# The First Pathloss Radio Map Prediction Challenge

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**Çağkan Yapar (TUB)**, Fabian Jaensch (TUB), Ron Levie (Technion), Gitta Kutyniok (LMU, UiT), Giuseppe Caire (TUB)

# Overview

- Introduction, problem setting
- Challenge task
- Training dataset
- Challenge results

# Introduction - Pathloss

- Radio maps are representations of quantities of interest for wireless communications applications, in a fine spatial grid. One important quantity of interest is the so-called **pathloss.**
- The **pathloss** (or **large-scale fading coefficient**), quantifies the loss of wireless signal strength between a transmitter (Tx) and receiver (Rx) due to large scale effects.
- By many factors, such as free-space propagation loss, penetration, reflection and diffraction losses by obstacles like buildings and cars in the environment.
- In dB scale, pathloss amounts to $\mathrm{P_L} = (\mathrm{P_{Rx}})_{\mathrm{dB}} - (\mathrm{P_{Tx}})_{\mathrm{dB}}$, where $\mathrm{P_{Tx}}$ and $\mathrm{P_{Rx}}$ denote the transmitted and received locally averaged (over multipath, small-scale phenomena) power (also called Received Signal Strength - RSS) at the Tx and Rx locations, respectively. **Path gain** (perhaps more accurately), **gain**, **channel strength** or **large scale fading coefficient** are also frequently used for the same quantity.

# Introduction - Pathloss prediction

- Many applications in wireless communication: device-to-device (D2D) link scheduling, user-cell site association, physical-layer security, power control in multi-cell massive MIMO systems, user pairing in MIMO-NOMA systems, precoding in multi-cell large scale antenna systems, path planning, and activity detection, and fingerprinting-based localization methods where the fingerprint is the signal strength (RSS) from different “anchor” infrastructure nodes (e.g., base stations or access points).

- The traditional approach to obtaining pathloss radio maps is through **measurement campaigns**, which are **very costly and difficult to achieve on a fine grid.** The alternative approach of **accurate computer simulations** (assuming the availability of an accurate geometric description of the environment, e.g. the buildings), **such as ray tracing/launching**, require **high computational times**, making it also unsuitable for many applications.

- Many recent works employed **supervised deep neural networks** to learn such accurate propagation models, and provide **much shorter run-times**.

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# Pathloss statistical modeling

- For given environment type (dense urban, sub-urban, rural, etc.) large number of pathloss measurements are collected.
- The collected measurements are assigned to the distance between Tx and Rx.
- The data are fitted with a piecewise linear model in the doubly logarithmic scale (pathloss exponent model) $P_L = \alpha \log_{10}(d) + \kappa$, where $d$ is the distance between Tx and Rx, $\alpha$ is the pathloss exponent, and $\kappa$ is a constant that depends on the geometry. $\alpha$ and $\kappa$ take different definitions depending on distance ranges (piecewise linear).
- The spread of the data around the piecewise linear curve is modeled as Gaussian in the log domain, introducing the log-normal **shadowing** random variable $\eta$: $P_L = \alpha \log_{10}(d) + \kappa + \eta$.

