (V/m) for RF-EMF radiation sources in the 27MHz-3GHz range in all 661 schools.

where U, S and R refer to urban, semi-urban and rural areas respectively, we can find from equation 16 that the minimum number of schools is 358.

B. MAIN STUDY

We decided to increase the number of schools of our sample from 358 to 661, in order to reduce the length of the confidence interval of the EFS mean values estimations, thus improving our error range. Of course, having a bigger sample would provide even better EFS approximation, but this would exceed our resource capacity. More specifically, based on the Greek schools' distribution described in equation 17, we took a sample of 338 schools from urban areas, 217 schools from rural areas and 105 schools from semi-urban areas. Looking at table 3 and Fig. 8, we can see that for all three areas the minimum value of EFS is 0.27 V/m, 1st (lower) quartile (Q1) is 0.30 V/m, median $M = 0.32$, 3rd (upper) quartile (Q3) is 0.44 V/m, and the maximum value is 1.92 V/m; we should also note that the 90th percentile is equal to 0.64 V/m, the 95th percentile is equal to 0.88 V/m, and the 99th percentile is equal to 1.17. The mean $\bar{X} = 0.42$ and the median $M = 0.32$ are also different, which indicates that the data are skewed as we can verify from the histogram (Fig. 8). A 95% confidence interval for the $\bar{X}_{st}$ is: $(0.40, 0.44)$ with central value equal to the sample mean 0.42 V/m. This value is significantly lower than the safety limit, which is considered to be the 21.7 V/m (i.e. the minimum EFS safety limit of all frequency bands as shown in table 1).

Fig. 8 gives an indication that our dependent variable (EFS) is probably not normally distributed. For a formal verification we have performed a Shapiro–Wilk test of normality. Under the hypothesis of normality we accept at level 5% ($W = 0.62$, p-value $< 2.2e - 16$) that our variable is not normally distributed. But our sample was big enough ($n = 661 > 50$) to perform the t-test; the t-value is $t = 0.41$, $df = 660$, which gives us a p-value of 0.68. Therefore, there is sufficient evidence at the $\alpha = 0.05$ level to conclude that the 95%

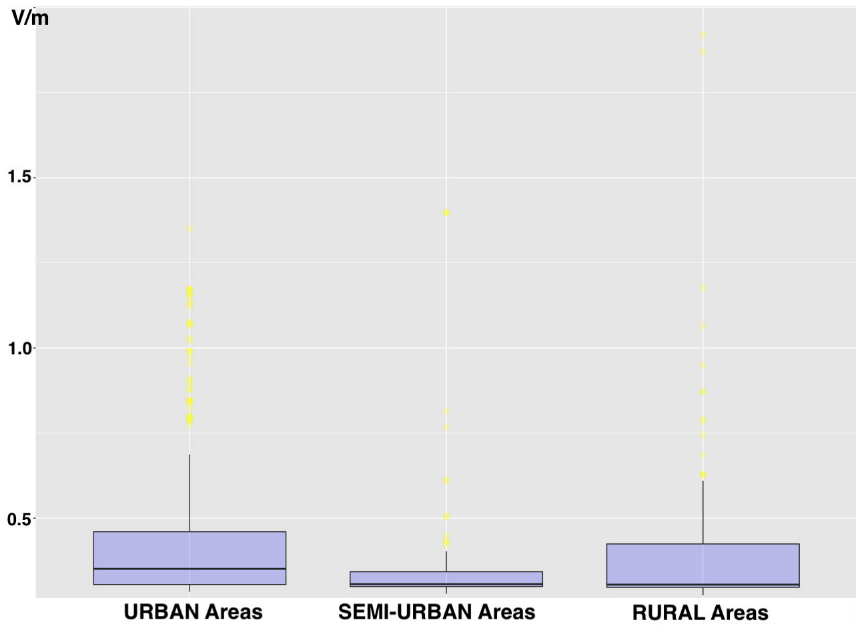

FIGURE 9. Boxplot of Electric Field Strength in all residential areas.

TABLE 3. EFS (V/m) for RF-EMF radiation sources in the 27MHz-3GHz range for all three areas in main study.

