

Article

Computational Sustainability as a Framework for a Bioelectromagnetically Conscious Urban Microenvironment

Duncan McRae ¹, Amanda Beraldo Brandao De Souza ¹, Mert Sehri ² and Riadh Habash ^{1,*}

¹ School of Electrical Engineering and Computer Science, University of Ottawa, Ottawa, ON K1N 6N5, Canada; smcra022@uottawa.ca (D.M.); abera050@uottawa.ca (A.B.B.D.S.)

² Department of Mechanical Engineering, University of Ottawa, Ottawa, ON K1N 6N5, Canada; msehr006@uottawa.ca

* Correspondence: rhabash@uottawa.ca

Abstract

The concept of computational sustainability in urban environments emphasizes integrating data engineering, artificial intelligence (AI), and computational techniques to advance the United Nations (UN) Sustainable Development Goals (SDGs). A bioelectromagnetically conscious microenvironment represents an architectural and spatial design approach that incorporates various disciplines to align with environmental well-being and regulate electromagnetic (EM) fields. As cities and high-density urban regions are increasingly saturated with EM fields from various sources, the integration of computational sustainability and bioelectromagnetics becomes essential to enhance the occupant experience when interacting with buildings and spaces. This study addresses EM anthropocene influence by presenting an EM exposure mapping (EMEM) framework that involves data acquisition (DAQ), interpolation to produce heatmaps, and machine learning (ML) algorithms for validation and prediction. An exploratory case study is conducted on a micro-environment comprising three buildings on the University of Ottawa campus in Canada. Although the results were limited to selected buildings, the proposed framework supports EMEM investigations across diverse components of the urban landscape. Upon additional validation across a diverse range of environmental conditions, this characterization method may serve as a blueprint for architects, engineers, regulators, and building certification systems to promote designs that are mindful of the visualization and management of ambient EM influences.

Keywords: urban microenvironment; computational sustainability; data acquisition; electromagnetic exposure mapping; interpolation; machine learning

Academic Editor: Miguel Amado

Received: 24 June 2026

Revised: 21 July 2026

Accepted: 24 July 2026

Published: 3 August 2026

Copyright: © 2026 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the [Creative Commons Attribution \(CC BY\)](https://creativecommons.org/licenses/by/4.0/) license.

1. Introduction

As the urban environment continues to expand rapidly, it is increasingly influenced by a pervasive array of human-made nonionizing EM fields, which present both anticipated benefits and undesirable health effects [1]. In such a smart environment, a diverse range of EM sources in the RF range (100 kHz to 300 GHz)—including cellular technologies and phones, WiFi, Bluetooth devices, smart meters, and Internet-of-Things (IoT)—collectively shape the landscape of wireless connectivity, leading to unprecedented challenges in managing the indoor environmental quality (IEQ) of wireless coverage [2–4]. In indoor environments, signal propagation and ambient EM fields are significantly

influenced by the diverse and composite functions of wireless sources, surface irregularities, and material properties, including those of walls, furniture, floors, and other interior components [5,6]. The occurrence of multipath effects, absorption, reflection, diffraction, and scattering results in highly complex and variable field distributions, which may lead to higher exposure levels for humans.

Sustainable urban development now requires integrating EM field management into urban planning, using spatial mapping and shielding technologies to create safer living spaces [7,8]. This is increasingly relevant to EMEM amid growing concerns about the potential health effects of long-term exposure to EM fields [9]. In today's architectural landscape, bioelectromagnetics offers innovative solutions that harmonize environmental and social needs by integrating urban design with smart technologies. This approach is founded on two essential pillars: wireless network coverage and exposure levels. Coverage evaluates the overall ambient field strength from diverse sources within a specific area, whereas exposure levels concentrate on individuals or communities. This ultimately redirects the emphasis from connectivity-driven performance to environmental health-conscious connectivity.

In this context, EM sustainability—defined as the capacity to coexist harmoniously with urban environments—plays a crucial role in comprehending and addressing the essential synergy between smart urbanism and public well-being. Achieving this coexistence requires precise EMEM for wireless coverage and the capability to identify potential areas of overexposure, enabling the implementation of monitoring or remedial measures to ensure health safety. The dual coverage/exposure approach is part of a genuine long-term environmental health policy, with the aim of homogenizing network coverage and exposure levels towards an acceptable average [10–13]. Therefore, creating precise EMEM is vital because they reveal how EM fields spread through urban and natural landscapes, help researchers quantify human and wildlife exposure, guide policymakers in setting evidence-based safety standards, and enable engineers to design greener, interference-free infrastructure [8,9]. This societal issue has prompted scientific efforts to measure and predict EM field levels in various settings, both indoor and outdoor.

The discourse surrounding the impact of EM fields on health is intricate and generates a range of opinions [14]. Prominent regulatory bodies, including the Institute of Electrical and Electronics Engineers (IEEE), the International Commission on Non-Ionizing Radiation Protection (ICNIRP), and the World Health Organization (WHO), have established working groups and conducted systematic reviews to evaluate the existing evidence regarding the health effects of both individual and population exposure to EM fields [15,16]. The IEEE and ICNIRP, along with other worldwide organizations, establish exposure standards and protection guidelines. On the other hand, WHO coined the term “sick building syndrome” (SBS) in 1984. However, the organization does not officially recognize EM fields as a physiological cause of SBS, even though not proven; several SBS symptoms are common with EM hypersensitivity [1].

Addressing this matter, which is at the heart of social-ecological debates, requires governments and regulatory authorities to establish a broader, integrative monitoring framework that links changes in the urban environment to human health. Despite advancements in this area, the complexity of monitoring EM exposure stems from the diverse range of parameters involved—such as materials, sensor arrangements, and environmental topology—making the process both time-consuming and costly [17].

In response to the above challenge, this paper aims to develop a blueprint for EMEM that elevates well-established hardware and software approaches through ML, a path that remains underexplored in the context of building EM safety. The paper is organized according to the proposed framework illustrated in Figure 1 and guided by the following research questions: RQ1: What is the significance of the proposed framework for urban

planners and public health officials? RQ2: In what ways can the EMEM framework serve as a crucial catalyst for enhancing EM sustainability in the urban environment? RQ3: Do RF field levels in the examined microenvironment (three buildings) remain within regulatory safety limits while preserving digital connectivity? RQ4: How can the insights gained from this study be integrated into more effective practices for assessing IEQ in general and EM fields in particular across various building certification systems?

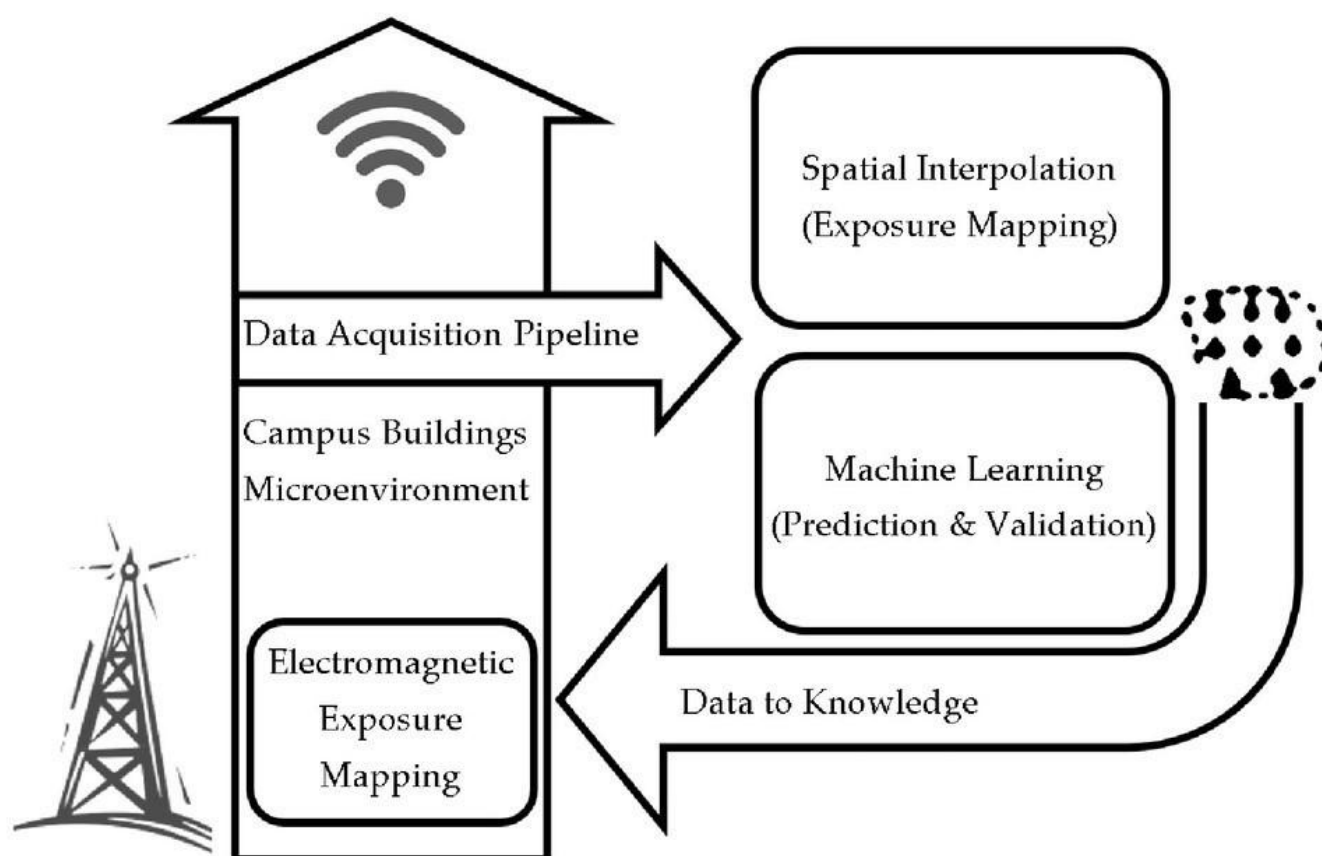


Figure 1. The proposed framework.

The organization of this study is as follows: Section 2 introduces the DAQ pipeline, including RF measurement methods, a dual-band exposimeter setup, and a microenvironment centered on three campus buildings, as well as the procedures for dataset collection and processing. Section 3 focuses on the spatial interpolation of the data collected from the buildings. In Section 4, the application of ML is explored for validation purposes. Section 5 reviews the key findings and addresses the four research questions that were posed. Finally, Section 6 concludes the paper by summarizing the study's outcomes, identifying research gaps, and suggesting avenues for future work.

2. DAQ Pipeline

DAQ relies on a several-step pipeline to translate physical, invisible signals into numeric, usable datasets. These include sensing and transduction, signal conditioning, analog-to-digital conversion (ADC), and data processing.

2.1. Measurement Methods

Recently, there has been an increase in both the number of measurement methods and digital technologies developed for sensor integration in buildings, enabling real-time

monitoring of EM field distribution [18]. The first method uses low-cost sensor meters to manually measure field strength at specific locations (spots) [19–25]. These devices offer a straightforward solution, making them ideal for small-scale or preliminary surveys. They can be used to provide the public and regulatory agencies with temporal and spatial EM field values [26,27]. Recently, methods for obtaining moving EM exposure measurements with devices mounted on the human body [28], vehicles, both terrestrial [29–31] and even using drones [32] have been used. Spot measurements by broadband meters or spectrum analyzers offer higher accuracy and allow characterization of large areas but require more effort. Internationally recognized assessment methods prefer the latter because of their higher accuracy and repeatability [33].

The second method involves deploying distributed sensor networks throughout a designated area. These stationary sensors provide continuous monitoring of the EM field strength over time. However, designing such a large-scale network presents computational challenges. A notable advantage of this approach is its ability to facilitate long-term, real-time monitoring, making it particularly well-suited for urban environments. However, the initial installation costs can be quite significant, and data collection is confined to the specific locations where the sensors are placed [34,35]. While both the first and second methods are of considerable interest, they are inherently localized, meaning that EM exposure is monitored only at select locations. Consequently, it is essential to construct an EMEM based on these measurements.

The third method uses synthetic data generated via numerical methods and mathematical models [36], which predict the distribution of EM fields based on known source parameters and environmental configurations. The primary benefit of this approach is its ability to estimate field values in otherwise inaccessible areas. However, the accuracy of these simulations depends heavily on the quality of the input data and the extent to which the model is calibrated against real-world measurements [3,37].