# Pathloss statistical modeling

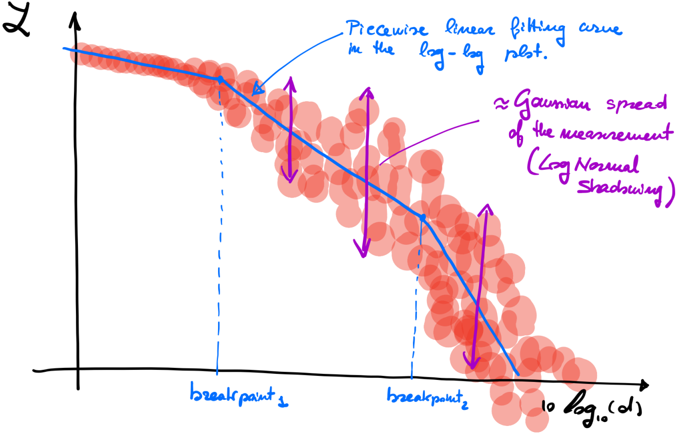
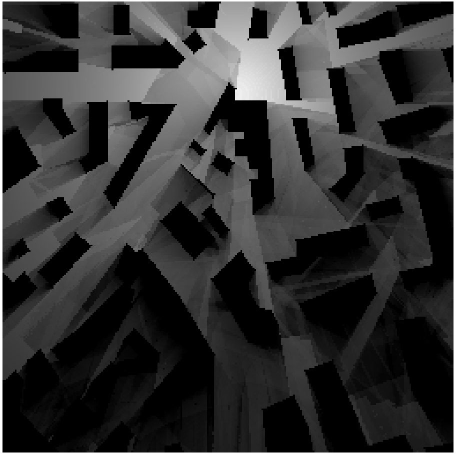



Figure: Courtesy of Giuseppe Caire

# Pathloss radio map in an urban environment



# Pathloss in an urban environment

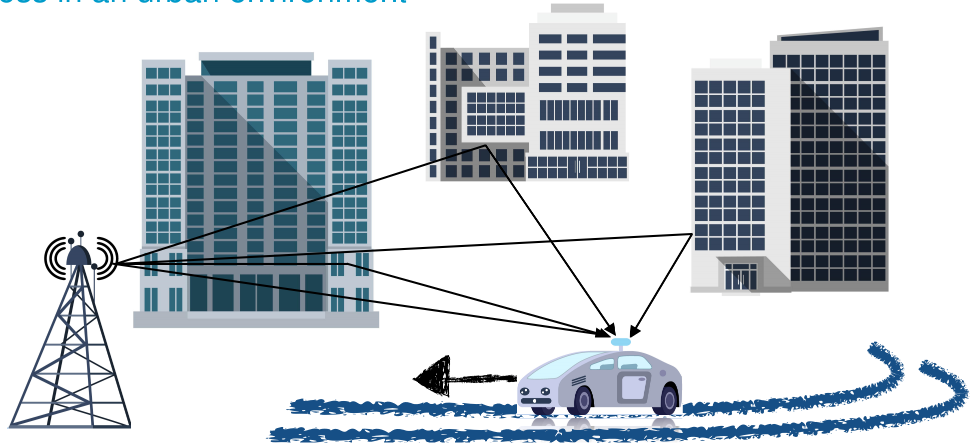


Figure: The used figures are designed by macrovector / Freepik.

# Challenge Task

- The task of the challenge was to **predict the pathloss radio map given the city map and the transmitter location**, i.e., the same task and input setting of deterministic simulation methods like ray tracing.

- The participants were allowed to design their input features (i.e. pre-processing) freely, as long as the **test run-time** of the proposed method was **orders of magnitude lower than the pathloss simulation by the ray tracing software.**

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# Training Dataset - RadioMap3DSeer

- Simulations by **WinProp from Altair [1]**, on a dataset of urban environments (city maps).
- The high accuracy of this propagation modeling software was demonstrated by field measurements in many cities such as Helsinki, Munich, Nancy, Stuttgart, and Hong Kong. Such simulation software are frequently used by e.g. cell operators, proving their efficiency.
- 701 city maps of size 256 $\times$ 256 square meters, which were fetched from **OpenStreetMap** from the cities Ankara, Berlin, Glasgow, Ljubljana, London, and Tel Aviv.
- 80 transmitter locations per map (amounting to a total of 56080 simulations).
- **Rooftop (3D/2.5D) simulations**: Tx located on the rooftops of the buildings, i.e., base-station setting.

[1] R. Hoppe, G. Wölfle, and U. Jakobus,"Wave propagation and radio network planning software WinProp added to the electromagnetic solver package FEKO",Proc. Int. Appl. Computational Electromagnetics Society Symp. - Italy (ACES), Florence, Italy, March 2017, pp. 1–2.



