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# *Learning from the Sky: Autonomous Flying access Networks for Beyond 5G*

*David Gesbert (EURECOM, France)*

***Keynote Speech***

***European Wireless Conference, May 2018, Catania***

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# Why flying access networks?

- **Drone-as-a-relay, Drone-as-a-base station (≠ Drone-as-a-terminal)**
- **Flexibly adapts to time-varying channel conditions and traffic patterns**
- **Maintains good connectivity to *both infrastructure and ground users***

**DaaR**

**Hot-spots, sport events, flashcrowds**

**DaaR**

**Range extension**
**Disaster recovery**

**DaaB**

**IoT data harvesting, smart city, agriculture, caching**

# Yet.. no lack of issues ☺

- **Regulatory**
  - **Safety (for autonomous flight), privacy**
- **Operational**
  - **Max payload weight, battery autonomy, density of UAVs**
- **Robotics**
  - **Navigation control**
  - **Packaging (esp. micro-drone)**
- **RF design**
  - **antenna design, RF coupling issues**
- **Networking**
  - **Handover**
  - **Intermittent connectivity**
  - ***interference issues***
- ***UAV (self-)Placement***

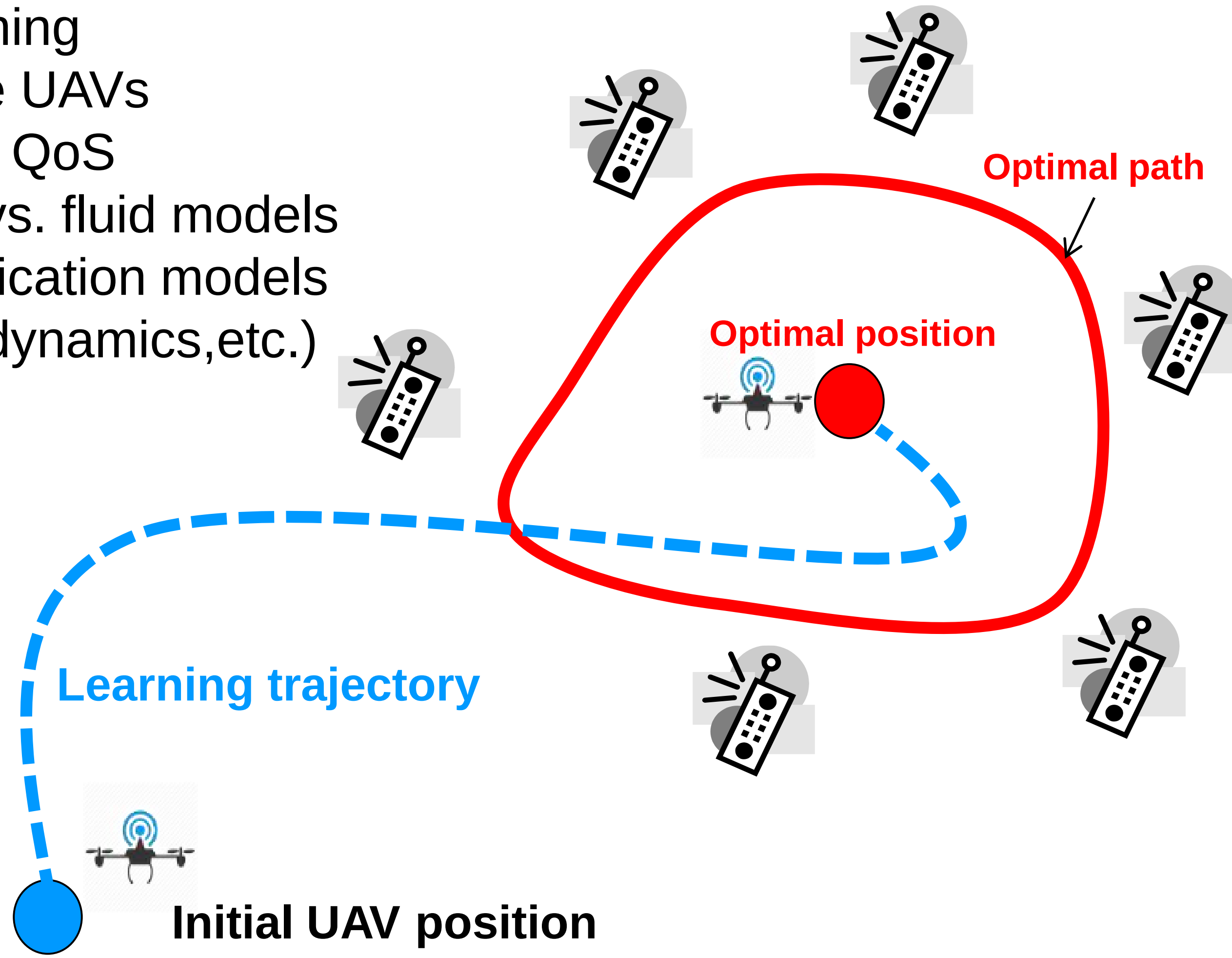
# Outline

- **Introduction to placement problems**
- Channel prediction
- Learning maps
- Using maps for UAV placement
- Perspectives

# Placement-related problems

- Optimal position vs. path planning
- Off line vs. on line learning
- Single UAV vs. multiple UAVs
- Max throughput vs. fair QoS
- Finite user population vs. fluid models
- Mixed robotic-communication models

(power usage, trajectory dynamics,etc.)