2.2. RF Exposimeter for a Microenvironmental Survey

One effective method for estimating exposure to RF fields is to conduct microenvironmental surveys, which refer to specific small-scale settings or human-made areas where individuals spend a substantial portion of their lives. These include residential neighbourhoods, industrial zones, educational institutions, or public transportation hubs [38,39]. Such distinct ecosystems influence not only physical safety but also health and mental well-being. A key benefit of performing microenvironmental surveys is their capacity to capture the significant spatial variability of RF fields within these spaces.

For direct measurements, the researchers built a portable and cost-effective dual-band RF exposimeter using off-the-shelf components to measure power levels across two frequency bands simultaneously. The ultra-high-frequency (UHF) sensor package comprises an RF module detector, AD8318, with a 70 dB logarithmic signal board for power measurement and environmental RF field strength detection, attached to a 2.4 GHz mini WiFi 2 dBi omnidirectional antenna. It produces an output of -25 mV per dBm, with an intercept at 20 dBm. The 2.4–2.5 GHz range is generally assigned for ISM (Industrial, Scientific, and Medical) applications. In buildings, it is primarily used for WiFi, Bluetooth, Zigbee, and IoT devices. Conversely, the very-high-frequency (VHF) sensor package uses the AD8307 logarithmic power meter (-75 to $+15$ dBm) for signal testing and measurement, attached to an antenna operating in the 136–174 MHz range, yielding 25 mV per dBm with an intercept of -84 dBm. The 136–174 MHz range is ideal for outdoor communication but performs poorly indoors. Because of its longer wavelength, these signals struggle to penetrate materials like concrete, steel, and heavily tinted glass, making them unsuitable for multi-floor indoor coverage. Both UHF and VHF packages generate analog voltages that an Arduino Nano captures via its analog input pins. The Arduino then converts these

voltages to digital signals using a 5 V reference across 1024 discrete steps. The digitized data is subsequently transmitted to a laptop for real-time processing and logging. Figure 2 shows the annotated hardware setup for data collection.

The raw output values from the 10-bit ADC were converted to power in dBm using the sensor datasheets as a reference. For the UHF channel, the conversion follows Equation (1)

$$P_{dBm}(high) = -\frac{V}{0.025} + 20 \quad (1)$$

For the VHF channel, the conversion follows Equation (2)

$$P_{dBm}(low) = \frac{V}{0.025} - 84 \quad (2)$$

where V is the voltage derived from the ADC output x using the standard Arduino conversion given in Equation (3)

$$V = \frac{5}{1023} \times x \quad (3)$$

The use of these simple equations does not substantiate the accuracy of the instruments but rather demonstrates the potential for a properly calibrated device to monitor the EM field strength within frequency ranges that are more prevalent in everyday exposure. Moreover, the straightforward design of the device eliminates the requirement for costly and complex exposimeter measurements. With enhanced calibration, which entails determining a more precise intercept for each equation, such simple devices can effectively identify areas with dangerously high electromagnetic fields at a low cost.

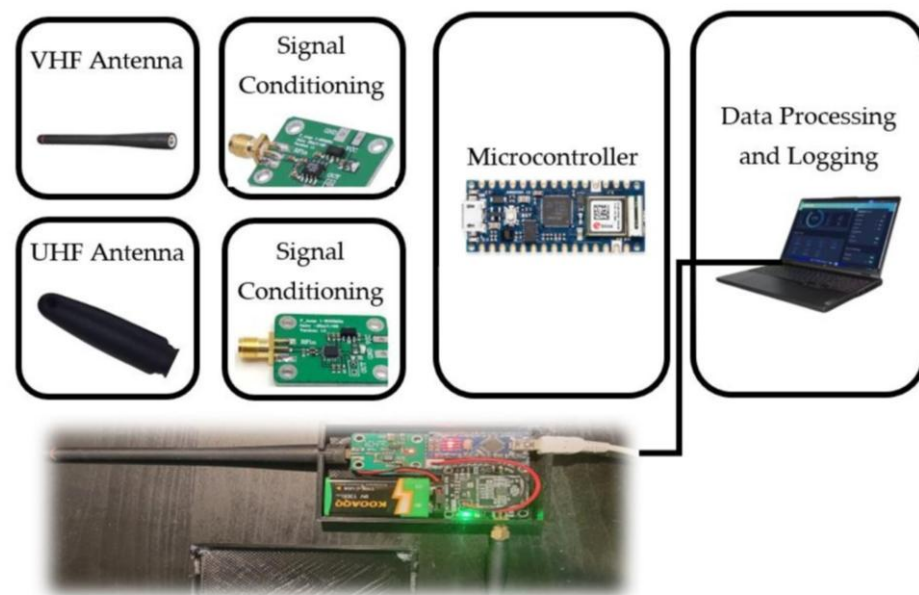


Figure 2. Setup for the RF exposimeter.

2.3. Data Collection and Dataset Description

In situ measurements were performed in three buildings on the University of Ottawa campus (Ottawa, Canada) in March 2026. Climate control systems maintain the indoor temperatures at approximately 22 °C, while the outdoor temperature averaged 1.5 °C during the measurement period. Each building was built in a different era: the Morisset Library (MRT) in 1972, the Faculty of Social Sciences (FSS) in 2012, and the Science, Technology, Engineering, and Mathematics (STEM) in 2018 (Figure 3). All three buildings are mostly made of concrete; however, FSS and STEM use drywall partitions to divide rooms inside. MRT has the smallest window openings of the three buildings, which makes it harder for RF fields to get in from outside. FSS and STEM, in contrast, feature larger

window areas that allow external signals to enter more easily. Both buildings have been awarded LEED Gold certification. LEED, which stands for Leadership in Energy and Environmental Design, serves as an international benchmark for excellence in green building practices. This certification provides independent third-party verification that a building has been designed and constructed using strategies to achieve high performance in key areas of human and environmental health. Selecting these three buildings enables a comparison of how RF fields interact with structures of varying ages, architectural styles, and building materials.

During the measurement survey, a researcher utilized a specially designed backpack to carry the measurement setup, ensuring minimal body shielding. The setup was securely housed in a case within the backpack to prevent any movement during measurements. A systematic grid-based mapping approach was employed, resulting in a total of 424 measurements, all conducted at a height of 1.5 meters above ground. The measurement points were strategically selected in open environments, away from walls and other obstacles, to reduce the impact of reflections. Signals were collected at regular intervals from grid points located on each accessible floor. The two horizontal axes indicate the positions of these grid points. There are positions on each axis labelled A through G. Position A is the closest to the grid origin, and position G is the farthest. The standard way to name each dataset file is building-floor-X-Y. The floor index can be anywhere from 0 (basement) to 6, depending on the building. The X and Y values tell us where the grid is. For example, the measurement file MRT-1-D-C refers to a place on the first floor at grid position (D, C). The dataset did not include places that were hard to get to because of physical barriers or restrictions on the number of people who could fit in a room. The grid mapping tables show these places as blank spaces.

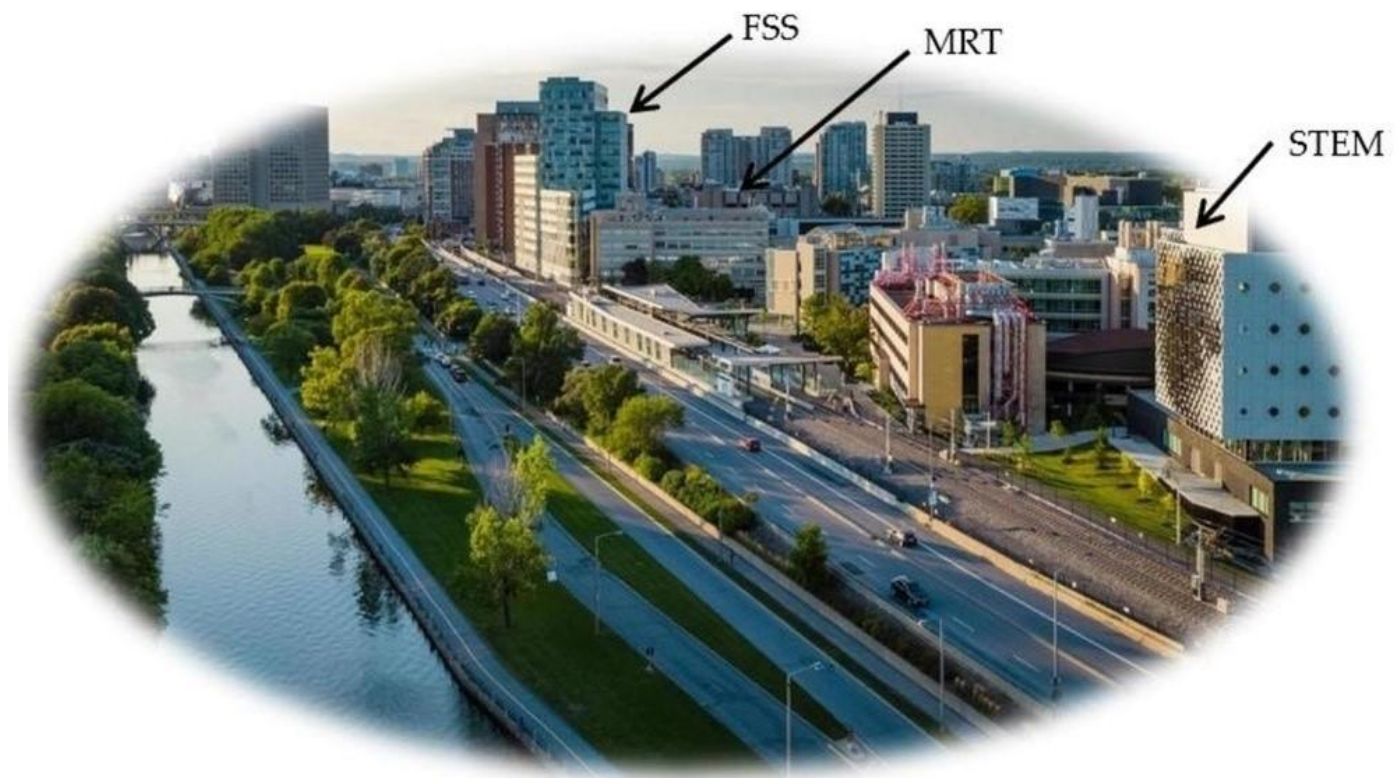


Figure 3. The three buildings on the University of Ottawa campus.

At each accessible grid point, 50,000 samples were recorded. These samples included power readings from both the UHF and VHF channels, stored as high dBm and low dBm, respectively. Each sample has a Unix timestamp that helps identify the signals in time. There are 424 survey locations across all three buildings. FSS has 94 locations on five floors, STEM has 99 locations on five floors, and MRT has 231 locations on six floors. This gives us a total dataset of about 21,200,000 samples. Table 1 summarizes the dataset structure for each building.

Table 1. Dataset summary for the campus buildings.

Building	Year Built	Floors Surveyed	Measured Locations	Total Samples
MRT	1972	1–6	231	11,550,000
FSS	2012	1–5	94	4,700,000
STEM	2018	0–4	99	4,950,000
Total	-	-	424	21,200,000

2.4. Dataset Preprocessing and Splitting

Before model training, the raw signals were preprocessed to extract meaningful statistical representations at each grid location. Since each location yields 50,000 samples across both frequency band channels, directly using the raw time-series data as model input would be computationally prohibitive and would not generalize well across locations. Instead, four statistical features were extracted per channel at each grid location: the mean, standard deviation, minimum, and maximum of the recorded power values (dBm). This resulted in a total of eight features per location. Four features from each UHF and VHF channel have been considered and summarized in Table 2. This feature representation maintains the important signal properties at each location, such as average signal strength, temporal variability, and dynamic range. It also makes the data smaller so that ML algorithms can be employed.

Table 2. Extracted features per grid location used as input to the ML models.

Feature	Channel	Description
Mean power	UHF (2400–2500 MHz)	Average signal strength across 50,000 samples
Std power		Signal variability across 50,000 samples
Min power		Minimum recorded power value
Max power		Maximum recorded power value
Mean power	VHF (136–174 MHz)	Average signal strength across 50,000 samples
Std power		Signal variability across 50,000 samples
Min power		Minimum recorded power value
Max power		Maximum recorded power value

After extracting features, the dataset was organized so that each row represents a single grid location, identified by its building, floor, and grid coordinates, along with its eight extracted features and the labels corresponding to each, for classification and regression tasks. Before splitting the dataset, locations with missing measurements due to room access restrictions were excluded. This left a final dataset of 424 labelled samples from the three buildings. Then, the dataset was split into training, validation, and test subsets using a stratified splitting method. This ensures that each subset has a fair number of buildings and floors. In total, 80% of the samples went into the training set, 10% into the validation set, and 10% into the test set. This means that there were about 339, 42, and 43 samples in each set. Stratification was applied with respect to the building label to prevent class imbalance across subsets, which is important given the unequal number of measured locations across the three buildings.

