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Electromagnetic Field(Emf) Exposure in 5g Utilizations

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Abstract: *Fifth-generationmoveable links is currently cultivated to encounter the spacious boost in information and connectivity, and it associates billions of gadgets via the web of things.A major benefit of 5G is the quick response time, also called latency, that is given by faster connections and better capability. As 5G is utilizing elevated frequencies as an example overhead 6GHz, individuals are worried about this Electromagnetic Field(EMF) vulnerability because it utilizes a multitude of transmitters. To understand the effect of the EMF in 5G, power density assessments were done for three distinct frequency bands in five distinct environmental scenarios in Umuahia Abia State, Nigeria. The outcomes of the power density assessment in frequency bands shows that there was no EMF vulnerability adjacent the transmitters. But sometimes, with the replication outcomes, it was shown that there exist an EMF vulnerability adjacent the transmitter when in view of diverse scenarios. So, when deploying the 5G connections in these environmental ailments, EMF regulations and limitations must be taken into better account and deployment must be conducted to play down this vulnerability. Consequently, when planning the 5G deployments, this exposed place must bemarked as a confined place that the overall public cannot entry.*

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Keywords*: Precision forestry, Remote sensing, Artificial intelligence, Mechanization, Sustainable forest management*

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1.0 Introduction

The advent of fifth-generation (5G) mobile communication technology has marked a significant leap in wireless telecommunications, offering unprecedented benefits such as ultra-low latency, enhanced data throughput, massive machine-type communication, and improved spectrum efficiency (ITU, 2020). Unlike its predecessors, 5G utilizes higher frequency bands, including millimeter waves (mmWave), which require the deployment of densely spaced base stations and small cells in urban environments to maintain signal strength and quality (Thakur & Chandel, 2020). This densification of infrastructure and the use of higher frequencies have raised concerns regarding increased exposure to electromagnetic fields (EMFs), especially in residential and workplace environments.

Numerous studies have investigated the potential biological and environmental implications of EMF exposure from mobile communication technologies. According to the International Commission on Non-Ionizing Radiation Protection (ICNIRP, 2020), the power density thresholds for public exposure must not exceed 10 W/m² in the frequency range used by 5G. Research by Nasim and Kim

(2019) employed computational modeling to estimate specific absorption rates (SAR) in human tissues due to mmWave exposure, revealing localized heating effects at higher frequencies. Similarly, Blackman and Forge (2019) highlighted the limited empirical data available for long-term human exposure to 5G-related EMF emissions, particularly in developing countries where infrastructure monitoring is lacking.

In Nigeria and many parts of sub-Saharan Africa, the deployment of 5G is still in its nascent stage. However, increasing pilot installations and growing public concerns have underscored the need for localized studies on EMF exposure. Most existing research has focused on developed countries with well-established regulatory and environmental monitoring frameworks. There is a significant gap in data concerning EMF levels in high-density areas of Nigerian cities where 5G infrastructure is being or will be deployed. Moreover, the impact of environmental factors such as building materials, terrain, and antenna height on power density distribution remains poorly understood in these local contexts.

This study aims to analyze the power density of electromagnetic fields generated by 5G base stations under various deployment scenarios in Umuahia, Abia State, Nigeria. By employing a modeling approach that incorporates different frequencies, distances, and environmental conditions, this research seeks to determine compliance with international safety standards and provide practical recommendations for deployment. The significance of this study lies in its potential to support evidence-based policy formulation, public health protection, and optimal infrastructure planning. It will provide baseline data for local regulators and help allay public fears by demonstrating the realistic extent of EMF exposure under various real-world conditions. Furthermore, it contributes to the global body of knowledge by offering insights from an underrepresented region in EMF exposure research.

2.0 Materials and Methods

To analyze the exposure, power density(P_D) radiated by a transmit antenna can be expressed as follows (Lucas and Mann 2022):

$$P_D = \frac{G_T P_T}{4\pi d^2} \tag{1}$$

where GT is transmitting antenna gain in dBi, PT is transmitting antenna power in dBm and d is the far-field distance. Far-field distance is defined as Fraunhofer distance and it can be expressed as follows.

$$d_{far\_field} = \frac{2D^2}{\lambda} \tag{2}$$

where D is the biggest dimension of the antenna and λ is the wavelength that corresponds to a frequency of manner (Tuovinen *et.al., (*2017).