RESULTS OF MAIN STUDY						
All three areas						
Minimum	Q_1	Median	Q_3	Maximum	Mean	SD
0.27	0.30	0.32	0.44	1.92	0.42	0.22
Urban areas						
Minimum	Q_1	Median	Q_3	Maximum	Mean	SD
0.28	0.31	0.35	0.46	1.35	0.44	0.21
Semi-urban areas						
Minimum	Q_1	Median	Q_3	Maximum	Mean	SD
0.28	0.30	0.31	0.34	1.40	0.38	0.22
Rural areas						
Minimum	Q_1	Median	Q_3	Maximum	Mean	SD
0.27	0.30	0.30	0.42	1.92	0.42	0.21

confidence interval is $(0.40, 0.43)$ for RF-EMF radiation sources in the 27MHz-3GHz in all Greek schools and the mean value is equal to 0.42 V/m.

As we may observe from table 3, the mean and median EFS values for urban areas are $\bar{x} = 0.44$ (confidence interval is $(0.41, 0.47)$) and $M = 0.35$ respectively, while for semi-urban areas are $\bar{x} = 0.38$ (confidence interval is $(0.34, 0.42)$) and $M = 0.31$ and for rural areas are $\bar{x} = 0.42$ (confidence interval is $(0.40, 0.45)$) and $M = 0.30$. Evidently, mean EFS values and respective confidence intervals of all examined areas are also significantly lower than the 21.7 V/m safety limit. Moreover, these results verify the findings of the pilot phase, i.e. the mean and median values diverge significantly both among the three areas and within each individual area as visually seen from Fig. 10. We can observe a similar distribution in the semi-urban as well as the rural areas (Figs. 9 and 10) with the difference that the boxplot of the rural areas has more outliers than the other areas' boxplots.

Due to the fact that our dependent variable (EFS) is not normally distributed for each group of the independent variable Area (Fig. 10), we performed a non-parametric test, the Kruskal-Wallis test, instead of using an ANOVA test. The Kruskal-Wallis test showed that there was a statistically significant difference in mean EFS values between the different areas, $\chi^2 = 41544, df = 2$, p-value $= 9.52e-10 \ll 0.05$.

Since we do not have strong evidence that the mean value of EFS is the same in the three areas, we performed three hypothesis tests to determine their ordinance as described in section II-C. The first t-test aimed at determining whether there is significant statistical evidence that the associated population means in semi-urban areas are smaller than those of urban areas. The t-value is $\mathrm{t} = 19.84$, $\mathrm{df} = 262$, standard error of difference equal to 0.03 which gives us a p-value less than 0.05. Therefore, there is sufficient evidence at the $\alpha = 0.05$ level to conclude that the mean EFS value in all Greek schools in semi-urban areas is smaller than those in urban areas. In the same manner, we found that the mean EFS value in all Greek schools in semi-urban areas are smaller than those in rural areas ($\mathrm{t} = 24.11$, $\mathrm{df} = 499$, $\mathrm{p-value} \ll 0.05$), which which mean EFS value is lower than those of urban areas ($\mathrm{t} = -0.70$, $\mathrm{df} = 553$, $\mathrm{p-value} = 0.02$).

IV. DISCUSSION

The present work has two main methodological novelties. The first concerns the very large sample size (n=661 schools), that accounts for approximately 5% of the Hellenic schools and contributes to an increased reliability of the mean EFS values estimations. While many similar research efforts