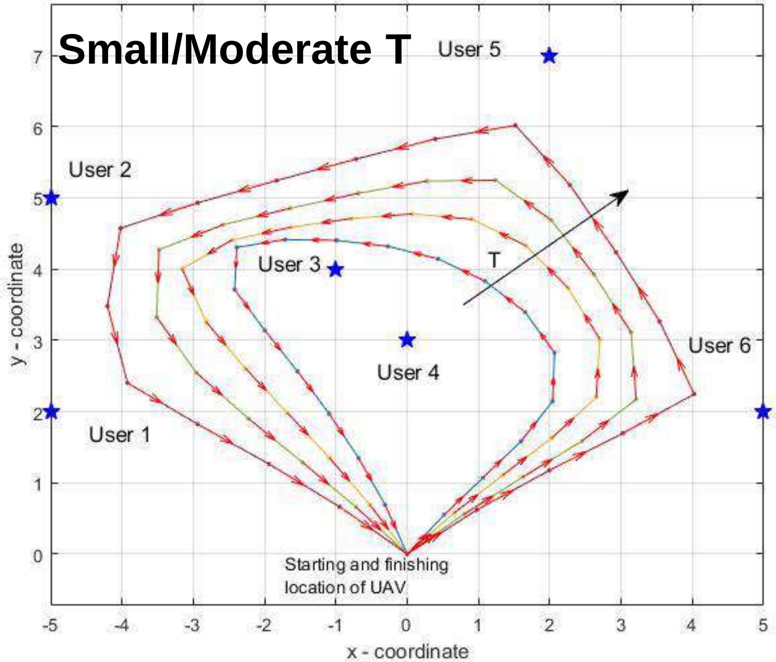


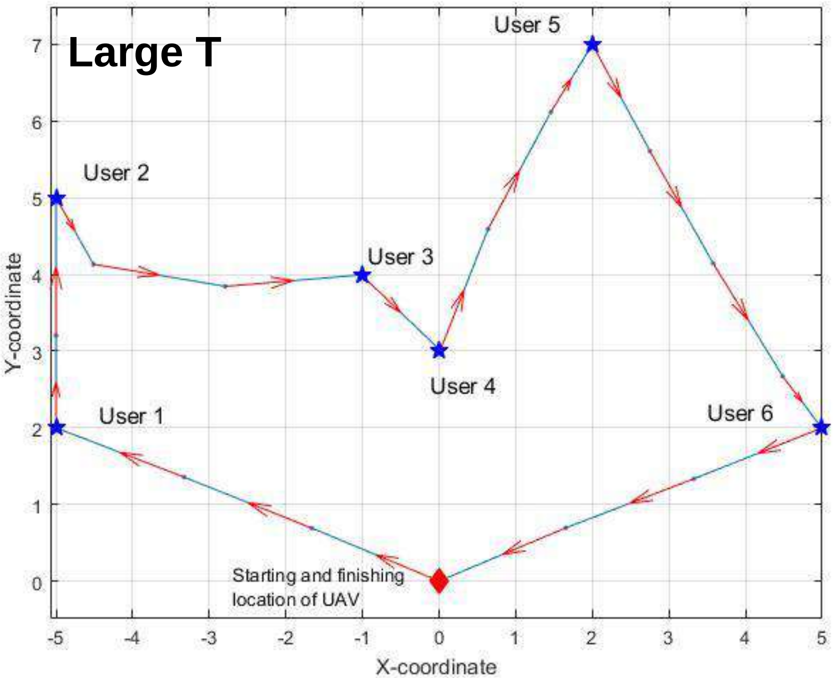
# Path planning (IoT scenario)

$$\max_{x(t),y(t)} \; min\left\{\int_{t=0}^{T} R_1(t)dt\,,\int_{t=0}^{T} R_2(t)dt\,\ldots,\int_{t=0}^{T} R_K(t)dt\right\}$$ **(Max-min rate)**