Because of the hurt 5G networks could cause to the overall public, the partially averaged and spatial-peak similar power densities could be assessed as follows:

$$S = \frac{P_{avg} . G_{\theta,\varphi}}{4\pi r^2} \tag{3}$$

If the reflecting ground plane is present, the following equation can be used.

$$S = (1 + |\mathbb{\Gamma}|)^2 . \frac{P_{avg} . G_{\theta,\varphi}}{4\pi r^2} \tag{4}$$

For a theoretical highest field strength scenario of a perfectly conducting ground plane, $\mathbb{\Gamma} = 1$ or for typical ground reflection condition $|\mathbb{\Gamma}| = 0.6$ .To set up the 5G environment, cell radius was calculated by considering the path loss model and the link budget estimation. The free space reference distance (CI) path loss model was considered as a path loss model for this research. The path loss model was considered for the different environment scenarios in Umuahia, Abia State, Nigeria.

$$PL^{CI}(f,d)[dB] = FSPL(f,1m) + 10n log_{10}\left(\frac{d}{d_0}\right) + X_\sigma^{CI} \tag{5}$$

where f is the operating frequency in *Hz* and *d* is the distance between the transmitter and the mobile station in meters. Free space path loss(FSPL) for a frequency of *f* is given by:

$$FSPL(f,1m) = 20log_{10}\left(\frac{4\pi f}{c}\right) \tag{6}$$

Then CI path loss model can be rewritten as:

$$PL^{CI}(f,d)[dB] = 20log_{10}\left(\frac{4\pi f}{c}\right) + 10nlog_{10}\left(\frac{d}{d_0}\right) + X_\sigma^{CI} \quad (7)$$

X_σ^{CI} is the shadow fading (SF) in terms of dB. It is a zero-mean Gaussian random variable with a standard deviation σ in dB. The standard deviation of this random variable is:

$$\sigma^{CI} = \frac{\sqrt{\sum X_\sigma^{CI^2}}/N}{\sqrt{(PL^{CI} - FSPL - n10log10(d))/N}} \quad (8)$$

CI model parameters are different from one scenario to another and the following table 1 shows how those values are changing according to the scenarios.

The link budget of the 5G NR connection, can be calculated as follows. Here assume that the attenuation due to rain and fog is equal to the 0.

$$P_{Rx}[dBm] = EIRP[dBm] - PL^{CI} + G_{Rx} \quad (9)$$

P_{Rx} is the power received by the mobile station(the signal level at the receiver). G_{Rx} is the antenna gain in dBi of the mobile station and the effective isotropic radiation power (EIRP) can be calculated by:

$$EIRP[dBm] = P_{Tx} + G_{Tx} - L_{Tx} \quad (10)$$

Once the path loss is known, then it is possible to calculate the cell radius with the use of receiver sensitivity.

$$\text{Receiver Sensitivity(dBm)} = \text{Noise Fig. (dB)} + \text{Thermal Noise(dBm)} + \text{SINR(dB)} \quad (11)$$

To calculate the path loss, the link budget formula (10) can be used and the signal level at receiver P_{Rx} can be replaced with the receiver sensitivity.

$$PL^{CI} = EIRP(dBm) + G_{Rx} - Receiver\ Sensitivity\ (dBm) \quad (12)$$

By using the link budget Equation in (11) and considering the simulation parameters given in Table 1 the cell radius can be calculated for different scenarios. The required number of base stations for the selected area is determined after calculating the cell radius. The following equation can be used to calculate the coverage of a single base station over a square area.

$$Coverage\ Area = R^2\pi \quad (13)$$

After calculating the coverage area, the required number of 5G base stations can be determined as follows:

$$No.of\ 5G\ NodeB = \frac{S_q}{C_a} \quad (14)$$

where Sq is the total surface area of the cluster in a square area and Ca is a single gNB's coverage area.