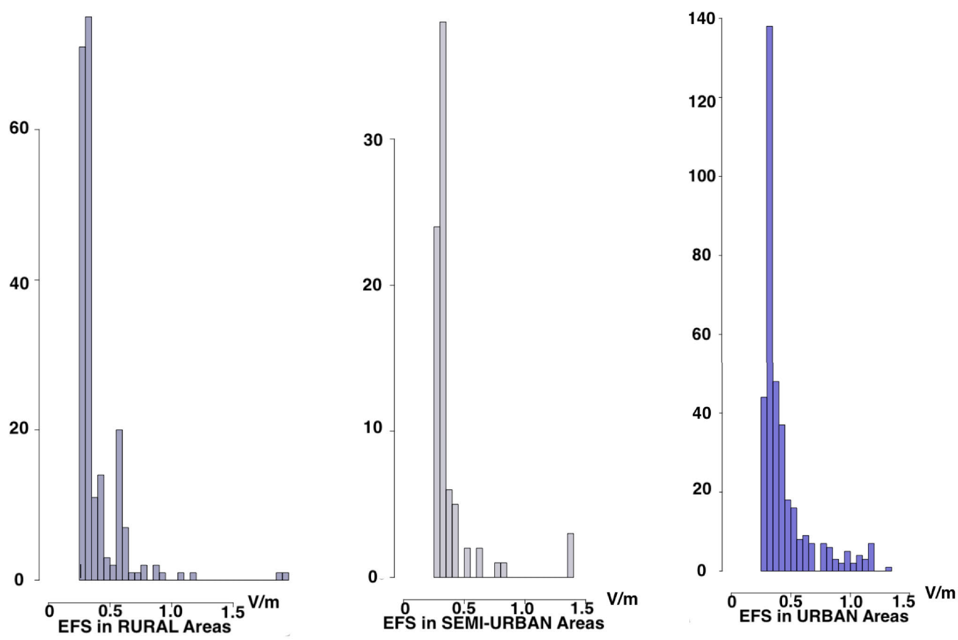

FIGURE 10. Histograms of Electric Field Strength in all residential areas.

are reported in the literature [39], the vast majority is limited to very small scale experiments including only a few schools as measurement sites. On the one hand, such studies can't lead to generalized EFS estimations on wider geographical areas (e.g. national contexts), and, on the other hand, comparability with the results of our study is limited.

The second one, refers to the sampling method, where a probabilistic method was used to select the points of measurements. This method allowed as to present the EFS estimations along with confidence intervals and gave us the tools to generalize the results to the population of interest by using the appropriate hypothesis tests. Confidence intervals are quite important for ensuring the validity of EMF exposures safety assumptions on the basis of EFS estimations. It should be emphasized that this has also added to the difficulty of limited comparability capacity with the results of other research efforts since most of them do not mention the confidence intervals of the EFS levels but only the range (i.e. from min to max value) obtained from the sample.

What can be drawn by the results of our study, is that the RF-EMF exposures in the Greek territory are well below national and international safety limits. Specifically, the mean EFS value (0.42 V/m) estimated for all Greek Schools is approximately 52 times lower than the 21.7 V/m Greek safety limit. It is also lower than 2% of the International Commission on Non-Ionizing Radiation Protection (ICNIRP) RF-EMF exposure limits, as well as the limits set by the IEEE safety standard, which range at the same values with the ICNIRP ones [51]. Likewise, EFS levels in each of the examined residential areas, i.e. rural, urban and semi-urban areas, are much lower than the national and international safety limits.

Indicatively, EFS values at 50% of the schools were 67 times below the Greek safety limit, at 75% of the schools were 63,5 times below the Greek safety limit and at 90% of the schools were 53 times below this limit. Our findings confirm the low EMF-RF exposure levels at outdoor environments and specifically at school buildings not only in Greece, but also internationally [27], [32], [52], [53], [54], [55], [56]. More specifically, the studies realized in Greece have so far shown similar results [58], [59] on the overall average value of electromagnetic radiation at children places (e.g. schools, playgrounds, etc.), without however providing corresponding confidence intervals to their estimations. This work confirms the findings of [52] and improves them with regard to the range of the confidence interval and the measurements scale.

Looking at EFS values per residential area, we can observe that urban and rural areas have a similar EFS distribution, while semi-urban areas present a significantly different distribution with lower mean. Another important point mainly illustrated by Fig. 9 concerns the fact that EFS values in semi-urban areas have a fairly lower range compared to urban and rural areas, which indicates low fluctuations of EFS values and a narrow distribution close to the respective mean. What can be inferred is that the cellular antenna system in the semi-urban areas, which is neither sparse nor too dense resulting in relatively low intensity antennas in tandem with the reduced traffic compared to urban areas are key factors of lower RF-EMF exposures.

Furthermore, our research highlights that while in rural areas the antennas emitting electromagnetic radiation are more sparsely placed, the mean radiation is at the same heights as that of urban areas, where the network is very dense resulting in the highest EFS mean value. However, EFS distribution in rural areas has the highest maximum values (42% and 37.4% higher than those of semi-urban and urban areas respectively), which is verified by the outliers shown in Fig. 9 that indicate special points of interest. It has to be mentioned however that EFS peaks in rural areas are about 11 times below the safety limit, but about 5 times higher than the sample mean of 0.42 V/m.