**Subject to** $\sqrt{\dot{x}(t)^2+\dot{y}(t)^2} \le V\,, t \in [0,T]$ **(Velocity Constraint)**

$x(0)=x_o, y(0)=y_o, x(T)=x_F, y(T)=y_F$ **(Start and end location)**



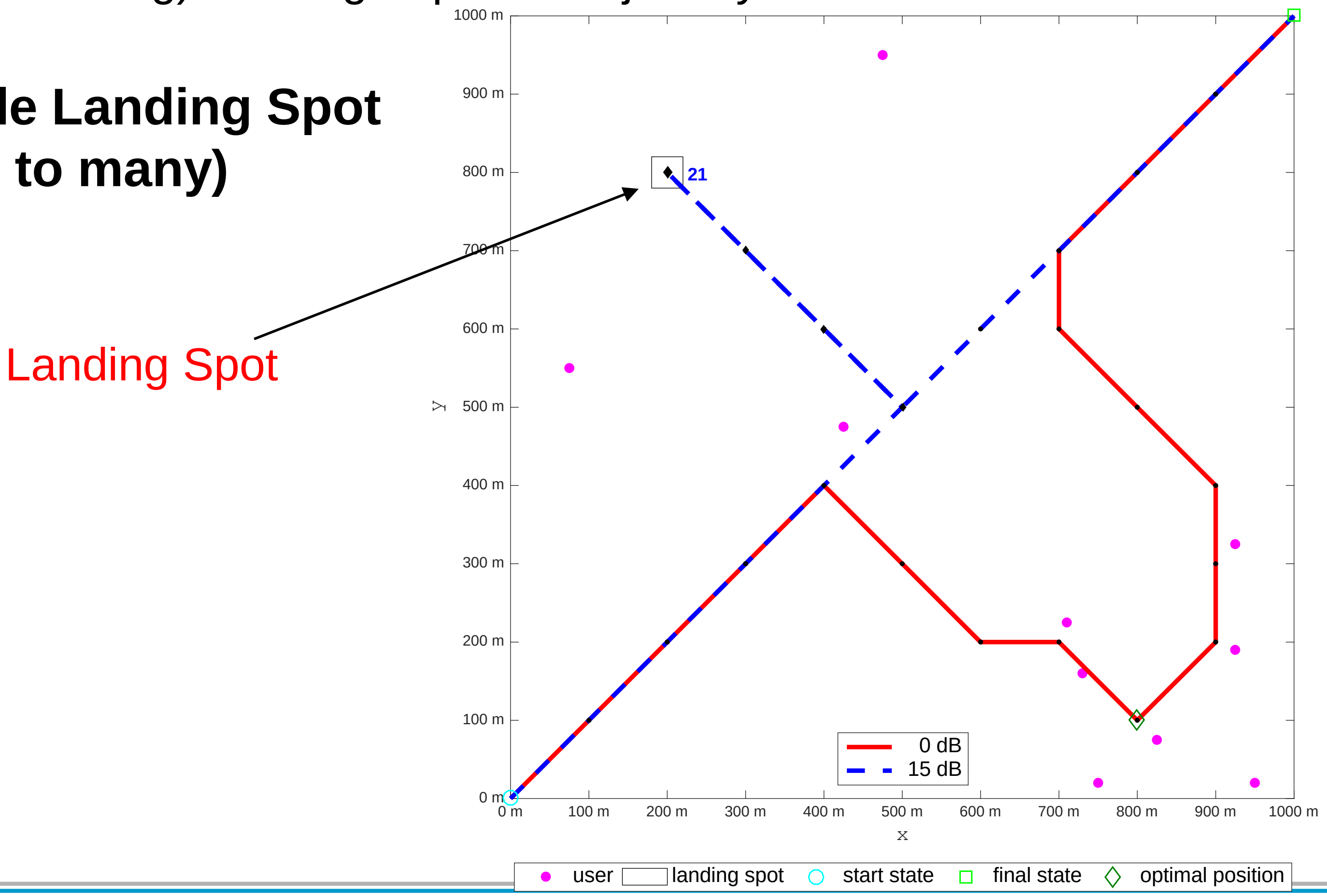




[1] R.Gangula, D.Gesbert, et.al “Trajectory Optimization for Mobile Access Point” Accepted in Asilomar 2017.
[2]A. T. Klesh, P. T. Kabamba, and A. R. Girard, “Path planning for cooperative time-optimal information collection,” in American Control Conference, June 2008, pp. 1991–1996.
[3] Q. Wu, Y. Zeng, and R. Zhang, “Joint Trajectory and Communication Design for UAV-Enabled Multiple Access,” , Apr. 2017.

# IoT Path planning with “Landing Spots”

- Goal: mitigate the UAV autonomy problem
- Introducing concept of Landing Spot akin to bird’s restspot
- Use DP (or maching learning) to design optimal trajectory

**Example with single Landing Spot (easily generalizes to many)**




[Gangula et al, ICC18 Workshop on UAVs]

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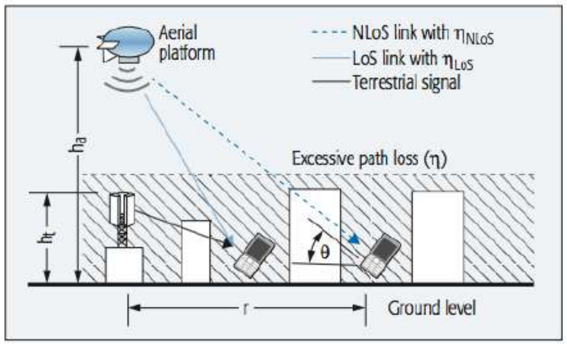
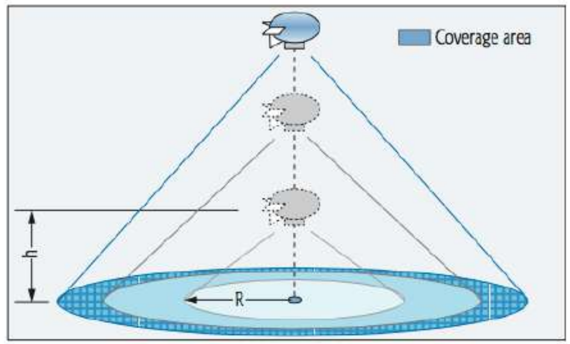
# Channel prediction

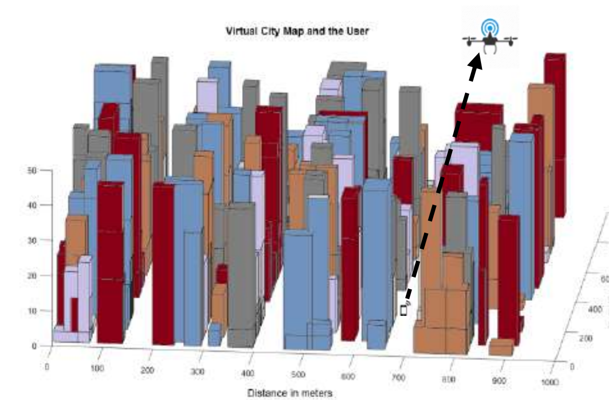
- **Probabilistic (LoS) prediction**
  - Ex: LoS probability model $$\mathbf{P}(\text{LoS},\theta) = \frac{1}{1 + a\exp\left(-b[\theta - a]\right)}$$