For this calculation as an input parameter, transmitter power (EIRP) in Watts and operating frequency was used. The power density can be found by using the following formula:

$$S = (1 + |\Gamma|)^2 \frac{P_t}{4\pi r^2} \quad (15)$$

The minimum distance (R) between the transmitter and the general public can be calculated as:

$$R = \sqrt{\frac{P_t(1+|\Gamma|)^2}{4\pi S}} \quad (16)$$

where S is the power density in W/m^2, Pt is transmitter power that is specified in EIRP in Watts, R is the radius in meters that is measured from the middle of the antenna and $|\Gamma|$ is the self-examination coefficient. A self-examination coefficient ($|\Gamma|$) =0.6, in this place it is assumed that the minimum distance between the transmitter and the overall public is never shorter than the reactive adjacent the area of study boundary of the antenna. Reactive adjacent area of study boundary is calculated as ($\lambda/2\pi$), where λ is the wavelength in meters. To analyze the radiation in the 5G network power density assessment value of 10W/m^2 was used for frequencies ranging from 2 to 300GHz for the general public. The power density was calculated using the equation 17 By that EMF exposure can be analyzed with the exposure limit value.

$$S = \frac{P_T * G_T}{4\pi R^2} \quad (17)$$

where PT is the power of the transmitting antenna, GT is the gain of the transmitting antenna and R is the distance between the antenna and the general public. The antenna's power is measured in dBm, and its gain is measured in dBi. So, before putting the equation together, the power value must be converted into Watts. As a result, the following equations were used to convert power and gain values into Watt and linear values:

$$P(Watt) = \frac{10^{\frac{P(dBm)}{10}}}{1000} \quad (18)$$

$$G_T = 10^{\frac{G_T(dBi)}{10}} \quad (20)$$

According to above equations (17) -(19) power density was calculated by one transmitter and analyzed the performance of power density when increasing the distance in three different frequency bands 700MHz, 1800MHz, and 3.5GHz.

To perform a realistic simulation of electromagnetic field (EMF) exposure resulting from 5G deployment in Umuahia, Nigeria, several technical and environmental parameters were defined. These parameters were used to model signal propagation, calculate power density, estimate cell radius, and determine the required number of base stations for effective coverage. Table 1 presents the simulation parameters adopted for the modeling process, including key variables such as transmission frequency, power levels, antenna gain, receiver sensitivity, and reflection coefficients. These values serve as inputs in the quantitative equations applied to assess the spatial distribution of EMF power density and ensure compliance with international exposure limits.

Table1: Simulation parameters

Parameter	Values
Frequency (f)	3.5GHz
Max EIRP	41dBm
Antenna Gain (GTx)	6dBi
Transmission Power (PTx)	35dBm
Receiver Antenna Gain (GRx)	0 dBi
Receiver Sensitivity	-78
BS Antenna Hight	6m
Maximum Transmission time	6 minutes
Power density	10W/m2
Reflection Coefficient (Γ)	0.6

3.0 Results and Discussion

By utilizing Equation (13), coverage place by one transmitter was calculated by taking into account the Uma-NLOS scenario.As per the scenario, the cell radius is 198m and the coverage place by one transmitter is 0 .123km^2. If we believe that we're planning a 5G contacts for the 1km x 1km square place, by utilizing Equation (14), number of demanded transmitters might be calculated. So, as specified by the calculation number of transmitter antennas to protect the 1km^2 is 8. Micro bottom station replication limits in the board (1) were utilized for the overhead calculation with a 3.5GHz frequency, and the bottom station antenna height is 6m.

As a consequence of, this bottom station antenna covers 0.123km^2, while a 1 km^2 square place needs 8 antennas functioning at 3.5GHz. The power density was calculated by utilizing Equations (17)-(19) and power density effectiveness was analyzed when growing the distance. An examination of power density efficiency was carried out up to 10 meters.

Fig. 1 shows the Power density versus distance when f=700MHz.