These higher peaks of EFS values in rural areas suggest that an IoT-based RF-EMF monitoring infrastructure deployment should follow a non obvious prioritization scheme, which would start from them, before being deployed to urban and semi-urban areas. While all residential areas exhibit considerably low mean EMF exposures, which as previously mentioned are well below safety limits, EFS peaks of rural areas could form potential risks that should be continuously monitored to assess their significance and determine appropriate mitigation actions.

V. CONCLUSION

This study assessed the RF-EMF levels in different residential areas in Greece, and sought for evidence to inform the decision process of a gradual deployment of smart city IoT-based RF-EMF monitoring systems in terms of spatial prioritization. After a carefully designed methodological approach that considered diverse aspects of the specific problem, we examined three types of residential areas (i.e. urban, semi-urban and rural areas) collecting RF-EMF measurements from 661 schools throughout Greece. Applying the stratified sampling method to estimate the mean EFS in the 27MHz-3GHz range we found that its values are well below Greek safety limits as the 95% confidence interval for the mean value of the EFS is (0.40, 0.44) with a central value equal to the sample mean 0.42 V/m. On residential area level, the mean EFS values were 0.44, 0.38 and 0.42 V/m for urban, semi-urban and rural areas respectively. It was also deduced that rural areas should be prioritized for installing IoT monitoring systems for RF-EMF radiation. Although urban areas had a slightly higher mean EFS value, rural areas displayed 42% higher peaks than the urban areas comprising cases of increased interest. This study can assist authorities and researchers to address public concern, increase the capacity of data-driven policy enactment for exposure prevention and reduction in smart cities and support installation of IoT infrastructures for ubiquitous monitoring of RF-EMF levels. Its utility is emphasized by the fact that by employing a formal methodology over a typical residential zone classification, our approach for assessing RF-EMF exposures facilitates adaptability and replicability in different national contexts.

COMPETING INTERESTS

The authors declare that they have no competing interests.

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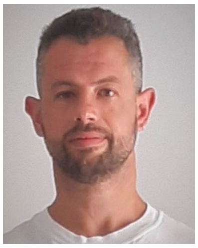

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CONSTANTINE KAPPAS was born in Athens, in 1954. He received the B.Sc. degree in physics from the University of Patras, Hellas, the M.Sc. degree in medical physics from the D. E. A.—C. P. A. T. Université Paul Sabatier, Toulouse, and the Doctorat de Spécialité and Doctorat ès Sciences degrees from the Institut Curie, Paris. He has studied with Basil Proimos and Jean-Claude Rosenwald. He is currently an Emeritus Professor with the Medical Physics, Medical School, University of Thessaly, Hellas. His research was mainly focused to the radiotherapy physics and he is known in particular for his work in inhomogeneity corrections in radiotherapy treatment planning and in the development of a new non-invasive stereotactic unit (K. Theodorou and Constantine Kappas), which was also the first installed in his country. He has participated in several UN—IAEA and other organization's scientific missions in developing countries for commissioning of therapeutic and diagnostic radiation units, gives lectures, and supports local clinical projects. His special distinction are Hellenic Association of Medical Physics (HAMP), in February 2013, announced the unanimous decision to choose the Professor of Medical and Radiation Physics, Medical School of Larissa, University of Thessaly, Constantine Kappas and characterized him to the International Scientific Community as "The personage whose, ethics, social action, educational, research, and clinical contribution in their country and in the world, represents, characterizes, and expresses their specialty in Greece for the second half of the last century and the dawn of the new millennium" and International Organization of Medical Physics—IOMP has chosen 50 distinguished experts—personalities worldwide, whose work in medical and radiation physics and the broader scientific field of therapeutic and diagnostic radiations worthily represents the scientific field for the second half of the last century and the dawn of the new millennium and among them, three Nobel Prize awarded Professors (Sir Godfrey Hounsfield, in 1979, Sir Peter Mansfield, in 2003, and Paul Lauterbur) and Professor Constantine Kappas (honored in Brighton U.K., in September 2013).