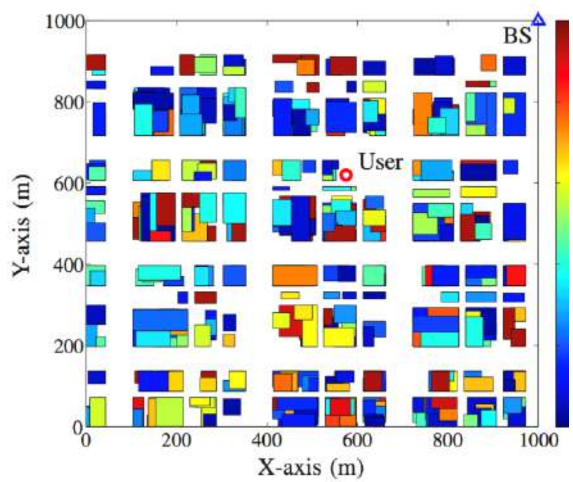


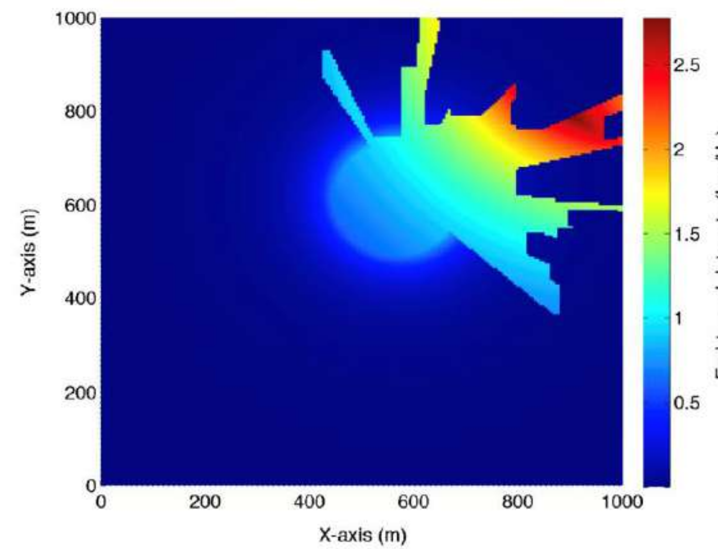




**[Hourani14]** **A. Al-Hourani, S. Kandeepan, and S. Lardner, "Optimal LAP Altitude for Maximum Coverage",** ***IEEE Comm. Lett.*****, 2014.**

- **Map-based prediction**



# Map-based vs Probabilistic models

| | Pros | Cons |
|---|---|---|
| Probabilistic [Hourani et al] [Mozaffari et al] [Zhang et al] [Verdone et al] | • Easily tractable<br>• Lends itself to mean performance analysis<br>• Altitude optimization | • No strict performance guarantee<br>• In-field implementation difficult |
| Map-based [Gesbert-Chen-Esrafilian] | • Powerful data sets (has local terrain features)<br>• Yields higher throughputs<br>• Enables in-field performance guarantee | • Non directly differentiable (?)<br>• Map non directly available (needs learning) |

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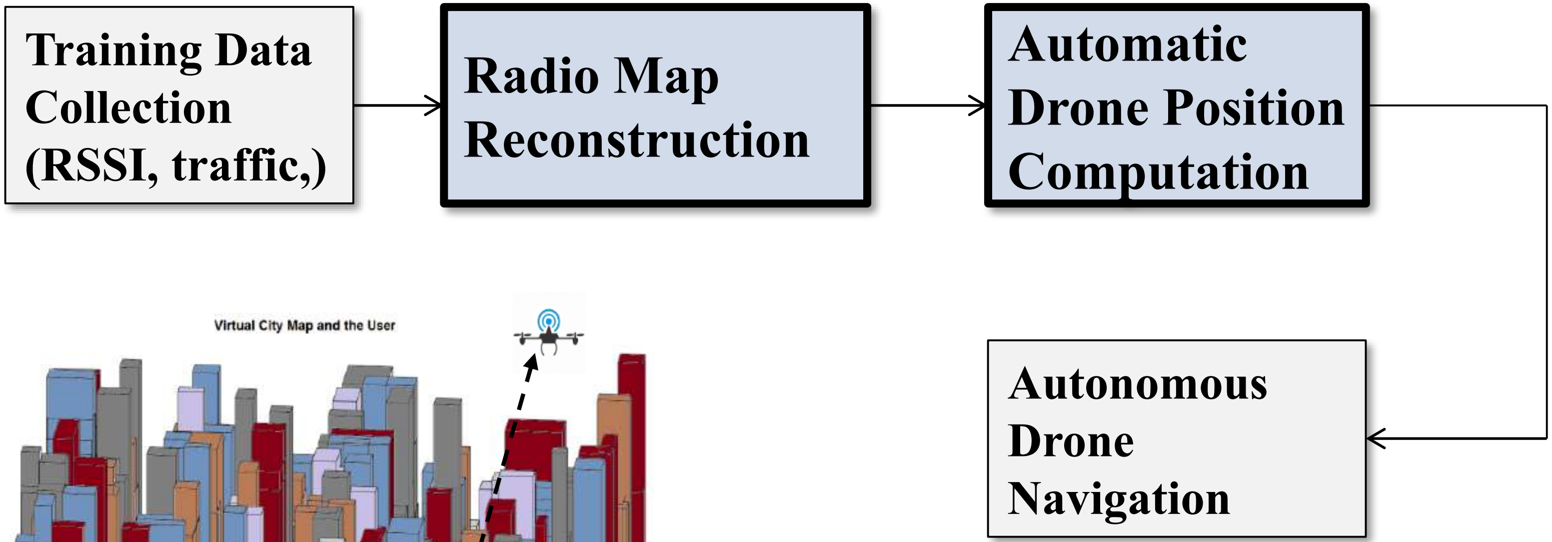
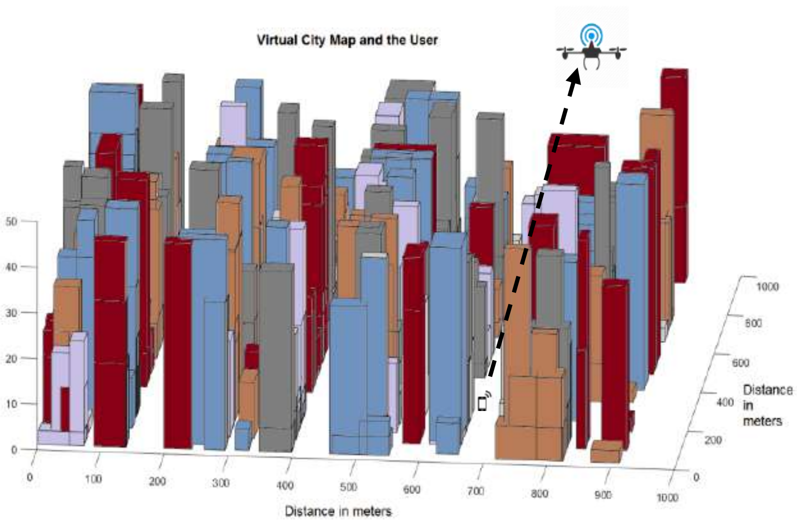
# Learning-based placement