3. Interpolation and Visualization

Interpolation techniques provide effective solutions for creating continuous, high-fidelity models that typically exhibit improved accuracy and adaptability to changing environments [40,41]. Conversely, efficient visualization is crucial for clearly conveying complex datasets to both engineers and the public. Visualization methods, such as heatmaps and contour plots, are particularly useful for identifying spatial distributions and densities.

3.1. Spatial Interpolation

Rather than depending on manual approximations, spatial interpolation effectively connects theoretical predictions with real-world sensor data, albeit still facing some uncertainty. Solving fundamental physical laws—such as Maxwell’s equations and the Helmholtz equation—to simulate and reconstruct RF fields produces heatmaps—visual colour-graded 2D/3D grids that show underlying field strength, interference zones, coverage quality, and potential human exposure limits. These visualization maps of mathematical interpolations in the plane or in space may take various forms depending on the complexity of the data and modelling [2].

Scientific research on the levels of RF exposure in both outdoor and indoor environments has been a highly active field in recent years. Several studies in the literature, such as those mentioned in [42–47], employed different interpolation approaches to create an EMEM for urban areas.

In mathematics, interpolation is a technique used to predict the values of unknown data points based on the values of nearby known data points. For precise spatial visualization, the *Interpolate* subpackage of the *Python* library *SciPy* was employed to generate continuous exposure heatmaps illustrating the spatial distribution of EM fields in the three buildings under consideration. Compared with other interpolation methods, such as *Kriging*, inverse distance weighting, and radial basis function interpolation, the *Interpolate* package demonstrated 1.98 dBm higher root mean squared error (RMSE) and 1.57 dBm mean absolute error (MAE), on average, in the Leave-One-Out Cross-Validation (LOOCV). Despite the limited performance, this method was selected due to its relatively low computational overhead and fewer parameter selections. It employs sparse measurement data samples collected through the measurement survey to estimate intermediate values between known data points, thereby generating continuous surfaces. Utilizing the *griddata* function with cubic interpolation, each measured data point is interpolated onto a smooth mesh and subsequently plotted. Inaccessible areas were left as missing data points. In *Python 3.13.9*, the plots are refined by creating polygons that approximate the shape of each floor, with the final visualizations generated using the *matplotlib* package. The floor shapes are manually drawn based on maps obtained from the university website [48–50]; however, these representations are not meant to serve as exact boundaries. To eliminate white gaps around the edges, the boundaries were assigned the same dBm value as the nearest real data point, provided that the wall was within one data-point distance.

3.2. Results

The heatmaps, shown in Figures 4–9, represent the results of 2D interpolation of the exposure values across all three buildings for both frequency bands. The results illustrate the distribution of spatial signal strength across all surveyed floors within each building. The measured grid locations are represented as grey dots overlaying the building floor outline. The colour scale indicates signal strength in dBm, where darker blue areas signify greater attenuation and warmer red areas indicate stronger signal levels. For clarity, various safety standard baselines have been included in the heatmap legends. Since these

values are provided as power densities, they needed to be converted to dBm using Equation (4), in which

$$P_r(\text{dBm}) = 10 \log_{10} \left(\frac{1000 S G c^2}{4\pi f^2} \right) \quad (4)$$

S is the power density in W/m^2 , G is the antenna gain in linear units, c is the speed of light in vacuum in m/s , and f is the frequency in Hz .

After conversion via effective aperture, the ICNIRP/IEEE limit of $10 \text{ W}/\text{m}^2$ corresponds to $+12.8 \text{ dBm}$ on the UHF and $+34.74 \text{ dBm}$ on the VLF. The Bioinitiative level of $3 \times 10^{-6} \text{ W}/\text{m}^2$ corresponds to -52.5 dBm (UHF) and -30.5 dBm (VHF) [51,52]. The Building Biology + Sustainability (IBN) no-concern level of $1 \times 10^{-7} \text{ W}/\text{m}^2$ corresponds to -67.2 dBm (UHF) and -45.3 dBm (VHF) [53].

Figure 4 shows how the UHF signal, mainly from WiFi using the 2.4 GHz band, is spread across the six floors of MRT. Figure 4a shows that Floor 1 has the most pronounced spatial variation of all the floors. Signal levels approaching -40 dBm are concentrated in the lower-left region, while attenuation reaches approximately -94 dBm in the upper-right interior zones. This gives the floor an extremely dynamic range of nearly 54 dBm . Figure 4b shows that Floor 2 has a pattern like that of Floor 1. The strongest signal exists in the lower center region, with a noticeable decline in strength as it extends to upper floors. This indicates that the signal sources influencing Floor 1 also impact the lower part of Floor 2. As illustrated in Figure 4c, Floor 3 shows a distinct change. The left side of the floor exhibits warmer signal levels, whereas the center-right side experiences moderate attenuation. This suggests a variation in structural obstructions or the placement of WiFi sources at mid-level within the building. The interior of the building on Floors 1 and 2 is predominantly hallways and classrooms, whereas upper floors are mainly occupied by rows of steel bookshelves. Figure 4d shows that Floor 4 has the warmest overall UHF distribution. The colours are mostly orange and red, with very few deep attenuation zones. This suggests that there is less exterior structural obstruction at higher elevations, where the density of the concrete core may be lower. Figure 4e reveals that Floor 5 has a warm distribution with red hotspots at the bottom and upper-right corners. Figure 4f shows that Floor 6 has moderate signal levels throughout. This could be attributed to fewer structural elements blocking the signal at the top of the building.

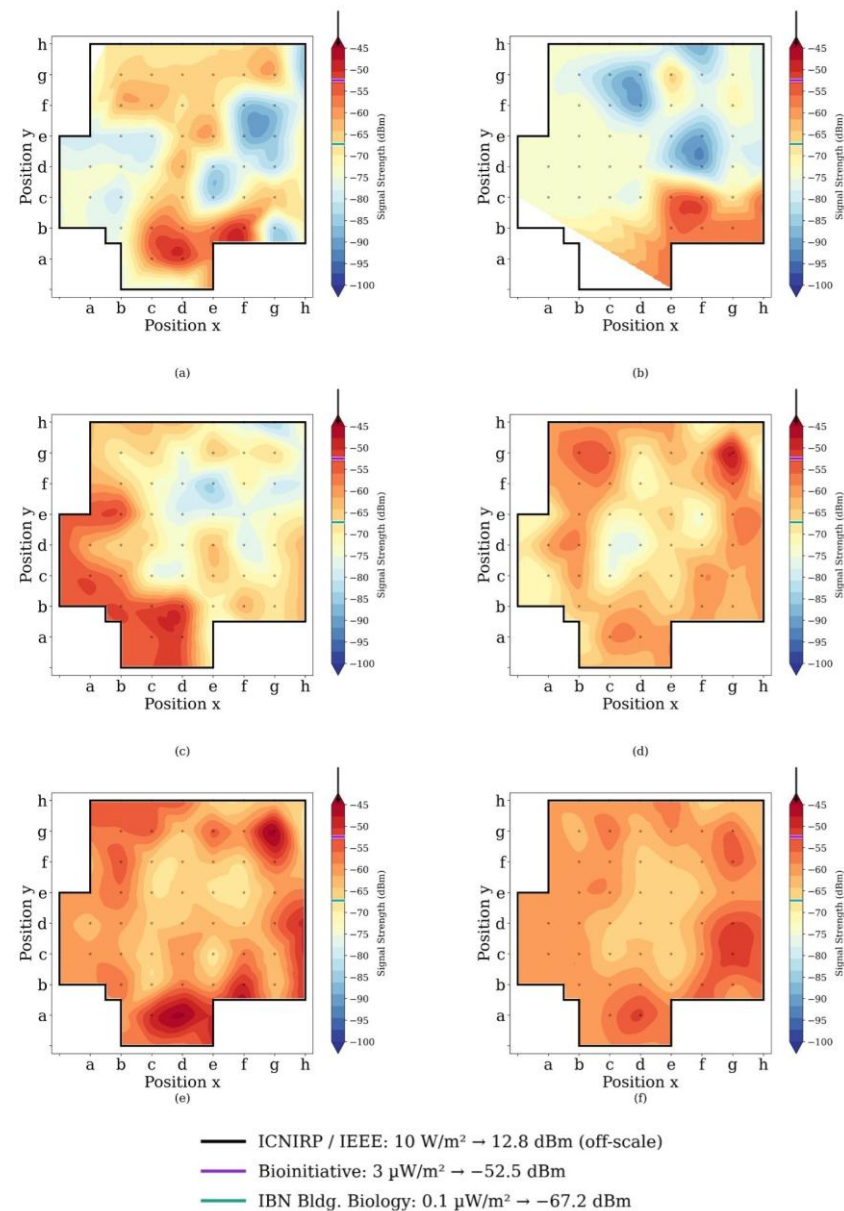


Figure 4. Interpolation heatmaps for MRT at UHF: (a) Floor 1, (b) Floor 2, (c) Floor 3, (d) Floor 4, (e) Floor 5, (f) Floor 6.

Figure 5 illustrates the distribution of the VHF signal across the six floors of MRT. The heatmaps indicate a limited dynamic range of approximately 27 dBm (ranging from -45 to -72 dBm) throughout all levels. VHF signals face significant challenges in penetrating solid building walls, as their longer wavelengths (approximately 1 to 10 meters) are substantially attenuated by dense materials. As depicted in Figure 5a, Floor 1 exhibits a mixed distribution, featuring warm spots in the center-right area and moderate attenuation toward the upper-left corner. This is because signals can only get through the limited window openings on this floor. Figure 5b indicates that Floor 2 has a warmer distribution overall, with signal strength focusing on the center of the floor plan. This suggests that the propagation conditions are better at this height. Figure 5c shows that Floor 3 is going back to cooler tones with more attenuation on the left side and moderate attenuation on the right side. Figure 5d,e show that Floors 4 and 5 have more attenuation on the left side of the floor plan. Floor 5 has the lowest signal, which means that the upper interior zones of this old concrete structure are the hardest for signals to penetrate. Figure 5f reveals that Floor 6 has the most evenly spread signal distribution, with cool blue tones throughout.

This further proves that the combination of dense concrete construction and few window openings reduces signal strength across UHF and VHF.

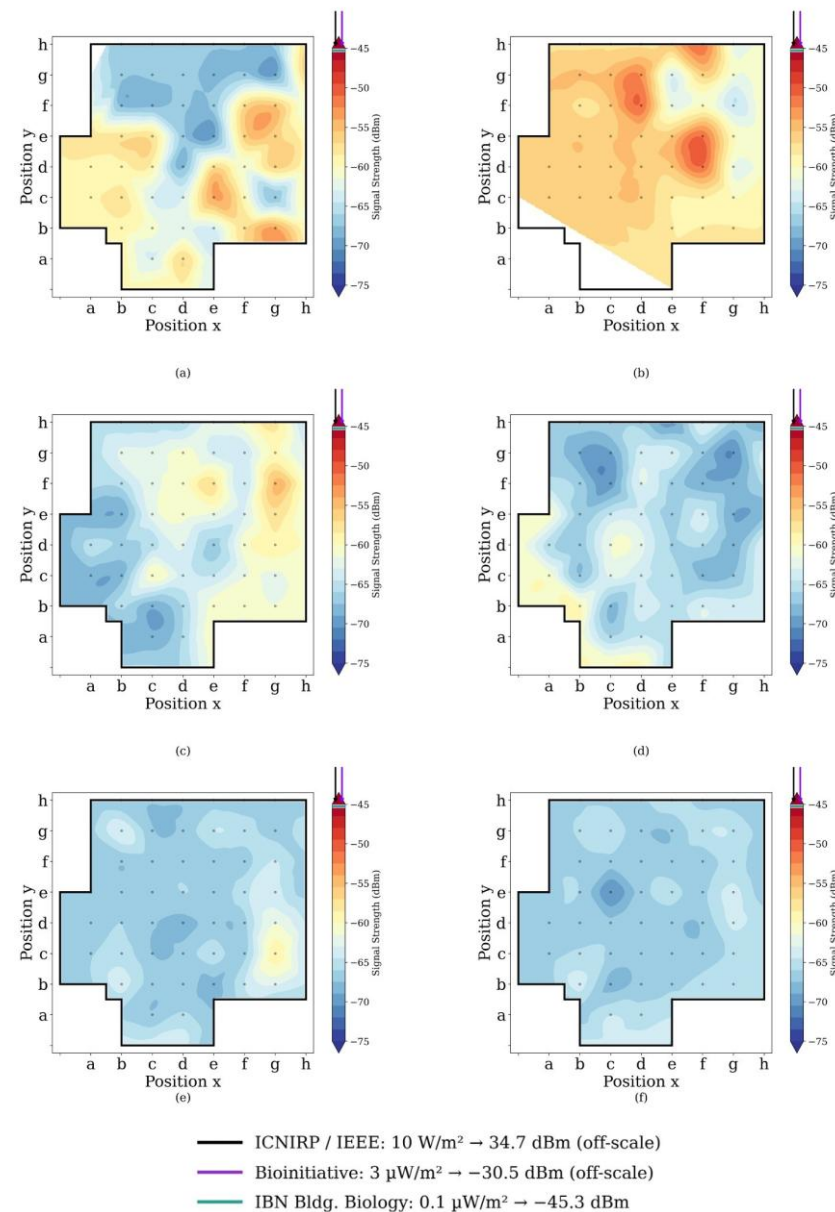


Figure 5. Interpolation heatmaps for MRT at VHF: (a) Floor 1, (b) Floor 2, (c) Floor 3, (d) Floor 4, (e) Floor 5, (f) Floor 6.