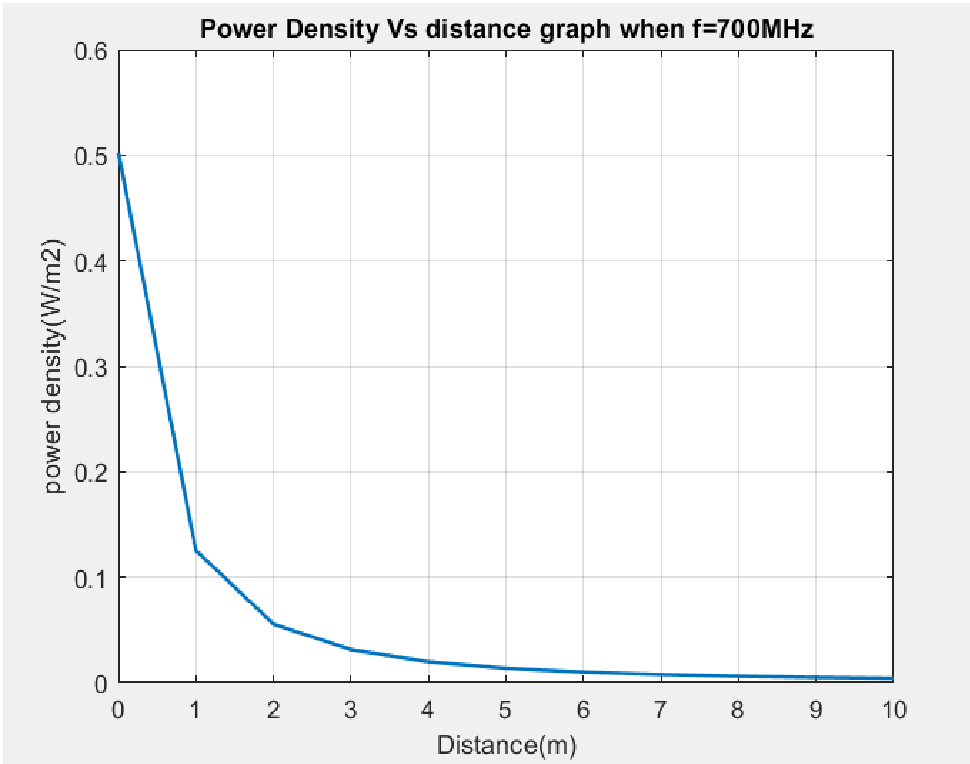

Fig. 1: Power density versus distance when f=700MHz

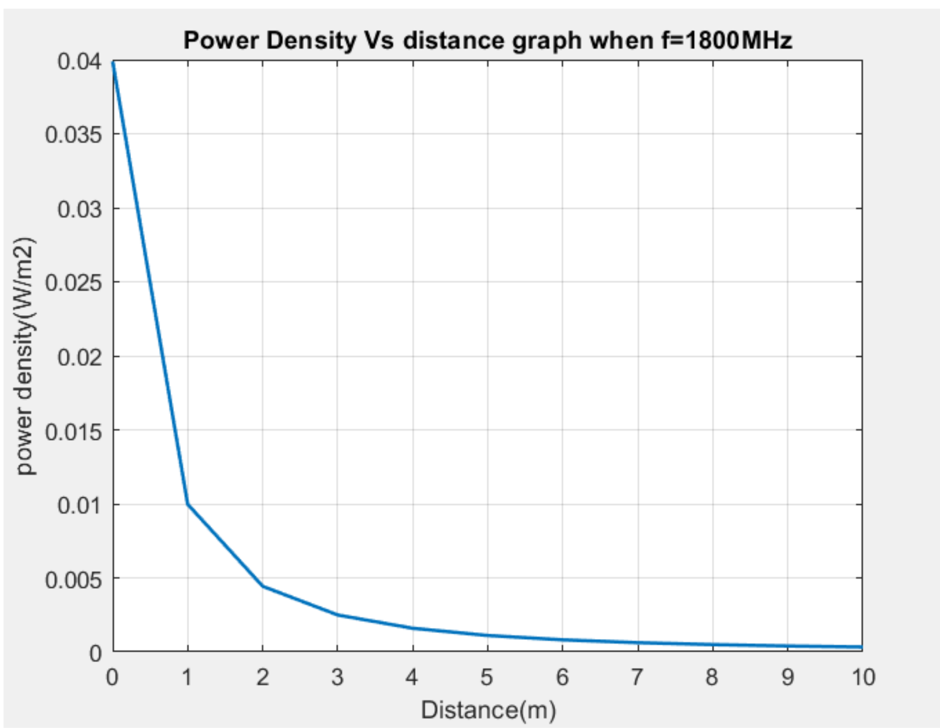

Fig. 2 shows the Power density versus distance when f=1800MHz

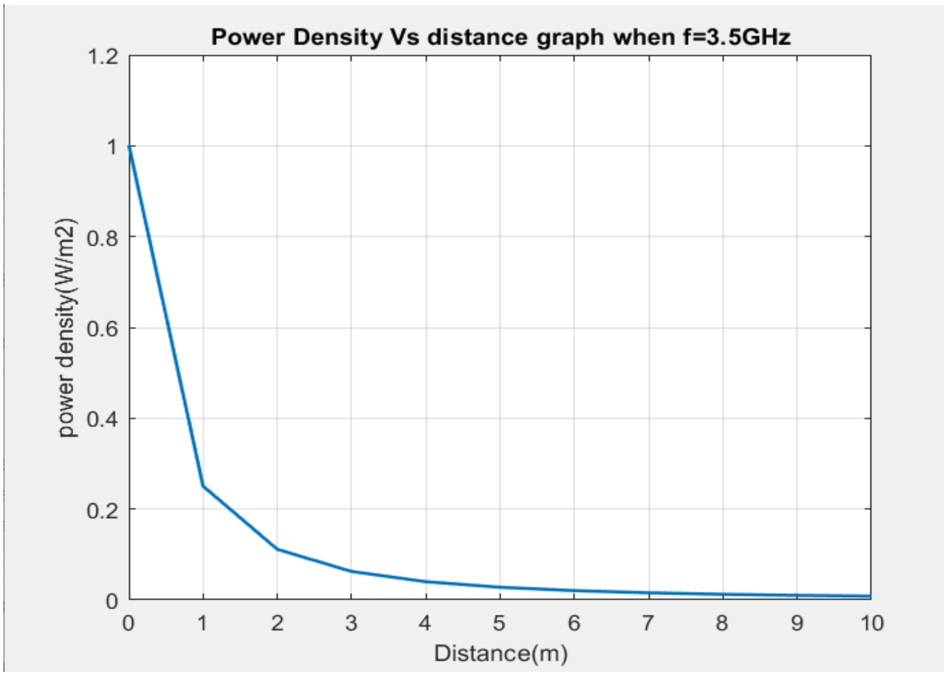

Fig. 3: Power density Vs Distance when f=3.5GHz

Figs. 1, 2 and 3 illustrate the alterations in power density with three distinct frequencies beyond range of 0 to 10 meters. When taking into account the 700MHz, at the beginning point power density is 0.5W/m^2 and when the distance is augmenting, power density information are decreasing, the power density worth for the overall public must be less than 10W/m^2. At all three frequencies, beginning power density worth is less than 10W/m^2 and when the distance is booming, power density worth is decreasing and it's going to zilch. 5G links planning was done for the frequency 3.5GHz and as per that frequency corresponding power density at 1 meter is 1W/m^2. When the person is in the cell radius(R) distance that is 198 m, by utilizing Equations (17) -(19), the power density is3x10-5W/m^2. The highest power density must be 10W/m^2, but sometimes, when an individual is in the cell radius distance of a deployed 5G links, the power density is tiny. The power density worth diminishes as the distance increases. As a consequence of, when the person is within the cell radius distance, the power density is tiny. If the person is at similar distance (R) from each transmitter and the transmitters have similar replication limits, the add up total potential of the power might be calculated as:

$$= 3 \times 10^{-5} * 3 = 9 \times 10^{-5} W/m^2$$

As per the overhead power density worth, the person's cell radius distance from the three transmitters with the frequency 3.5GHz is tiny. That intends if the person is far absent from the transmitters, there exist less EMF vulnerability. So, minimum distance must be calculated from the bottom station to the overall public and overhead the minimum distance that is 0.8m, It is said that the EMF vulnerability is low.