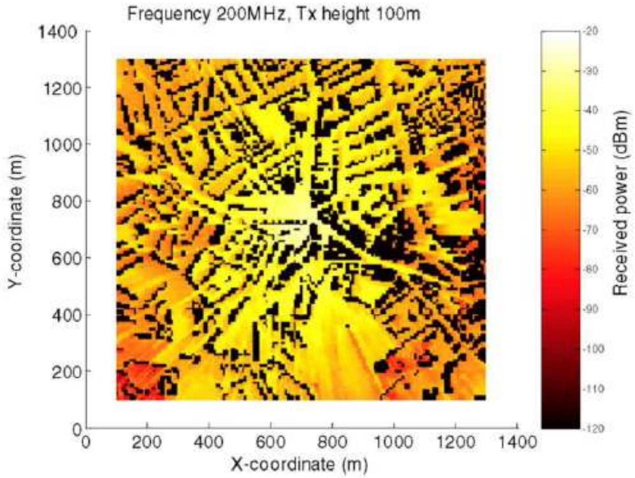


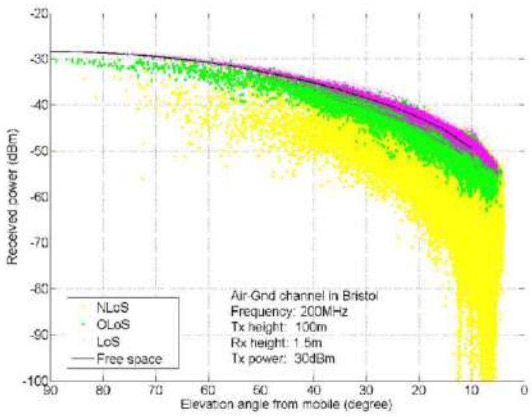




**On-line**
**Off-line**

# Segmented Channel model

**Received power map UAV 100 meter above center of Bristol**




## Proposed Model: Ray-tracing with **Segmented Approximation**

- Classical log-distance model

$$10\log_{10}\left(g_{\mathrm{U}}(\mathbf{x})\right) = 10\log_{10}(\beta) - 10\alpha\log_{10}\left(\|\mathbf{x}-\mathbf{x}_{\mathrm{U}}\|\right) + \boxed{\xi}$$

Shadowing (e.g., LOS/NLOS), reflection, and diffraction, etc.

$$\xi_k + \tilde{\xi}_k$$

Ignore small residual

- Segmented propagation model: $K$ segments

$$g_{\mathrm{U}}(\mathbf{x}) = \sum_k g_k(\mathbf{x})\mathbb{I}\{(\mathbf{x},\mathbf{x}_{\mathrm{U}})\in\mathcal{D}_k\}$$

$$10\log_{10}\left(g_k(\mathbf{x})\right) = 10\log_{10}(\beta_k) - 10\alpha_k\log_{10}\left(\|\mathbf{x}-\mathbf{x}_{\mathrm{U}}\|\right)$$

Captured by classification to propagation segments, e.g., LOS/NLOS

# Segmented Regression Learning

- **Noisy power *y* measurement on UAV position x** $\boxed{y = \alpha_k g(\mathbf{x}) + \beta_k + \tilde{\xi}_k}$
- **PDF at x:** $p_k(\mathbf{x}, y) = \frac{1}{\sqrt{2\pi}\sigma_k} \exp\left\{-\frac{(y - \alpha_k g(\mathbf{x}) - \beta_k)^2}{2\sigma_k^2}\right\}$
- **$\mathbf{z}^{(l)}$ = $(z_1, z_2, \ldots, z_K)$ segment-fitting vector for training UAV point $\mathbf{x}^{(l)}$**

- **Objective: Max likelihood Estimate of** $\boxed{\boldsymbol{\theta} = \{\alpha_k, \beta_k, \sigma_k, \pi_k\}_{k=1}^{K}}$

$$\begin{aligned} \underset{\boldsymbol{\theta}, \{\mathbf{z}^{(l)}\}}{\text{maximize}} \quad & \prod_{l=1}^{N} p(\mathbf{x}^{(l}, y^{(l)}, \mathbf{z}^{(l)} | \boldsymbol{\theta}) \\ \text{subject to} \quad & \sum_{k=1}^{K} \pi_k = 1 \end{aligned}$$