Figure 6 shows how the UHF signal spreads across the five floors of FSS. Figure 6a shows that Floor 1 has a localized red hotspot in the upper-left area that is close to -45 dBm. This could be a result of large window openings nearby. There is also an isolated attenuation pocket in the center-right area that reaches about -94 dBm. This may be because there is a concrete structural core in that area. Figure 6b indicates that Floor 2 still has a strong signal in the upper-left corner, but the center and lower zones show a clear increase in deep attenuation. This could be due to more concrete getting in the way of floor slabs and internal walls at this level. Figure 6c proves that Floor 3's yellow distribution becomes more even, with moderate attenuation pockets mostly in the center-left. This means that the signal conditions stabilize at mid-building elevation as the effects of both ground-level and rooftop sources fade. Figure 6d illustrates that Floor 4 features warm

orange tones and relatively few areas of deep attenuation. This can be attributed to the larger window openings in FSS, which allow more external signals to penetrate the upper levels. In contrast, Figure 6e highlights Floor 5, characterized by a warm and consistent spatial distribution. This makes it the most uniform UHF floor in FSS, with only minor attenuation pockets located in the center, a reflection of the reduced structural obstructions near the top of the building.

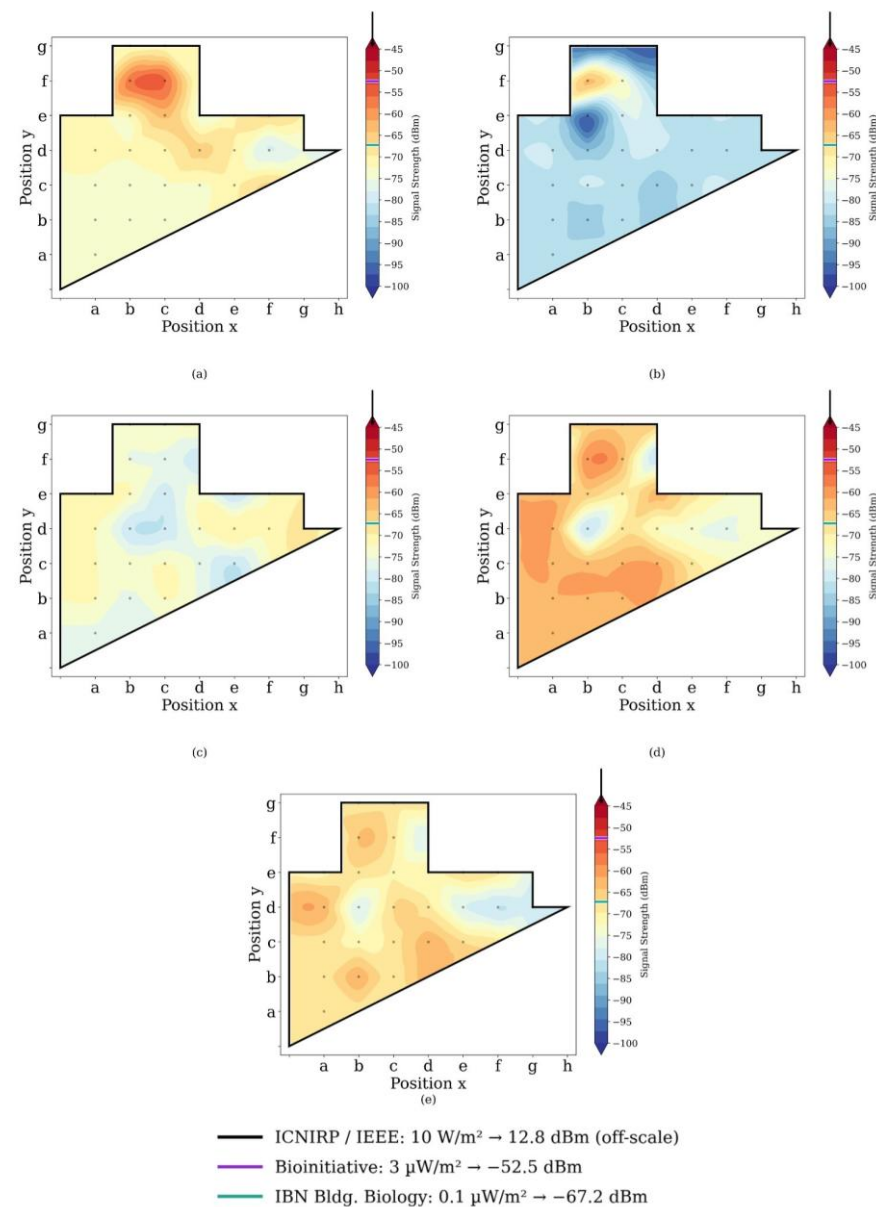


Figure 6. Interpolation heatmaps for FSS at UHF: (a) Floor 1, (b) Floor 2, (c) Floor 3, (d) Floor 4, (e) Floor 5.

Figure 7 shows how the VHF signal is spread out over the five floors of FSS. As seen in MRT, the VHF band has a smaller dynamic range of about 27 dBm (-45 to -72 dBm) across all FSS floors than that of the UHF band. This confirms that VHF signals are stronger through concrete structures. Figure 7a indicates that Floor 1 has a mixed distribution, with a warm signal concentrated on the left side and moderate attenuation on the right side. This is because FSS has larger window openings that let in some signals. Figure 7b reveals that the warm signal on Floor 2 is mostly in the lower-left corner, and the attenuation spreads to the upper and right zones. Figure 7c proves that Floor 3 has the

strongest and most consistent signal distribution across all FSS floors. It is mostly warm orange-red tones, which suggests that being higher up in the building in FSS is best for propagation. Figure 7d,e show that Floors 4 and 5 lead to a gradual return to attenuation. Floor 5 has the coolest signal distribution of all FSS floors, with blue tones dominating. This means that upper floors in FSS experience more VHF attenuation, even though they have a larger window area than lower floors.

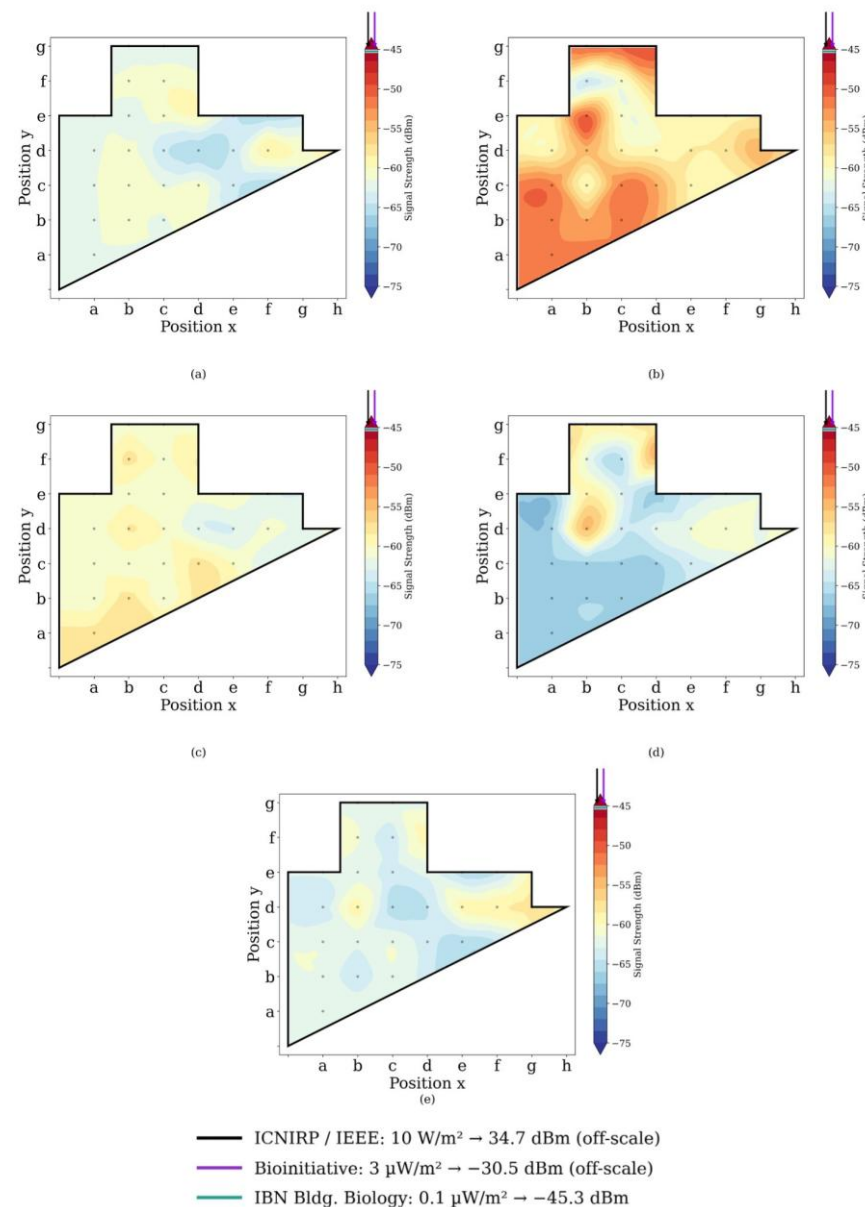


Figure 7. Interpolation heatmaps for FSS at VHF: (a) Floor 1, (b) Floor 2, (c) Floor 3, (d) Floor 4, (e) Floor 5.

Figure 8 shows how the UHF signal spreads out over the five floors of STEM. Figure 8a shows that the basement level, or Floor 0, has a strong overall signal distribution that is mostly warm orange tones. There is only a narrow vertical band of moderate attenuation toward the center-left. This is a strong result for a basement floor, potentially a result of STEM being built with larger window openings and modern concrete compositions that allow more signals to pass through, even at the basement level. Figure 8b shows that Floor 1 has a warm signal that is mostly in the upper corners and a blue attenuation zone that spreads across the lower center. This is because of the concrete floor slab and the way

the walls are set up on the ground floor. Figure 8c indicates that Floor 2 has a strong localized signal reading in the center-left area that is close to -45 dBm. This is one of the strongest readings recorded across all three buildings. This is because STEM has larger window openings that let signals in from the outside at this height. Figure 8d demonstrates that Floor 3 has the most uneven UHF distribution of all STEM floors. The warm signal is most prominent on the left side, while a distinct blue attenuation zone appears in the center-right, indicating that structural elements such as elevator shafts or mechanical cores at this level are obstructing signals. Figure 8e illustrates that the left half of Floor 4 is a warm orange colour, in contrast to the right half, which displays a significantly attenuated hue. This variation highlights that the structural asymmetry on the upper floor leads to uneven UHF signal coverage.