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# Training Dataset - RadioMap3DSeer (Cont.)

- Each building in a city map was assigned a height which lies between 2 to 6 stories (a story corresponding to 3.3m). This range of 13.2m (from the minimum of 6.6 meters to the maximum of 19.8m) was divided into 255 equal length levels and building heights were found by picking one of these levels uniformly.
- All simulations were saved with a resolution of 1m per pixel, as `.png` images.
- Building images with encoded height as gray levels are provided, along with the corresponding polygons (2.5D) in `.json` format.
- Transmitters were generated on the buildings which have a height of at least 5 stories (16.5m). The transmitters were placed close to the edges to reflect the realistic deployment. The transmitter height from the rooftop is set to 3m. The Tx were restricted to be positioned within the $150 \times 150$ area in the center of the $256 \times 256$ city map when possible (otherwise $230 \times 230$).

# Simulation Method - Intelligent Ray Tracing (IRT)

– The environment is discretized and visibility relations among the elements are calculated as a pre-processing step, which can be re-used for each possible Tx deployment for a given environment.

– The maximum number of ray interactions is set by the user. In RadioMap3DSeer it was set to 2.

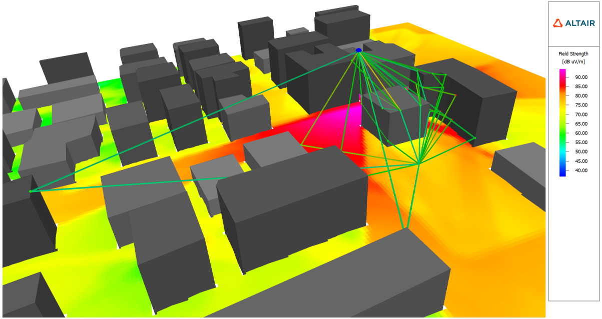
– Another parameter of the IRT simulations that affects the fineness of the reflection patterns is the length of the segments/tiles of the objects (buildings and cars in our datasets). We set this as 10m in our dataset.

– All buildings were assumed to have the same generic material property.

– More details about the dataset can be found in our dataset paper [2].

[2] Ç. Yapar, R. Levie, G. Kutyniok, and G. Caire, "Dataset of Pathloss and ToA Radio Maps with Localization Application", 2022, arxiv.org/abs/2212.11777

# An Example Simulation From the RadioMap3DSeer Dataset



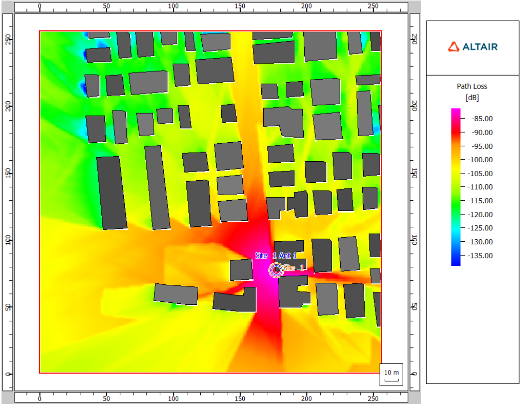




Figure: A simulated map from the dataset. The rays arriving at a chosen pixel are shown. Tx mounted on the rooftop of a high building.