**Expectation-Maximization Algorithm**

# **Kernel-based** Radio Map Reconstruction

**Given a position x, find a set of points from training data set** $\{\mathbf{x}^{(m)}\}$

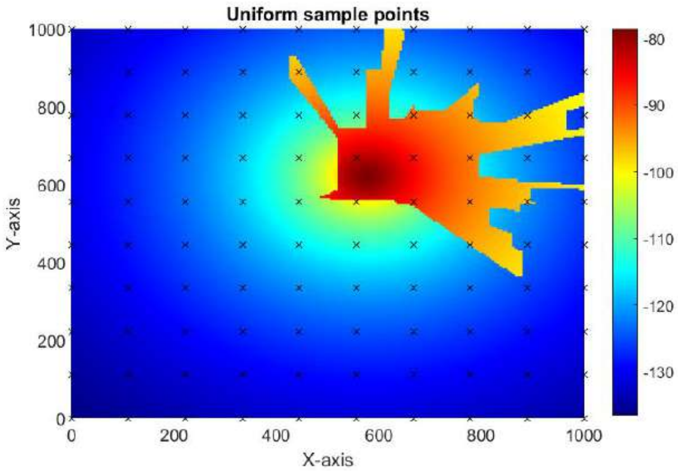
$$\mathcal{N}(\mathbf{x}) \triangleq \arg\min_{\mathcal{S}\subseteq\{1,2,\ldots,N\},|\mathcal{S}|=M} \sum_{m\in\mathcal{S}} \|\mathbf{x}-\mathbf{x}^{(m)}\|$$

**Estimate segment labels through:** $\hat{\mathbf{z}}(\mathbf{x}) = \mu \sum_{m\in\mathcal{N}(\mathbf{x})} \mathcal{K}(\mathbf{x},\mathbf{x}^{(m)})\bar{\mathbf{z}}^{(m)}$

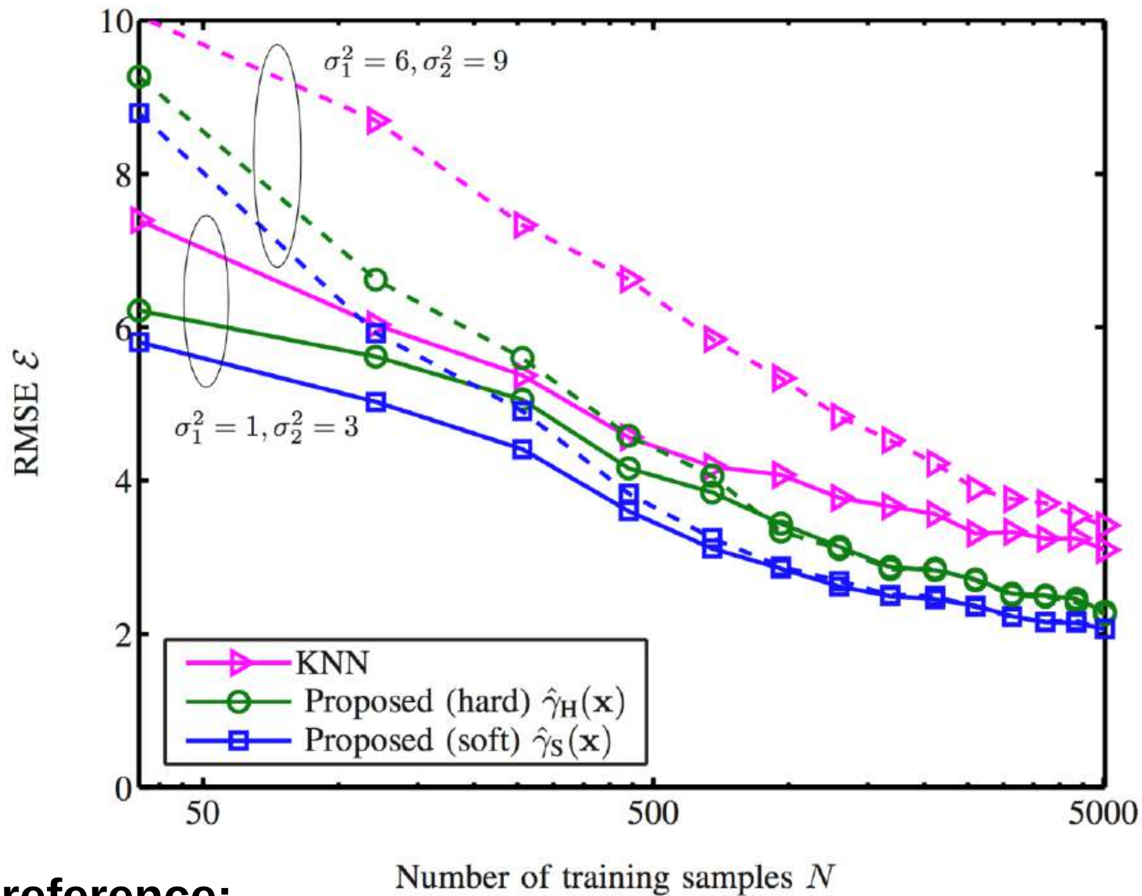
**using the kernel function** $\mathcal{K}(\mathbf{x},\mathbf{x}^{(m)}) = \exp\{-\|\mathbf{x}-\mathbf{x}^{(m)}\|^2/s\}$

**Soft SNR reconstruction**

$$\hat{\gamma}_{\mathrm{S}}(\mathbf{x}) = \sum_{k=1}^{K} \left(\beta_k - 10\alpha_k \log_{10} d(\mathbf{x})\right) \hat{z}_k(\mathbf{x})$$