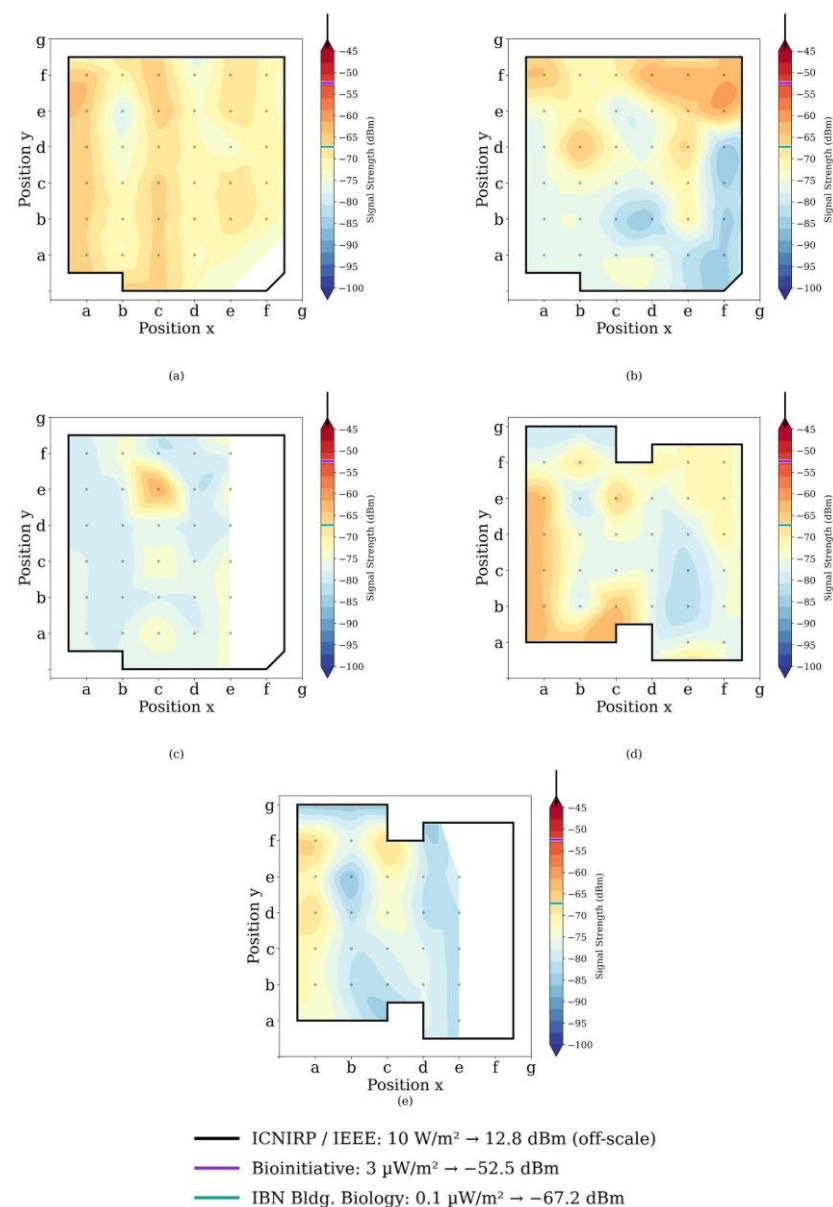


Figure 8. Interpolation heatmaps for STEM at UHF: (a) Floor 0, (b) Floor 1, (c) Floor 2, (d) Floor 3, (e) Floor 4.

Figure 9 shows how the VHF signal is spread out over the five floors of STEM. The VHF band has a smaller dynamic range of about 27 dBm (-45 to -72 dBm) across all STEM floors, which is consistent with what we saw in MRT and FSS. Figure 9a shows that Floor

0 has the most attenuated VHF distribution. The cool blue tones are mostly on the left side, with only a little warmth toward the center-left. This is because the VHF signal is limited at the below-grade level, even though STEM is a modern building. Figure 9b,c reveals that Floors 1 and 2 exhibit similar patterns: the warm signal primarily resides on the right side, gradually weakening as it extends towards the left and upper zones. This observation suggests that both floors receive signals from the same source. In contrast, Figure 9d illustrates that Floor 3 exhibits a mixed distribution, showcasing a warm signal in the center-right area, with diminished signals observed towards the left and upper regions. Furthermore, Figure 9e reveals that Floor 4 has the most spatial variability of all the floors, presenting a warm signal in the upper-left section while significant attenuation is noticeable throughout the center and lower zones. This indicates that the top floor demonstrates the highest VHF spatial variability among all the levels measured in this building.

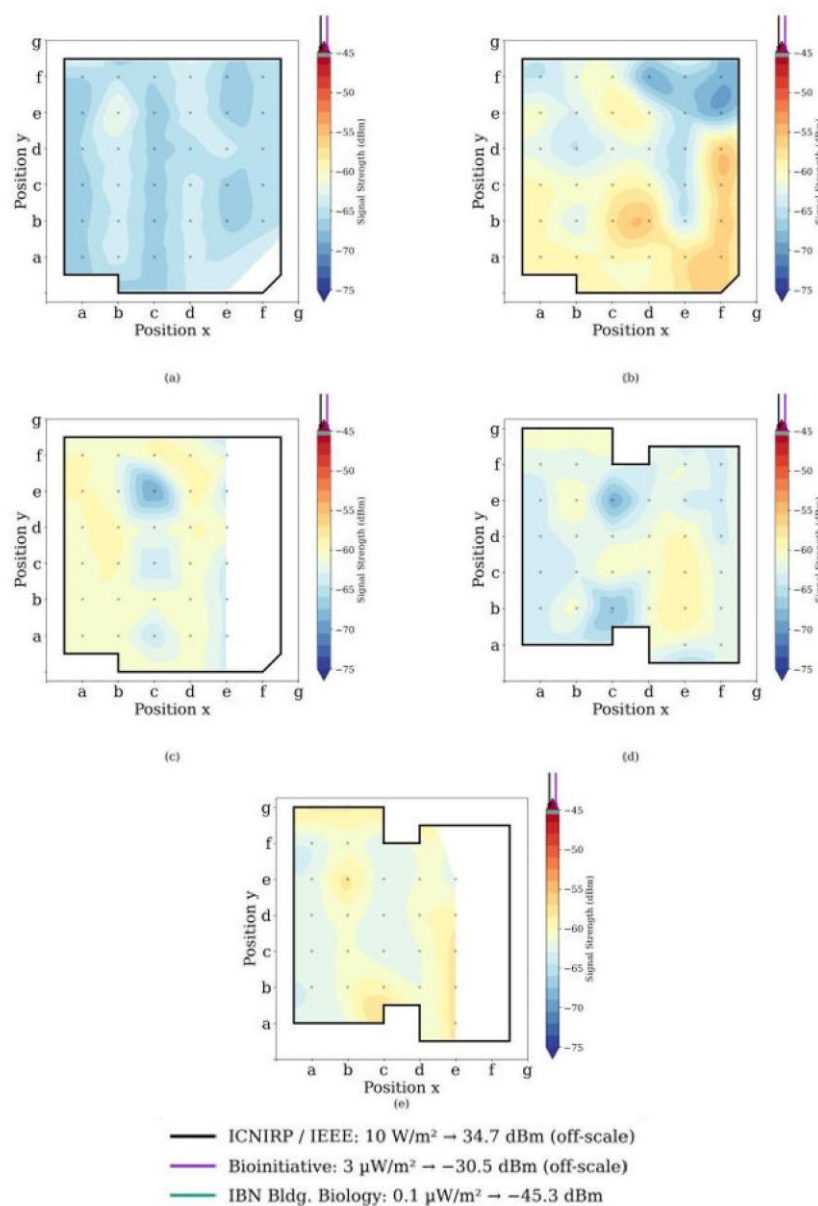


Figure 9. Interpolation heatmaps for STEM at VHF: (a) Floor 0, (b) Floor 1, (c) Floor 2, (d) Floor 3, (e) Floor 4.

4. ML for Prediction and Validation

ML is a term in AI that encompasses a range of data analysis and validation techniques to streamline model development. The convergence of ML, data engineering, environmental science, and public health depends significantly on robust frameworks for prediction and validation. During the validation phase, several key statistical metrics are assessed to evaluate a model's predictive performance, including RMSE and MAE. Today, the validation process also prioritizes evaluating explainability, ensuring that the model's predictions remain consistent with scientific reality.

The application of ML models to predict EM field distribution in the urban environment has grown in recent years. Several investigations in the literature [54–57] proposed a novel ML method based on neural networks (NNs) to assess RF exposure generated by WiFi sources in indoor scenarios. Manassas et al. [58] explored the application of ML and deep learning in predicting RF field exposure levels in urban environments to estimate the electric field (E , in V/m) at specific locations without requiring direct measurements.

Traditional interpolation methods rely solely on geometric and spatial proximity. However, by incorporating ML, it is possible to identify hidden anomalies, verify physical consistency, and quantify prediction uncertainty. The heatmaps presented in Section 3 illustrate the spatial distribution of EMEM across the three buildings. Nevertheless, they do not capture the differences among the various floors and buildings, nor do they assess whether these variations are significant enough to be automatically recognized. For instance, some floors exhibited prominent signal hotspots, while others revealed extensive areas of signal attenuation. These discrepancies may arise from various factors, including differences in construction materials, floor geometries, structural cores, window placements, the layout of wireless infrastructure, and occupancy patterns. To tackle these issues, both Random Forest (RaF) and Gaussian Process Regression (GPR) are employed, each serving distinct yet highly complementary roles within the predictive process.

4.1. RaF Results

The RaF regression model utilizes an ensemble approach that combines multiple decision trees to make predictions. In this method, each decision tree is trained on a random subset, or fold, of the available data and evaluates only a random selection at each branching decision [59]. The RaF methodology identifies building characteristics and floor levels based on extracted signal features. Additionally, it evaluates whether RF signal characteristics are adequate for differentiating buildings from various construction periods.

Two separate RaF classifiers were trained: the first to predict the building label (MRT, FSS, and STEM) from the eight extracted signal features, and the second to predict the floor level within each building. The number of estimators was set to 500 decision trees, and the maximum number of features considered at each split was set to the square root of the total number of features, following standard practice for classification tasks. The RaF classifier for building identification obtained a test accuracy of 66.7% and a weighted F1-score of 0.659, as shown in Table 3. Figure 10a shows the confusion matrix for building classification in MRT, which achieved the best performance: precision 0.76, recall 0.80, and F1-score 0.78. A total of 16 out of 20 test samples were correctly identified, indicating that the RF signal characteristics of the 1972 concrete structure with few window openings are sufficiently distinct to be reliably identified from dual-band signal features alone. FSS and STEM, on the other hand, had lower F1-scores of 0.53 and 0.40, respectively. FSS was misclassified as MRT in two cases, and STEM as MRT in three. This is because the RF propagation environments of these two modern buildings are similar. Both buildings use similar construction materials, have larger window openings, and have drywall partitioning. Figure 10b shows that low mean VHF signal power was the most important feature for building classification, accounting for 18.0% of the total importance. High std (16.2%) and

low std (15.7%) came in second and third place, respectively. This finding indicates that the average VHF signal strength and signal variability across both bands are the principal distinguishing features of each building's EM environment, aligning with the noted variations in window size and structural density across the three construction eras.

The confusion matrix offers valuable insights into the relationships between buildings. The diagonal values of the matrix represent the number of correctly classified samples for each specific building; higher values indicate that a building possesses a unique EM profile. Conversely, off-diagonal entries reflect misclassifications, suggesting that two buildings share similarities in their EM environments. The frequent misclassification of MRT samples as FSS may imply that these buildings exhibit comparable signal propagation characteristics, construction features, architectural elements, or wireless infrastructure layouts. In contrast, buildings with fewer misclassifications tend to have more distinct profiles, making them easier for the model to differentiate. Therefore, the confusion matrix serves not only to assess classification performance but also to shed light on the degree of EM similarity among the buildings under analysis.

Table 3. RaF classification results on the test set.

Classifier	Accuracy	Precision	Recall	F1-Score
Building (FSS/STEM/MRT)	0.667	0.659	0.667	0.659
Floor (1–6)	0.424	0.453	0.424	0.397

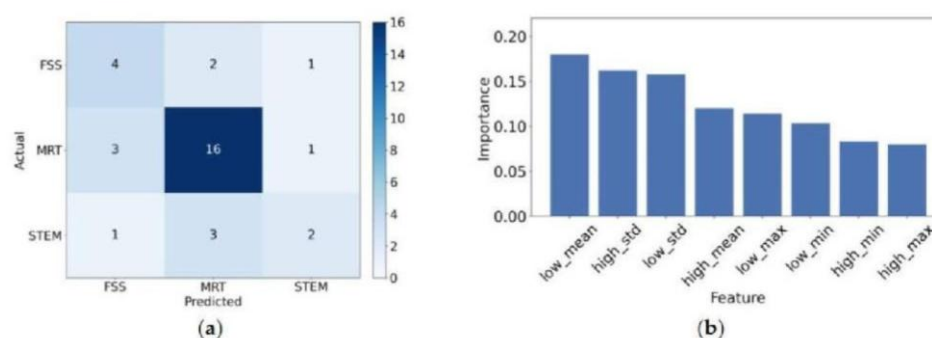


Figure 10. (a) Confusion matrix for building classification. (b) Feature importance for building classification.