# An Example Simulation From the 3D (2.5D) Dataset (Cont.)

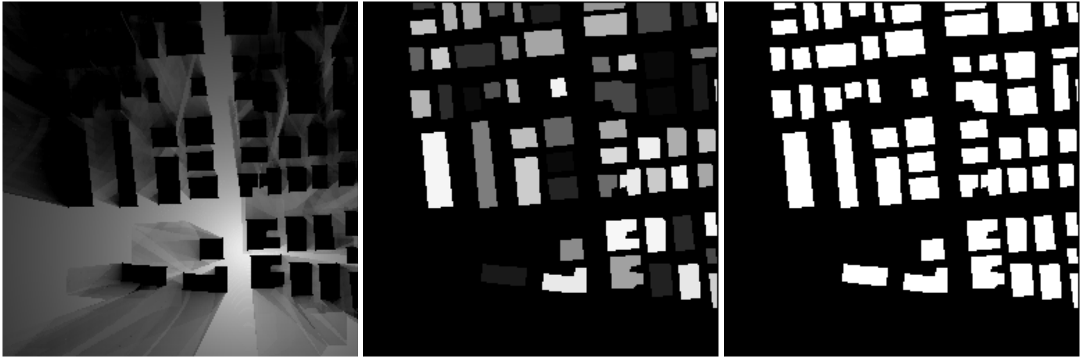


Figure: Example images from the 3D dataset. In **(b)**, the building heights are encoded in the gray shade of the polygons with lower (resp., higher) corresponding to darker (resp. lighter) shades.

# Baseline Method: RadioUNet [3]

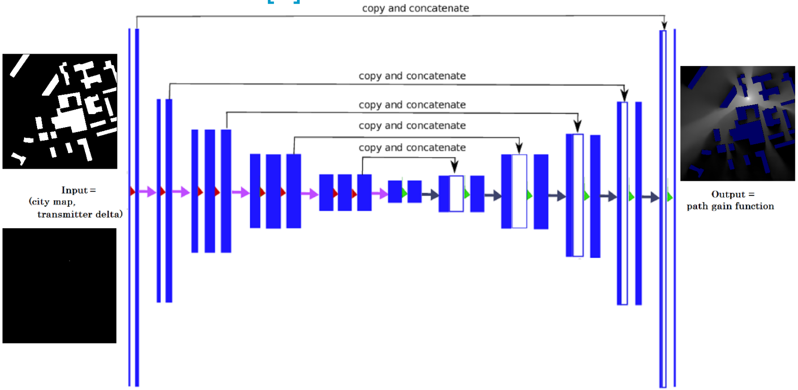
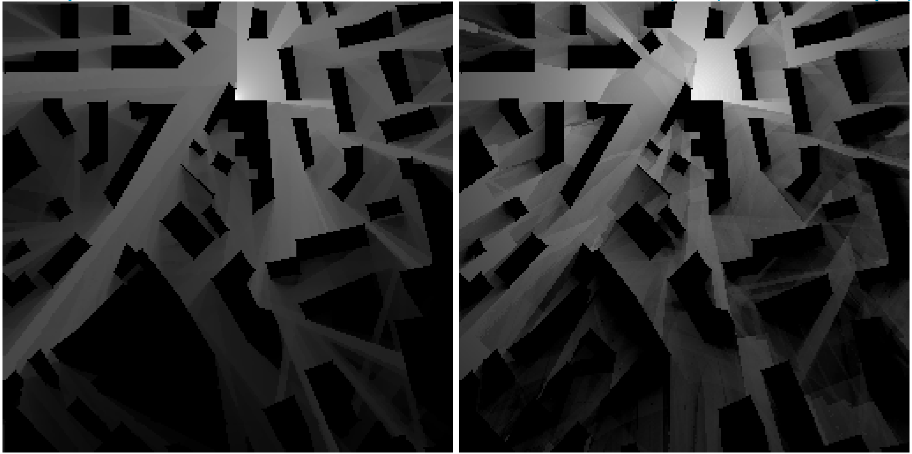



Figure: Courtesy of Ron Levie

[3] R. Levie, Ç. Yapar, G. Kutyniok, and G. Caire, "RadioUNet: Fast radio map estimation with convolutional neural networks", IEEE Trans. Wireless. Comm., 2021.