The effectiveness of power density with distance was analyzed for indoor hotspots, compact urban, and urban micro scenarios. For the indoor hotspot 3.5GHz and 26GHz frequency bands have been utilized and analyzed the efficiency. These transmitter powers are not just limited to one transmitter. For an indoor hotspot with the frequency 3.5GHz, compact urban, micro, and micro replication transmitter antenna power is for four transmitters and an indoor hotspot with the frequency 26GHz is for two transmitters.

Fig. 4 shows Power density Vs Distance for typical indoor hotspot when f=3.5GHz.

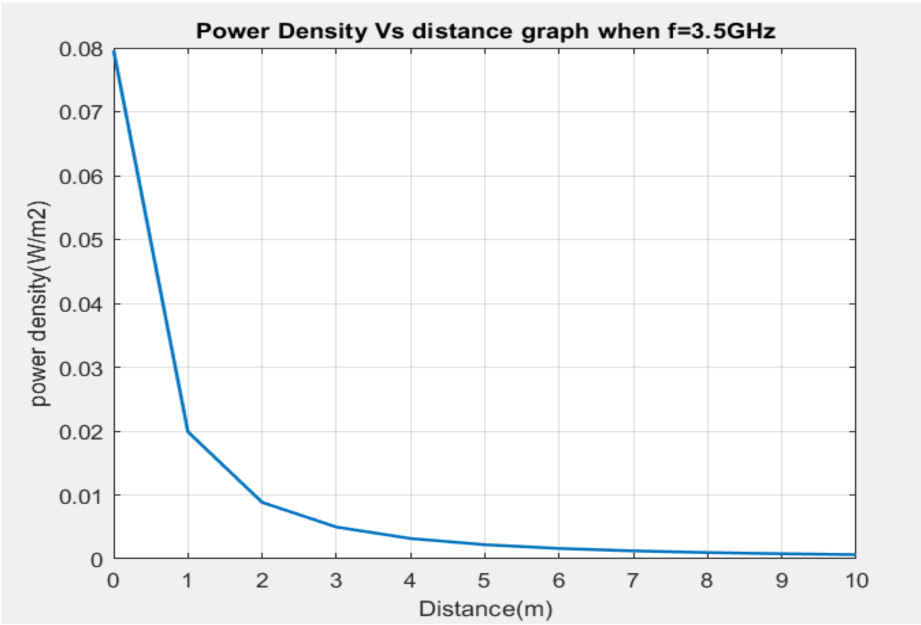

Fig. 4: Power density Vs Distance for typical indoor hotspot when f=3.5GHz

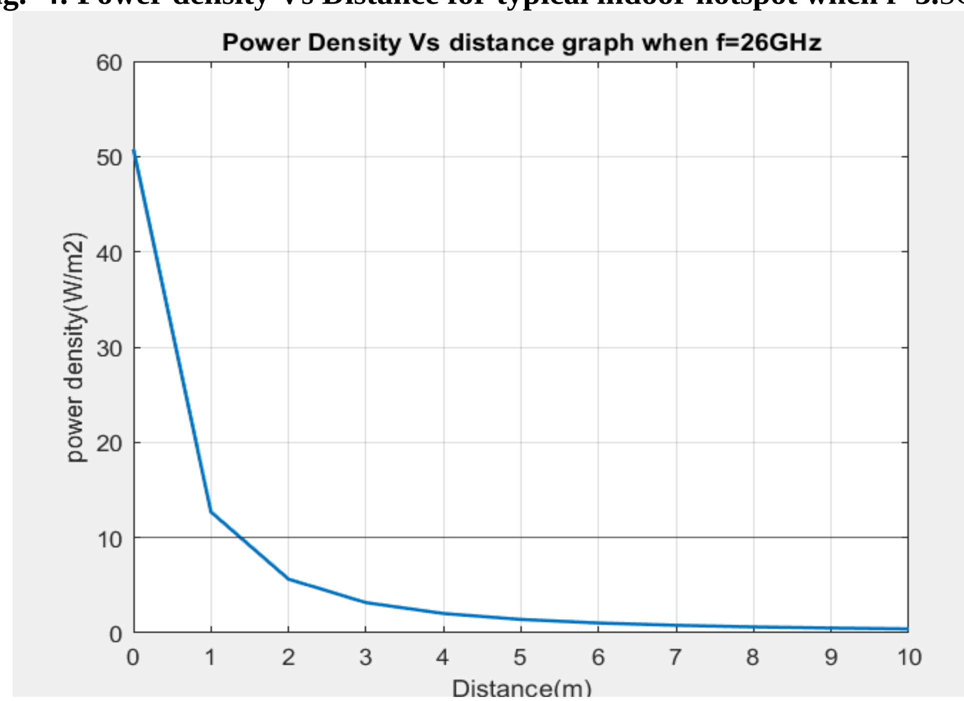

Fig. 5: Power density Vs Distance for typical indoor hotspot when f=26GHz

As specified by the outcomes in the compact urban place at the frequency 3.5GHz, it could be seen that as reported by the rule and guidelines, the minimum distance between the transmitter and the overall public is 0. 3m. In this allotment, gazing upon the EMF vulnerability assessment from a single transmitter. but sometimes, when the replication outcomes of an ordinary 5G connections in a compact urban place are considered, this distance is 0.9m. But sometimesin this scenario, the transmitter power is for four transmitters, and the minimum distance is 0.9m.As per the guidelines,it is considered highest power data and it illustrates the worse cases.

So, virtually to prevail against this minimum distance from the overall public, the transmitters might be placed in towers, poles, roof-mounted structures, or as diminutive cells offering localized coverage. Because as specified by Fig. s 4 and 5, when the overall public is movedfar from the transmitter, the vulnerability is decreasing. These bottom station transmitters typically control at lower power than in these worse cases. Additionally, before deploying the associations, this minimum distance ought to be calculated and these areas of interest must be provided as a confined place that the overall public cannot enter There must be a consideration for a minimum distance to play down vulnerability when the transmitters are co-located, and elevated towers or buildings could be utilized to play down this. The overall public must be kept indeed 2.2 meters absent from the transmitter, as per the replication outcomes. In this replication, only three frequency bands were utilized: 700MHz, 1800MHz, and 3.5GHz. So, if various associations operators use similar tower for transmission, they have to contemplate the EMF vulnerability from the tower to the overall public and decide the minimum distance before deploying the contacts.