Table 3 shows that the RaF classifier for identifying floors achieved a test accuracy of 42.4% and a weighted F1-score of 0.397 across floors 1 through 6. Figure 11a shows a floor confusion matrix indicating that Floor 6 achieved perfect recall (1.00), as all three test samples were correctly identified. This is because it was only present on MRT, which made it easy to find in the dataset. Floor 3 had the most balanced performance, with a precision of 0.56 and an F1-score of 0.56. Floor 1 had the lowest F1-score, at 0.22. Misclassifications were spread across floors 2 through 5, showing how hard it is to distinguish between ground-level floors, where external signal ingress patterns are most variable across buildings. The floor classification accuracy is not very high, which makes sense because the signal characteristics are expected to change gradually from one floor to the next in the same building, rather than dramatically from one building to the next, as the building classifier does. Figure 11b shows that the importance of each of the eight features for floor classification was more evenly spread out, with only 6.8 percentage points between the highest (high mean at 16.6%) and lowest (low min at 9.8%) contributing features. This means that no one feature is more important than the others for floor-level discrimination and that all statistical signal descriptors are important for this task.

Moreover, the confusion matrix offers valuable insights into the similarities between the floors. Each diagonal entry in the matrix represents the number of correctly classified samples for a specific floor. High diagonal values indicate that a floor possesses a distinctive EM signature. Conversely, off-diagonal entries reflect misclassifications, suggesting that two floors share similar characteristics. For instance, if Floor 1 is frequently misclassified as Floor 2, it implies that their EM environments exhibit comparable propagation conditions, signal strengths, or structural influences. In contrast, floors that experience few misclassifications possess unique attributes that the model can easily differentiate.

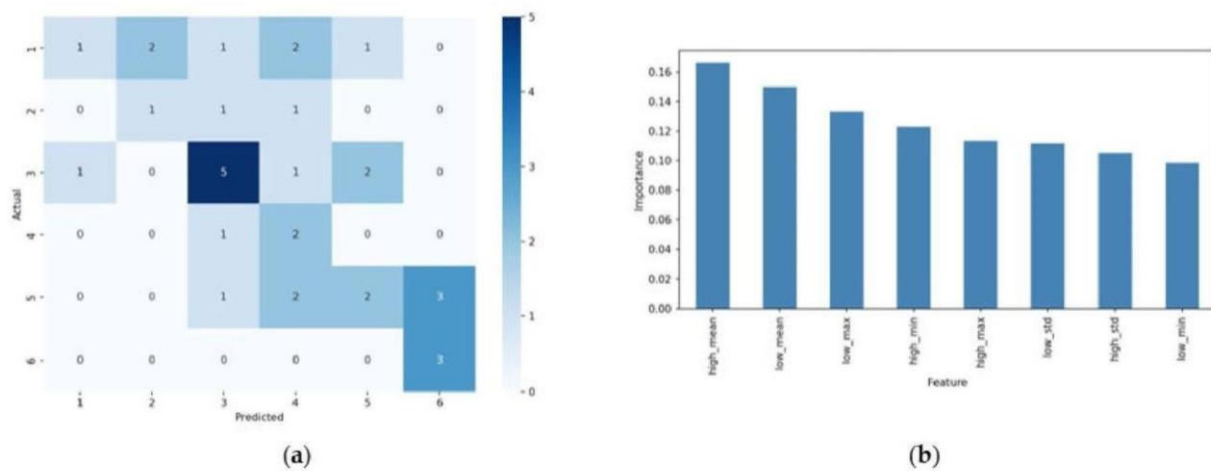


Figure 11. (a) Confusion matrix for floor classification (Floors 1–6). (b) Feature importance for floor classification.

ML results can provide a quantitative assessment of EM similarity and dissimilarity between different floors. The heatmaps and their interpretations align well with one another. Floors that exhibit distinctive heatmap distributions typically achieve higher classification accuracy, whereas those with similar spatial exposure patterns are more prone to being misclassified by the model. This correlation between interpolation analyses and ML results enhances confidence in the existence of floor-specific environments. From a sustainability and building evaluation standpoint, these findings suggest that EM conditions need not be assessed solely at the building level. Typical building assessments often treat a structure as a single entity; however, the results indicate that significant variability in EM exposure may exist between floors within the same building.

It is important to address the implications of the floor classifier's low accuracy of 42.4% for the reliability of the overall EMEM framework. This performance is below that of the building-level classifier (66.7%), indicating that the eight statistical features (mean, standard deviation, minimum and maximum power per band) are not, on their own, sufficient to reliably differentiate between floors within the same building. This is expected, as floor-to-floor propagation conditions change gradually with vertical position, whereas building-to-building differences are driven by more distinct factors such as construction era, wall material, and window-to-wall ratio. Given this limitation, the floor-level confusion matrix and feature importance results reported above should be interpreted as exploratory, qualitative indicators of relative EM similarity between floors rather than as a validated diagnostic tool suitable for automated floor-level identification in a building certification context. Practically, this indicates that the EMEM framework is best supported at the building level, where classification performance is more reliable, while floor-level differentiation should be treated as a proof of concept rather than a production-ready capability.

4.2. GPR Results

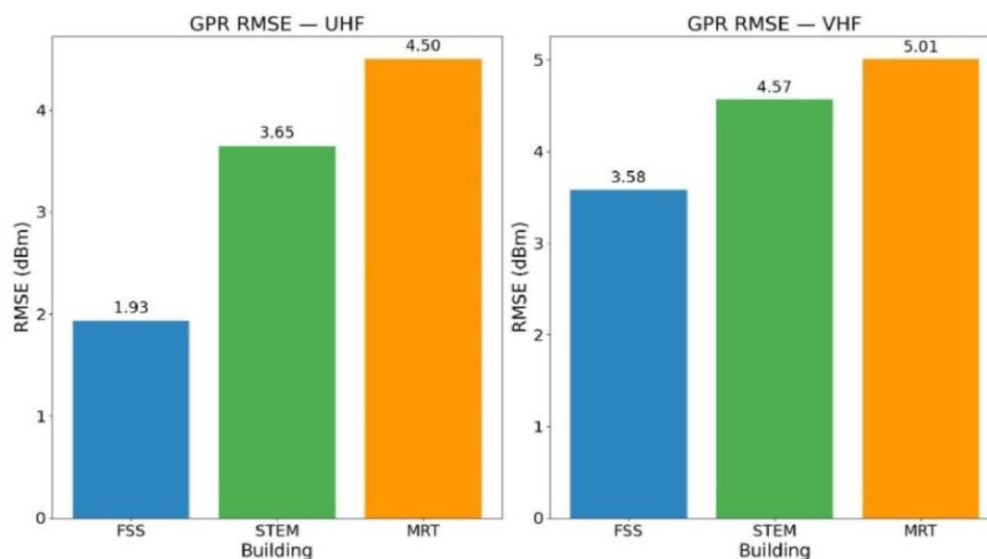
GPR is a non-parametric Bayesian technique that can model complex, non-linear relationships between input and output variables [60]. It is a powerful predictive algorithm, but it is also known for being a self-validating algorithm. It was applied independently to each floor of each building to predict the mean signal power at unmeasured grid points, using the grid coordinates (x, y) as input features and the mean UHF and VHF power values as regression targets. A Matérn kernel with smoothness parameter $\nu = 3/2$ was selected as the covariance function, as it is well-suited for physical signal propagation phenomena that exhibit moderate spatial smoothness [4]. A white noise kernel was added to the Matérn kernel to account for measurement noise inherent in the sensing hardware.

Because a separate GPR model was fitted per floor, per building, and per frequency channel, rather than on the pooled 424 location dataset, the training and evaluation procedure differs from the stratified 80/10/10 split described in Section 2.4 for the RaF classifiers. For each floor, the available grid locations were randomly partitioned into a training subset of 80% of that floor's locations and a held-out test subset consisting of 20%, and the RMSE and MAE values reported below were computed on these held-out test points, never on locations used for training; floors with fewer than four measured locations were excluded from GPR evaluation due to insufficient data for a meaningful train/test split. Kernel hyperparameters, specifically the Matérn length scale and the White Kernel Noise level, were not fixed but were optimized independently for each floor-level model by maximizing the log marginal likelihood using the default Limited-memory Broyden–Fletcher–Goldfarb–Shanno with Bound constraints (L-BFGS-B) optimizer implemented in scikit-learn's GPR, using five random restarts (`n_restarts_optimizer = 5`) to reduce the risk of convergence to a local optimum.

Model performance was evaluated using MAE and RMSE computed on the test set, and the resulting interpolated signal maps were visualized as spatial heatmaps for each floor. Matérn kernel ($\nu = 3/2$) and a white noise kernel were used to test the GPR model for each building separately. The results are shown in Table 4 and Figure 12. The FSS building had the lowest prediction error in both frequency bands. The UHF RMSE was 1.93 dBm, and the MAE was 1.51 dBm. The VHF RMSE was 3.58 dBm, and the MAE was 3.20 dBm. This means that the FSS signal environment is the most spatially predictable of the three buildings. This result is in line with the uniform signal distributions seen in the FSS building heatmaps (Figures 6 and 7). This is because the building has a modern open floor plan and larger window openings that make the spatial signal gradients more gradual, which makes it easier for GPR to interpolate. MRT had the most prediction errors in both bands, with a UHF RMSE of 4.50 dBm and MAE of 3.99 dBm, and a VHF RMSE of 5.01 dBm and MAE of 4.22 dBm. This is because the building's dense concrete construction and few window openings create abrupt signal gradients between adjacent grid locations, as shown in Figures 5 and 6. The STEM had intermediate GPR errors, with an RMSE of 3.65 dBm for UHF and 4.57 dBm for VHF. This is much higher than FSS, even though STEM is the newest building. This is because STEM has a more complicated floor plan that makes the signal more variable in space, which makes GPR interpolation less accurate. The VHF band always had higher RMSE values than the high-frequency band in all three buildings. This suggests that VHF signal propagation is more spatially irregular in these indoor spaces, potentially because its longer wavelength interacts with structural elements on each floor more broadly.

Table 4. GPR results per building (average across floors).

Building	Year Built	UHF		VHF	
		RMSE (dBm)	MAE (dBm)	RMSE (dBm)	MAE (dBm)
MRT	1972	4.50	3.99	5.01	4.22
FSS	2012	1.93	1.51	3.58	3.20
STEM	2018	3.65	3.13	4.57	3.63

**Figure 12.** GPR RMSE comparison across buildings for the UHF and VHF bands.

As a Bayesian method, GPR characterizes predictive uncertainty and point prediction at every location, in addition to the RMSE and MAE values reported in Table 4. A full characterization of this predictive uncertainty was beyond the scope of the present study, which focused on creating baseline point prediction accuracy. Predictive uncertainty in GPR is expected to be higher near floor boundaries, corners, and grid positions adjacent to locations excluded from measurement due to access restrictions, reflecting poor model confidence farther from observed data points, and lower in the interior sampled floors than those in FSS. Systematic aggregation and visualization of this uncertainty as spatial maps alongside the interpolated mean maps in Figure 12 represents a valuable extension for future iterations of this framework, especially for applications such as regulatory compliance mapping where quantifying confidence near safety thresholds is important.

5. Discussion

An essential component in the advancement of sustainable intelligent communities is the creation of spaces that are friendly to and responsive to bioelectromagnetic factors, considering both human and ecological aspects. To achieve this, thorough research into EMEM using cost-effective technologies and techniques is required. Although numerous studies have investigated specific aspects of EM urban environments, there remains a persistent need for a cohesive, comprehensive overview of EMEM methodologies. In this context, Kiouvrekis et al. [2] presented a literature review that effectively addresses this gap by systematically analyzing computational approaches employed for mapping in both wireless networks and public health. This study addresses this gap by enabling the building industry to tap into the opportunities presented by the global wellness market, a form of disruptive innovation. By following best practices, it is crucial to ensure that the

technologies emerging in this bioelectromagnetic era promote social–ecological cohesion and align with the UN SDGs 7, 9, 11, and 13.