# Reconstruction performance

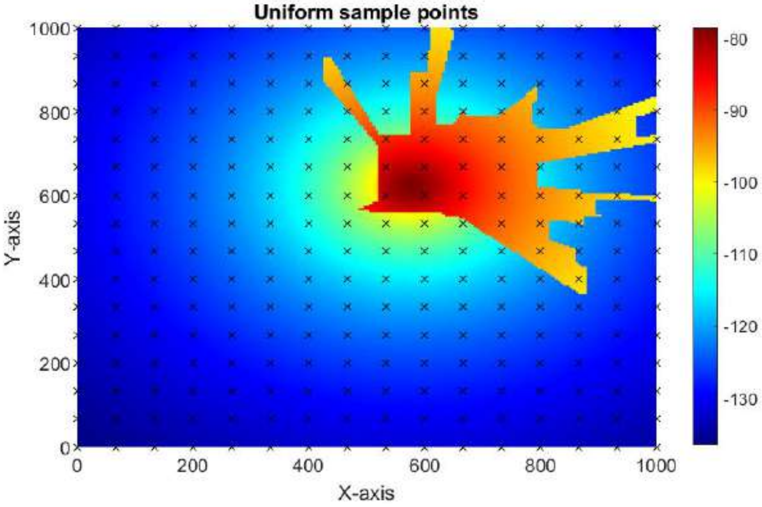



**Comparison reference:**
**K nearest neighbors (KNN) applied on signal power vectors (no channel model)**

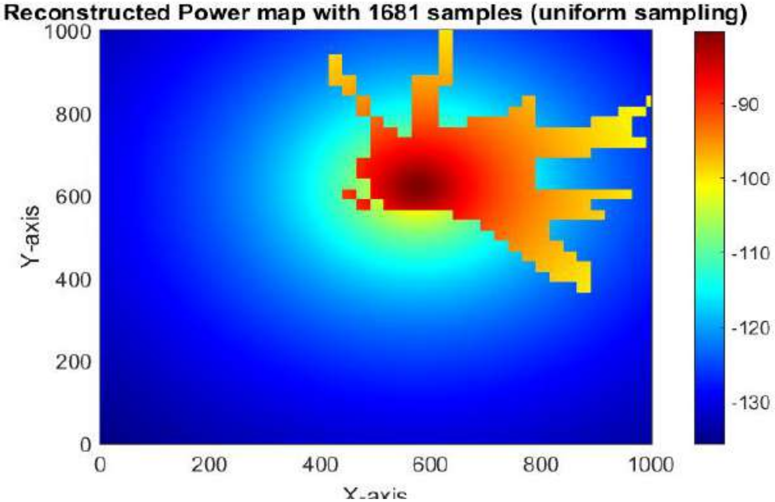
$$\hat{\gamma}_{\mathrm{KNN}}(\mathbf{x}) = \sum_{m \in \mathcal{N}(\mathbf{x})} \mathcal{K}(\mathbf{x}, \mathbf{x}^{(m)}) y^{(m)}$$