# Pathloss map in an urban environment - Ground level (2D) vs Rooftop (2.5D)



# Learning 2.5D radio maps

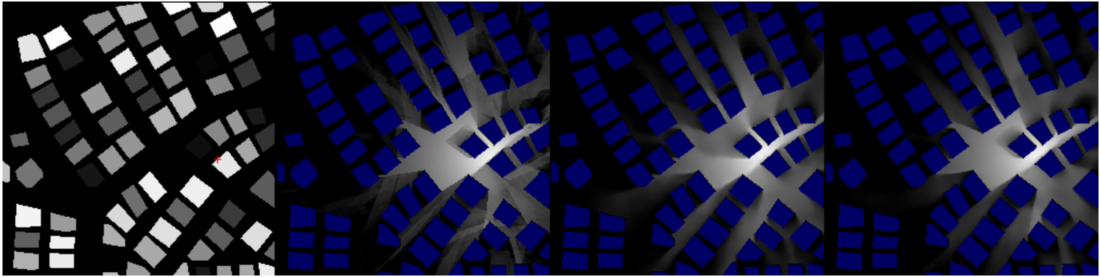


Figure: From left to right: The height-encoded city map and the Tx location (red plus sign), ground truth, and the radio map predictions by the naive and the 3D adapted RadioUNet [3] variants, cf. [2] for details.

[2] Ç. Yapar, R. Levie, G. Kutyniok, and G. Caire,"Dataset of Pathloss and ToA Radio Maps with Localization Application", 2022, arxiv.org/abs/2212.11777
[3] R. Levie, Ç. Yapar, G. Kutyniok, and G. Caire, "RadioUNet: Fast radio map estimation with convolutional neural networks", IEEE Trans. Wireless. Comm., 2021.

# Evaluation Methodology

The accuracy was evaluated by the root mean square error

$$\mathrm{RMSE} = \sqrt{\frac{1}{|\mathcal{T}|}\sum_{n\in\mathcal{T}} \mathrm{RMSE}(n)^2}$$

where $\mathcal{T}$ is the test set and $\mathrm{RMSE}(n)$ is the RMSE for the radio map $n$, defined as

$$\mathrm{RMSE}(n) = \sqrt{\frac{1}{RC}\sum_{i=1}^{R}\sum_{j=1}^{C}\left(\tilde{\mathrm{P}}_{\mathrm{L}}^{(n)}(i,j) - \mathrm{P}_{\mathrm{L}}^{(n)}(i,j)\right)^2}$$

where $\tilde{\mathrm{P}}_{\mathrm{L}}^{(n)}$ and $\mathrm{P}_{\mathrm{L}}^{(n)}$ are the predicted and the ground truth radio maps, $R$ and $C$ are the number of rows and columns in a radio map image ($R = C = 256$ in our dataset), respectively.

While evaluating the prediction performance of the submitted methods, the pixels of the radio map predictions known to be occupied by the buildings was set to zero, i.e., given that the ground truth value at such pixels is zero, the prediction error was guaranteed to be zero for such pixels.

# Test dataset

- A test dataset which was not published before was prepared for evaluation.
- The same dataset generation procedure and simulation parameters were used as for the training dataset - RadioMap3DSeer.
- 84 city maps of size 256×256 were obtained from **OpenStreetMap** (`https://OpenStreetMap.org/`) in Istanbul, resulting in 6720 simulations.
- The participants were asked to submit their radio map predictions for the challenge test set (which was sent them without the ground truth) along with the trained models and the code that runs the evaluation.

# Challenge results - Examples from the test set

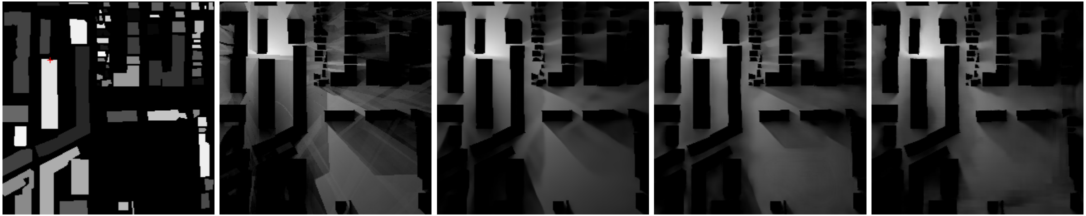


Figure: Examples from the test set. **From left to right: 1)** Height-encoded city map (the brighter the pixel, the higher is the building. Tx location is shown with a red plus sign), **2)** Ground truth simulation, **3,4,5)** Predictions of the successful methods: PMNet [4], Agile [5], PPNet [6].