This study demonstrates a rudimentary exploration into a new method for the acquisition, analysis, and presentation of EMEM data. This method employs hardware that is effective without expensive and time-consuming equipment. The measurements captured to support this study required a short period of time to complete using only one device. Further improvements in the accuracy, effectiveness, and acquisition speed of similar devices could produce hardware that could be operated by any individual and incorporated into public health policies to promote sustainable, EM-aware environments.

The research questions driving this study focus on the development and implementation of an integrated EMEM framework. The answer to RQ1 goes first; this study equips urban planners and public health officials with a comprehensive understanding of localized EM fields. It facilitates the optimization of wireless network coverage without compromising compliance standards. It is essential for decision-makers to enable municipalities to monitor infrastructure, assess potential health risks, enforce safety guidelines, and transparently address public concerns about modern digital networks. It holds considerable value for data-informed infrastructure siting, focused epidemiological research, risk communication, and enhancing community transparency regarding the local EM environment.

In relation to RQ2, computational techniques significantly enhance urban EM sustainability by enabling the optimization of wireless infrastructure. This study illustrates that the incorporation of spatial interpolation and ML predictive techniques is effective in developing an EMEM framework based on sparse measurement data. The proposed framework demonstrates effective mapping and predictive performance, with good interpretability; however, it is important to note that the dataset is limited to measurements collected during a single season (Winter 2026) and is confined to the geographic boundaries of three specific buildings. This limitation may affect the model's generalizability to other buildings or microenvironments with different urban structures, population densities, or wireless infrastructure characteristics. The interpolated heatmaps together provide a physical visualization of RF exposure patterns, while the ML results suggest that each floor has a distinct EM environment. ML models address this limitation by classifying floors and buildings based on statistical descriptors derived from measurements. The successful classification of floors demonstrates that the EM properties of each floor vary sufficiently to produce distinct fingerprints. As a result, the findings from the ML models provide quantitative validation for the qualitative insights identified in the heatmaps. The integration of both interpolation and validation is crucial for developing a framework that transforms data into knowledge, shifting from reactive mitigation to proactive planning. Moreover, as cities establish EM living zones—such as schools and hospitals—a comprehensive EMEM will play a key role in defining these zones and facilitating the incorporation of advanced shielding materials.

The answer to RQ3 underscores the importance of the study outcomes for evaluating EM exposure levels across the three buildings relative to the safety limits set by various regulatory agencies. Given the campus's physical infrastructure and survey conditions, the exposure measurements taken at various points across the buildings showed that EM field levels were well below the IEEE- and ICNIRP-established safety limit (10 W/m^2). Several locations in the buildings are above the $3 \mu \text{ W/m}^2$ Bioinitiative level and the $0.1 \mu \text{ W/m}^2$ limit for the IBN no-concern level. The common exposure limits established by ICNIRP and IEEE represent the scientific consensus, while the more stringent limits set by the Bioinitiative and IBN are rooted in precautionary principles and research on mutagenic effects, EM hypersensitivity [61], as well as the downstream pathological effects associated with the activation of voltage-gated calcium channels (VGCC) [62].

RQ4 integrates intuitions from the previous questions. The knowledge gained from this study is crucial for effectively translating the framework's insights into actionable regulatory decisions. By adopting a balanced approach that considers both wireless connectivity needs and health concerns, it will be possible to create an environment where occupants benefit from wireless technology while minimizing potential risks to their well-being. This approach has broader applications in health diagnostics contexts, where spatial exposure, environmental variables, and diverse data sources are pivotal. For instance, a similar computational framework could be used to model energy efficiency and IEQ parameters such as air quality, thermal comfort, and noise pollution in the urban environment, which is particularly valuable in health and environmental justice scenarios [63]. The challenge of designing bioelectromagnetically conscious buildings can be part of the IEQ agenda, in which all domains are essential to a more sustainable future. Furthermore, the evolution of occupant behaviour can be significantly enhanced through rapid, real-time feedback enabled by computational techniques and digital technologies. Integrating EMEM into prominent international building certification systems, such as LEED, which emphasizes environmental sustainability and energy efficiency, alongside the human-centric WELL building standard, could significantly enhance overall building health. Currently, the IBN acknowledges the critical role of EM-protected design, making it increasingly vital to optimize design characteristics to address these issues intelligently. The IBN employs the precautionary principle to establish strict, health-based exposure guidelines for EM fields. The certification and assessment protocol, rather than merely the recommended limits, may provide a valuable framework for other systems.

The findings from all research questions highlight significant interconnections, demonstrating that the combination of physical measurements and computational techniques—such as interpolation algorithms and ML—can effectively bolster the EMEM framework. This integration ultimately enhances proactive environmental management and urban design.

6. Concluding Remarks

This study introduces a foundational EMEM framework that encompasses a DAQ pipeline, interpolation and mapping, along with ML prediction and validation. While the data presented may not be particularly remarkable, as the current measurements are exploratory and should not be regarded as a fully calibrated, compliance-grade exposure assessment, the methodology outlines a process that can be further refined to develop a more robust EMEM. Future research should aim to expand the scope of this study in several important areas. Firstly, comprehensive validation measurements were not conducted, which represents a limitation of this research. As such, the DAQ system would benefit from enhancements through the integration of advanced measurement technologies and improving its applicability across various environments. Secondly, other spatial representation techniques, such as 3D Kriging or similar interpolation methods, could be utilized to create exposure maps that explore alternative options. Finally, additional work should leverage ML to refine floor-level separation by examining structural covariates, including floor area, ceiling height, distance to the nearest exterior wall, and the locations of known wireless access points, before relying on floor-resolved outputs for regulatory or certification-level decisions. In conclusion, this study shows promise for advancing EMEM development and, in the long run, certifying healthy microenvironments.

Author Contributions: Conceptualization, D.M., A.B.B.D.S., M.S. and R.H.; methodology, D.M., A.B.B.D.S., M.S. and R.H.; software, D.M., A.B.B.D.S. and M.S.; validation, D.M., A.B.B.D.S., M.S. and R.H.; formal analysis, D.M., A.B.B.D.S., M.S. and R.H.; investigation, D.M., A.B.B.D.S., M.S. and R.H.; resources, D.M., A.B.B.D.S., M.S. and R.H.; data curation, D.M., A.B.B.D.S., M.S.; writing—

original draft preparation, R.H.; writing—review and editing, D.M., A.B.B.D.S., M.S. and R.H.; visualization, D.M., A.B.B.D.S. and M.S.; supervision, R.H.; project administration, R.H. All authors have read and agreed to the published version of the manuscript.

Funding: This study received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: All data presented in this study are available on request from the corresponding author.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Habash, R.; Baho, G.Y. Transition pathways towards electromagnetic sustainability in the built and lived environment. *Sustainability* **2025**, *17*, 10252.
2. Kiouvrekis, Y.; Panagiotakopoulos, T. Electromagnetic field distribution mapping: A taxonomy and comprehensive review of computational and machine learning methods. *Computers* **2025**, *14*, 373. <https://doi.org/10.3390/computers14090373>.
3. An, J.; Tao, Y.; Zhang, X.; Hua, Z.; Wang, S.; Pan, G.; Yang, X.; Niyato, D.; Karagiannidis, G.K. Electromagnetic situation awareness and modeling for space-air-ground integrated networks. *Nat. Sci. Rev.* **2025**, *13*, nwaf492. <https://doi.org/10.1093/nsr/nwaf492>.
4. Habash, R. *Sustainability and Health in Intelligent Buildings*, 1st ed.; Woodhead Publishing: Cambridge, UK, 2022.
5. Chiamello, E.; Bonato, M.; Focchi, S.; Tognola, G.; Parazzini, M.; Ravazzani, P.; Wiart, J. Radio frequency electromagnetic fields exposure assessment in indoor environments: A review. *Int. J. Environ. Res. Public Health* **2019**, *16*, 955. <https://doi.org/10.3390/ijerph16060955>.
6. Koutlia, K.; Bojović, B.; Lagén, S.; Giupponi, L. Novel radio environment map for the ns-3 NR simulator. In Proceedings of the WNS3 '21, Virtual, Association for Computing Machinery, New York, NY, USA, 23–24 June 2021; pp. 41–48.
7. Ashraf, M.A.; Celik, T. Evaluating radiofrequency electromagnetic field exposure in confined spaces: A systematic review of recent studies and future directions. *Radiat. Prot. Dosim.* **2024**, *200*, 598–616. <https://doi.org/10.1093/rpd/ncae045>.
8. Bennett, N.D.; Croke, B.F.W.; Guariso, G.; Guillaume, J.H.A.; Hamilton, S.H.; Jakeman, A.J.; Marsili-Libelli, S.; Newham, L.T.H.; Norton, J.P.; Perrin, C.; et al. Characterizing performance of environmental models. *Environ. Model. Softw.* **2013**, *40*, 1–20.
9. Kioverkis, Y.; Panagiotakopoulos, T.; Nouse, E.; Filippopoulos, I.; Ploussi, A.; Spyratou, E.; Efstathopoulos, E.P. Explainable machine learning for radio environment mapping: An intelligent system for electric field strength monitoring. *IEEE Access* **2025**, *13*, 75105.
10. Exem. Mapping the Electromagnetic Environment. Available online: <https://www.exem.fr/en/expertise/mapping/> (accessed on 18 June 2026).
11. Levie, R.; Yapar, C.; Kutyniok, G.; Caire, G. RadioUNet: Fast radio map estimation with convolutional neural networks. *IEEE Trans. Wirel. Commun.* **2021**, *20*, 4001–4015.
12. Jalilian, H.; Eeftens, M.; Ziaei, M.; Röösli, M. Public exposure to radiofrequency electromagnetic fields in everyday microenvironments: An updated systematic review for Europe. *Environ. Res.* **2019**, *176*, 108517.
13. Frank, J.W. Electromagnetic fields, 5G and health: What about the precautionary principle? *J. Epidemiol. Community Health* **2021**, *75*, 562–566.
14. Dürrenberger, G.; Fröhlich, J.; Röösli, M.; Mattsson, M.O. EMF monitoring-concepts, activities, gaps and options. *Int. J. Environ. Res. Public Health* **2014**, *11*, 9460–9479. <https://doi.org/10.3390/ijerph110909460>.
15. International Commission on Non-Ionizing Radiation Protection (ICNIRP). Guidelines for limiting exposure to electromagnetic fields (100 KHz to 300 GHz). *Health Phys.* **2020**, *118*, 483–524.
16. Bailey, W.H.; Bodemann, R.; Bushberg, J.; Chou, C.-K.; Cleveland, R.; Faraone, A.; Foster, K.R.; Gettman, K.E.; Graf, K.; Harrington, T.; et al. Synopsis of IEEE std c95. 1™-2019 IEEE standard for safety levels with respect to human exposure to electric, magnetic, and electromagnetic fields, 0 Hz to 300 GHz. *IEEE Access* **2019**, *7*, 171346–171356.
17. Teganya, Y.; Romero, D. Data-driven spectrum cartography via deep completion autoencoders. In Proceedings of the ICC 2020-2020 IEEE International Conference on Communications (ICC), Virtual, Dublin, Ireland, 7–11 June 2020; pp. 1–7.