4.0 Conclusion

The review revealed that the integration of modern technologies such as remote sensing, artificial intelligence (AI), and mechanized operations significantly enhances the efficiency, precision, and sustainability of forest management practices. Remote sensing technologies, including satellite imagery, UAVs, and LiDAR, offer scalable and accurate forest monitoring capabilities, enabling better estimation of forest cover, biomass, and health. AI tools like machine learning and deep learning models improve species classification, disease detection, and growth prediction, contributing to timely and data-driven decision-making. Mechanized operations, when guided by geospatial data, reduce labor intensity, optimize resource use, and minimize environmental impacts such as soil compaction and fuel consumption. Case studies from Finland, Brazil, Canada, Sweden, and Indonesia demonstrate measurable improvements in carbon monitoring, deforestation control, and operational efficiency through these innovations.

In conclusion, the implementation of precision forestry technologies fosters more adaptive, transparent, and sustainable forest governance. However, challenges such as high initial investment costs, the need for reliable digital infrastructure, and regulatory and policy gaps in developing regions must be addressed to ensure equitable adoption.

It is recommended that future efforts focus on developing cost-effective and scalable tools, strengthening infrastructure in rural and forested areas, and promoting policy frameworks that encourage innovation. Integrating blockchain for traceability, deploying autonomous forest robots, and expanding AI-powered mobile applications for forest workers can further accelerate global adoption and impact.

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Declaration

Consent for publication

Not applicable

Availability of data

Data shall be made available on demand.

Competing interests

The authors declared no conflict of interest

Ethical Consideration

Not applicable

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Authors' Contribution

Chibuisi Iroegbu conceptualized the study, developed the modeling framework, and led the data analysis. Enefiok A. Etuk contributed to simulation design, coding, and result interpretation. Charles Efe Osodeke supported literature review, compiled references, and assisted in manuscript drafting. All authors reviewed the final manuscript and contributed to the discussion on electromagnetic field exposure from 5G infrastructure.