[4] J.-H. Lee, J. Lee, S.-H. Lee, and A. F. Molisch, "PMNet: Large-scale channel prediction system for ICASSP 2023 First Pathloss Radio Map Prediction Challenge", in Proc. IEEE Int. Conf. on Acoustics, Speech and Signal Processing (ICASSP), 2023.

[5] E. Krijestorac, H. Sallouha, S. Sarkar, and D. Cabric, "Agile radio map prediction using deep learning", in Proc. IEEE Int. Conf. on Acoustics, Speech and Signal Processing (ICASSP), 2023.

[6] K. Qiu, S. Bakirtzis, H. Song, I. Wassell, and J. Zhang, "Deep learning-based path loss prediction for outdoor wireless communication systems", in Proc. IEEE Int. Conf. on Acoustics, Speech and Signal Processing (ICASSP), 2023.

# Challenge Results

| Method | RMSE |
|---|---|
| PPNet [6] | 0.0507 |
| Agile (MSE) [5] | 0.0514 |
| Agile (MSE, LoS) [5] | 0.0461 |
| Agile (KL, LoS) [5] | 0.0451 |
| PMNet (w/ Fine Tuning) [4] | 0.0959 |
| PMNet (w/ Data Aug.) [4] | 0.0633 |
| PMNet ($\frac{H}{8} \times \frac{W}{8}$) [4] | **0.0383** |

- Based on our evaluations and the declarations of the participants, a large degradation of performance of all the submitted methods on the test set is observed (with respect to testing on a hold-out subset of *RadioMap3DSeer*).
- All participants reported run-times of about $\sim$10 ms.

[4] J.-H. Lee, J. Lee, S.-H. Lee, and A. F. Molisch, "PMNet: Large-scale channel prediction system for ICASSP 2023 First Pathloss Radio Map Prediction Challenge", in Proc. IEEE Int. Conf. on Acoustics, Speech and Signal Processing (ICASSP), 2023.

[5] E. Krijestorac, H. Sallouha, S. Sarkar, and D. Cabric, "Agile radio map prediction using deep learning", in Proc. IEEE Int. Conf. on Acoustics, Speech and Signal Processing (ICASSP), 2023.

[6] K. Qiu, S. Bakirtzis, H. Song, I. Wassell, and J. Zhang, "Deep learning-based path loss prediction for outdoor wireless communication systems", in Proc. IEEE Int. Conf. on Acoustics, Speech and Signal Processing (ICASSP), 2023.

# Thank you!

# Questions?

# References


- **SP Grand Challenge** at **ICASSP 2023:** "The First Pathloss Radio Map Prediction Challenge" `https://RadioMapChallenge.GitHub.io/`
- **Dataset:** "Dataset of Pathloss and ToA Radio Maps with Localization Application" on **arXiv:** `https://arxiv.org/abs/2212.11777` on **IEEE DataPort:** `dx.doi.org/10.21227/0gtx-6v30`
- E. Krijestorac, H. Sallouha, S. Sarkar, and D. Cabric, "Agile radio map prediction using deep learning", in Proc. IEEE Int. Conf. on Acoustics, Speech and Signal Processing (ICASSP), 2023.
- K. Qiu, S. Bakirtzis, H. Song, I. Wassell, and J. Zhang, "Deep learning-based path loss prediction for outdoor wireless communication systems", in Proc. IEEE Int. Conf. on Acoustics, Speech and Signal Processing (ICASSP), 2023.
- J.-H. Lee, J. Lee, S.-H. Lee, and A. F. Molisch, "PMNet: Large-scale channel prediction system for ICASSP 2023 First Pathloss Radio Map Prediction Challenge", in Proc. IEEE Int. Conf. on Acoustics, Speech and Signal Processing (ICASSP), 2023.