18. Karipidis, K.; Henderson, S.; Wijayasinghe, D.; Tjong, L.; Tinker, R. Exposure to radiofrequency electromagnetic fields from Wi-Fi in Australian schools. *Radiat. Prot. Dosim.* **2017**, *175*, 432–439.
19. Najera, A.; Alpuente-Hermosilla, I.; González-Rubio, J.; Sánchez-Montero, R.; López-Espí, P. Exposure to radiofrequency electromagnetic fields (RF-EMF) assessment: Comparison between spot and personal exposimeter measurements in Tarancón (Spain). In Proceedings of the Joint Annual Meeting of the Bioelectromagnetics Society and the European BioElectromagnetics Association (BioEM2018), Piran, Slovenia, 25–29 June 2018; pp. 25–29.
20. Kurnaz, C.; Engiz, B.K.; Bozkurt, M.C. Measurement and evaluation of electric field strength levels in primary and secondary schools in a pilot region. *Radiat. Prot. Dosim.* **2018**, *179*, 282–290.
21. Tang, C.; Yang, C.; Cai, R.S.; Ye, H.; Duan, L.; Zhang, Z.; Shi, Z.; Lin, K.; Song, J.; Huang, X.; et al. Analysis of the relationship between electromagnetic radiation characteristics and urban functions in highly populated urban areas. *Sci. Total Environ.* **2019**, *654*, 535–540.
22. Kljajic, D.; Djuric, N. Comparative analysis of EMF monitoring campaigns in the campus area of the University of Novi Sad. *Environ. Sci. Pollut. Res.* **2020**, *27*, 14735–14750.
23. Chiaramello, E.; Plets, D.; Fiocchi, S.; Bonato, M.; Tognola, G.; Parazzini, M.; Le Brusquet, L.; Martens, L.; Joseph, W.; Ravazzani, P. Innovative stochastic modeling of residential exposure to radio frequency electromagnetic field sources. *IEEE J. Electromagn. RF Microw. Med. Biol.* **2021**, *5*, 62–69.
24. Suarez, F.L.; Yepes, S.M.; Escobar, A. Assessment of the electromagnetic field exposure due to wireless communication technologies in two university campuses of Medellin, Colombia. *Heliyon* **2023**, *9*, e20323.
25. Ramirez-Vazquez, R.; Escobar, I.; Arribas, E.; Vandenbosch, G.A.E. Systematic review of exposure studies to radiofrequency electromagnetic fields: Spot measurements and mixed methodologies. *Appl. Sci.* **2024**, *14*, 11161. <https://doi.org/10.3390/app142311161>.
26. Colombi, D.; Ghasemifard, F.; Joshi, P.; Xu, B.; Paola, C.D.; Törnevik, C. Methods and practices for in situ measurements of RF EMF exposure from 5G millimeter wave base stations. *IEEE Trans. Electromagn. Compat.* **2022**, *64*, 1986–1993.
27. Deprez, K.; Colussi, L.; Korkmaz, E.; Aerts, S.; Land, D.; Littel, S.; Verloock, L.; Plets, D.; Joseph, W.; Bolte, J. Comparison of low-cost 5G electromagnetic field sensors. *Sensors* **2023**, *23*, 3312. <https://doi.org/10.3390/s23063312>.
28. Bladel, H.V.; Stroobandt, B.; Veludo, A.F.; Deprez, K.; Röösli, M.; Tognola, G.; Parazzini, M.; Thuróczy, G.; Polańska, K.; Politański, P.; et al. RF-EMF exposure assessment with add-on uplink exposure sensor in different microenvironments in seven European countries. *Environ. Int.* **2025**, *197*, 109368. <https://doi.org/10.1016/j.envint.2025.109368>.
29. Paniagua-Sánchez, J.M.; García-Cobos, F.J.; Rufo-Pérez, M.; Jiménez-Barco, A. Large-area mobile measurement of outdoor exposure to radio frequencies. *Sci. Total Environ.* **2023**, *877*, 162852.
30. Aslan, C.A.; Korunur Engiz, B.; Kurnaz, C.; Cheema, A.A.; Karadag, T. In situ assessment of EMF exposure across urban districts of Samsun, Türkiye. *Electronics* **2026**, *15*, 68. <https://doi.org/10.3390/electronics15010068>.
31. Tukimin, R.; Sapuan, S.Z.; Yunoh, W.S.W.; Zainal, N.A. Measurement and mapping of radiofrequency electromagnetic field (RF-EMF) radiation exposure in Malaysia's environment. In Proceedings of the 2024 IEEE 15th Control and System Graduate Research Colloquium (ICSGRC), Shah Alam, Malaysia, 17 August 2024; pp. 23–28. <https://doi.org/10.1109/ICSGRC62081.2024.10690979>.
32. García-Cobos, F.J.; Paniagua-Sánchez, J.M.; Gordillo-Guerrero, A.; Marabel-Calderón, C.; Rufo-Pérez, M.; Jiménez-Barco, A. Personal exposimeter coupled to a drone as a system for measuring environmental electromagnetic fields. *Environ. Res.* **2023**, *216*, 114483.
33. C95.1–1991; IEEE Standard for Safety Levels with Respect to Human Exposure to Radio Frequency Electro-Magnetic Fields, 3kHz to 300GHz. IEEE: New York, NY, USA, 1992.
34. Wang, S.; Wiart, J. Sensor-aided EMF exposure assessments in an urban environment using artificial neural networks. *Int. J. Environ. Res. Public Heal.* **2020**, *17*, 3052.
35. Aerts, S.; Vermeeren, G.; Van den Bossche, M.; Aminzadeh, R.; Verloock, L.; Thielens, A.; Leroux, P.; Bergs, J.; Braem, B.; Philippron, A.; et al. Lessons learned from a distributed RF-EMF sensor network. *Sensors* **2022**, *22*, 1715. <https://doi.org/10.3390/s22051715>.
36. Zhang, T.; Wei, Y.; Li, R. Research on behavior mathematical modeling of CGF based on reinforcement learning under complex electromagnetic environment. In Proceedings of the IEEE International Conference on Data Science and Computer Application, Dalian, China, 29–31 October 2021; pp. 781–784.
37. Phillips, C.; Sicker, D.; Grunwald, D. A survey of wireless path loss prediction and coverage mapping methods. *IEEE Commun. Surv. Tutor.* **2013**, *15*, 255–270.

38. Velghe, M.; Aerts, S.; Martens, L.; Joseph, W.; Thielens, A. Protocol for personal RF-EMF exposure measurement studies in 5th generation telecommunication networks. *Environ. Health*. **2021**, *20*, 36.
39. Veludo, A.F.; Stroobandt, B.; Bladel, H.V.; Sandoval-Diez, N.; Guxens, M.; Joseph, W.; Rösli, M. Exploring RF-EMF levels in Swiss microenvironments: An evaluation of environmental and auto-induced downlink and uplink exposure in the era of 5G. *Environ. Res.* **2025**, *266*, 120550. <https://doi.org/10.1016/j.envres.2024.120550>.
40. Jeong, S.; Lin, T.-H.; Tentzeris, M.M. A real-time range-adaptive impedance matching utilizing a machine learning strategy based on neural networks for wireless power transfer systems. *IEEE Trans. Microw. Theory Techn.* **2019**, *67*, 5340–5347.
41. Mahmud, S.A.A.; Jayathurathnage, P.; Tretyakov, S.A. Machine learning assisted characteristics prediction for wireless power transfer systems. *IEEE Access* **2022**, *10*, 40496–40505.
42. Regrain, C.; Caudeville, J.; de Seze, R.; Guedda, M.; Chobineh, A.; de Doncker, P.; Petrillo, L.; Chiaramello, E.; Parazzini, M.; Joseph, W.; et al. Design of an integrated platform for mapping residential exposure to RF-Emf sources. *Int. J. Environ. Res. Public Heal.* **2020**, *17*, 5339. <https://doi.org/10.3390/ijerph17155339>.
43. Tesanovic, M.; Conil, E.; De Domenico, A.; Aguero, R.; Freudenstein, F.; Correia, L.M.; Bories, S.; Martens, L.; Wiedemann, P.M.; Wiart, J. The LEXNET project: Wireless networks and EMF: Paving the way for low-EMF networks of the future. *IEEE Veh. Technol. Mag.* **2014**, *9*, 20–28.
44. Varsier, N.; Plets, D.; Corre, Y.; Vermeeren, G.; Joseph, W.; Aerts, S.; Martens, L.; Wiart, J. A novel method to assess the human population exposure induced by a wireless cellular network. *Bioelectromagnetics* **2015**, *36*, 451–463.
45. Rufo-Pérez, M.; Antolín-Salazar, A.; Paniagua-Sánchez, J.M.; Jiménez-Barco, A.; Rodríguez-Hernández, F.J. Spatial and temporal mapping of RF exposure in an urban core using exposimeter and GIS. *Sensors* **2025**, *25*, 1301. <https://doi.org/10.3390/s25051301>.
46. Panagiotakopoulos, T.; Kiourekis, Y.; Ploussi, A.; Spyratou, E.; Efstathiopoulos, E.P. Comparative analysis of interpolation models for IoT-enabled RF-EMF exposure mapping in urban areas. *IEEE Access* **2025**, *13*, 67006–67016.
47. Guillén-Pina, J.; Pérez-Aracil, J.; Chocano-del-Cerro, R.; Sánchez-Montero, R.; López-Espí, R.-L.; Salcedo-Sanz, S. Efficient design of electromagnetic field exposure maps with multi-method evolutionary ensembles. *Environ. Res.* **2025**, *278*, 121636. <https://doi.org/10.1016/j.envres.2025.121636>.
48. University of Ottawa. Morisset Hall (MRT) Build. Map. Univ. Ott. Adm. Serv. Available online: <https://www.uottawa.ca/about-us/administration-services/facilities/campus-maps/building/morisset-hall-mrt> (accessed on 9 July 2026).
49. University of Ottawa. STEM Complex Build. Map. Univ. Ott. Adm. Serv. Available online: <https://www.uottawa.ca/about-us/administration-services/facilities/campus-maps/building/stem-complex> (accessed on 9 July 2026).
50. University of Ottawa. Soc. Sci. Build. (FSS) Build. Map. Univ. Ott. Adm. Serv. Available online: <https://www.uottawa.ca/about-us/administration-services/facilities/campus-maps/building/social-sciences-building> (accessed on 9 July 2026).
51. Ramirez-Vazquez, R.; Escobar, I.; Vandenbosch, G.A.E.; Arribas, E. Personal exposure to radiofrequency electromagnetic fields: A comparative analysis of international, national, and regional guidelines. *Environ. Res.* **2024**, *246*, 118124. <https://doi.org/10.1016/j.envres.2024.118124>.
52. The Committee on Man and Radiation (COMAR). COMAR technical information statement: Expert reviews on potential health effects of radiofrequency electromagnetic fields and comments on the BioInitiative report. *Health Phys.* **2009**, *97*, 348–356.
53. IBN. Building Biology Evaluation Guidelines for Sleeping Areas, Supplement to the Standard of Building Biology Testing Methods SBM. Available online: <https://buildingbiology.com/site/wp-content/uploads/richtwerte-2015-englisch.pdf> (accessed on 18 March 2026).
54. Tognola, G.; Plets, D.; Chiaramello, E.; Gallucci, S.; Bonato, M.; Fiocchi, S.; Parazzini, M.; Martens, L.; Joseph, W.; Ravazzani, P. Use of machine learning for the estimation of down- and up-link field exposure in multi-source indoor WiFi scenarios. *Bioelectromagnetics* **2021**, *42*, 550–561. <https://doi.org/10.1002/bem.22361>.
55. Nyakyi, C.P.; Mpeshe, S.C.; Dida, M.A. Optimization of RF-EMF exposure to public in Tanzania using artificial neural network and multi linear regression models. *Environ. Chall.* **2025**, *18*, 101066.
56. Mallik, M.; Kharbech, S.; Mazloun, T.; Wang, S.; Wiart, J.; Gaillot, D.P.; Clavier, L. EME-Net: A U-net-based indoor EMF exposure map reconstruction method. In Proceedings of the 2022 16th European Conference on Antennas and Propagation (EuCAP), Madrid, Spain, 27 March–1 April 2022; pp. 1–5.
57. Mehrjouresht, P.; Volski, V.; Gryech, I.; Beerten, R.; Svezhentsev, A.Y.; Mercuri, M.; Soh, P.J.; Schreurs, D.M. M.-P. Indoor safety of wireless power transfer: A machine learning approach. *IEEE Trans. Microw. Theory Tech.* **2026**, *74*, 2076–2088.
58. Manassas, A.; Delidimitriou, S.; Wiart, J.; Samaras, T. Predicting electromagnetic field exposure using artificial intelligence methods. *IEEE Access* **2025**, *13*, 79832–79844.

59. Hashemi, S.M.; Botez, R.M.; Ghazi, G. Robust trajectory prediction using random forest methodology application to UAS-S4 Ehécatl. *Aerospace* **2024**, *11*, 49. <https://doi.org/10.3390/aerospace11010049>.
60. Rasmussen, C.E.; Nickisch, H. Gaussian processes for machine learning (GPML) toolbox. *J. Mach. Learn. Res.* **2010**, *11*, 3011–3015.
61. de Vocht, F.; Rössli, M. Electrohypersensitivity: What is belief and what is known? *Front. Public Heal.* **2025**, *13*, 1603692.
62. Pall, M.L. Wi-Fi is an important threat to human health. *Environ. Res.* **2018**, *164*, 405–416. <https://doi.org/10.1016/j.envres.2018.01.035>.
63. Kent, M.G.; Parkinson, T.; Schiavon, S. Indoor environmental quality in WELL-certified and LEED-certified buildings. *Sci. Rep.* **2024**, *14*, 15120. <https://doi.org/10.1038/s41598-024-65768-w>.

Disclaimer/Publisher’s Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.