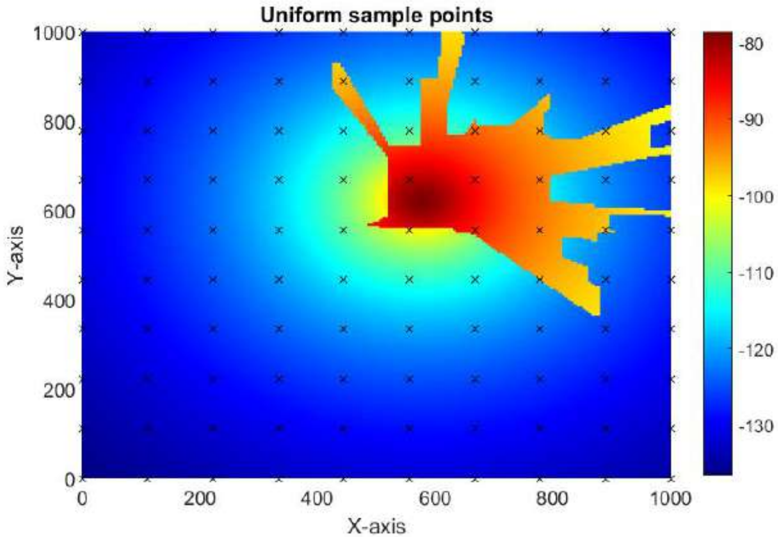
*[J. Chen & D. Gesbert, ICC17]*

# Radio map reconstruction

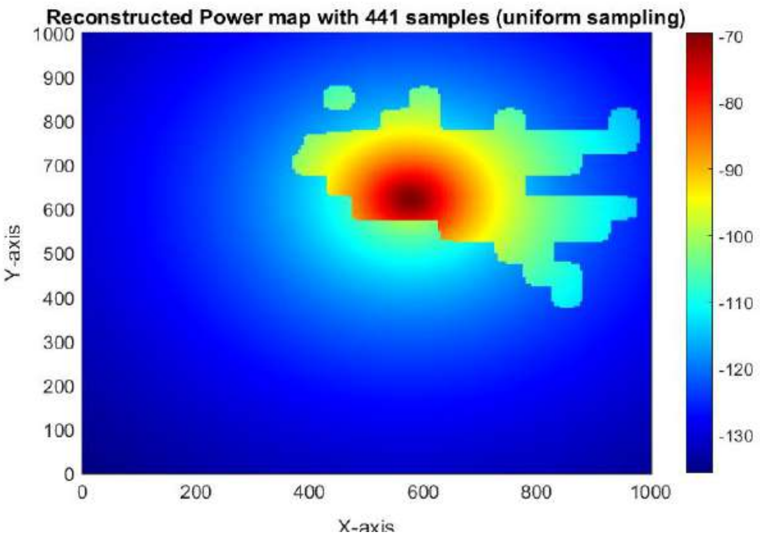



**Dense Training**




**Sparse Training**




**Role of 3D maps?**

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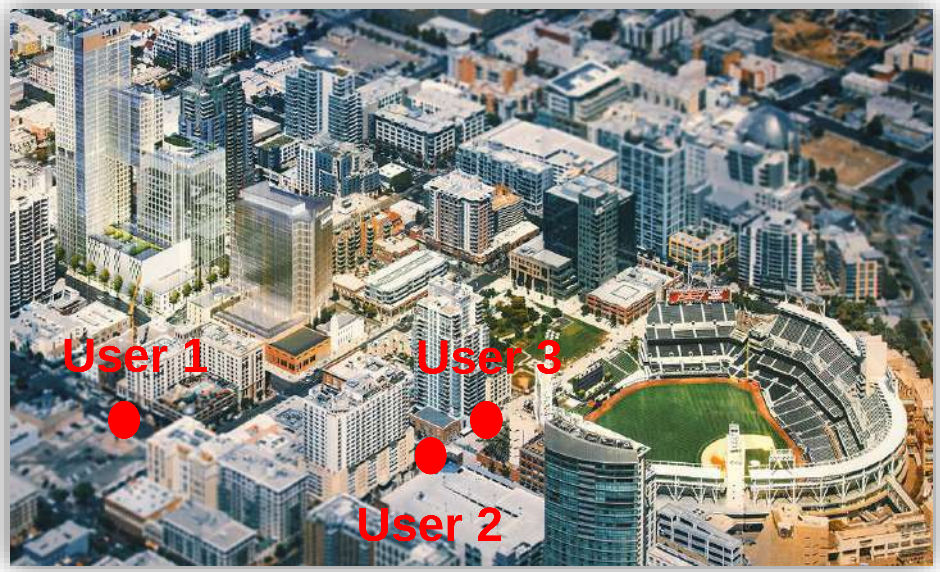
# Role of 3D maps in UAV-aided networks

- ✓ 3D maps reveal the topology which correlates radio maps across users
- ✓ 3D maps can be obtained “for free” as side-product of UAV flight mission
- ✓ 3D maps play a role to enhance radio map reconstruction

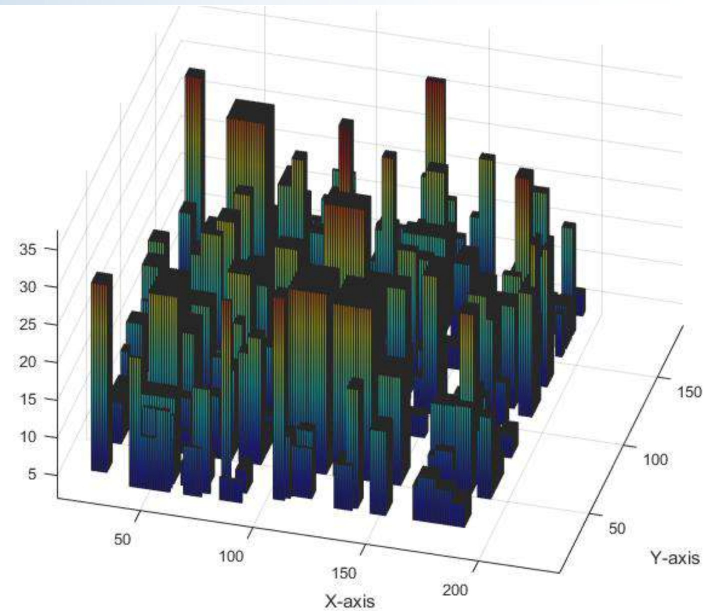
→ **Joint 3D and radio map reconstruction!**



# Learning the 3D map from radio measurements

**Traditional 3D city map reconstruction:**

1. Camera image processing
2. Laser image processing
3. Radar processing




**Proposed concept:**

1- Learn propagation parameters using previous EM algorithm
2- Soft-classify users into LoS/NLoS
3- Reconstruct 3D map from "radio shadow" data


Connections with
-**3D Imaging with WiFi** [Y. Mostofi et al. @ UCSB]
-**GPS based 3D imaging** [Madhow et al @ UCSB]

# 3D Building map reconstruction algorithms

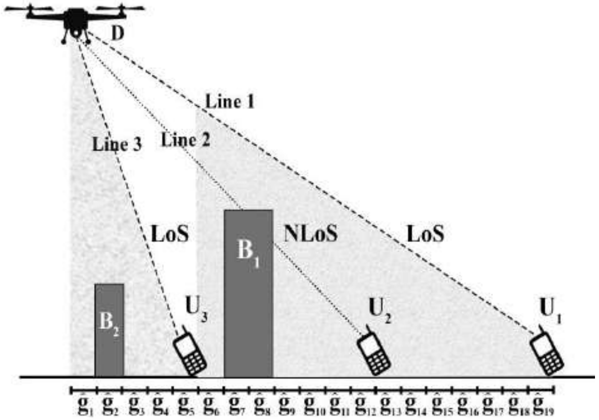
City discretized over 2D grid coordinates $\hat{G} = \{\hat{g}_1, \hat{g}_2, \dots, \hat{g}_n \mid \hat{g}_i = (x_i, y_i, \hat{z}_i)\}$

## 1. Deterministic Reconstruction using hard LoS decision

- For each LoS user $X_U$ and UAV located at $X_D$, we solve for inequalities:
  - $$\hat{z}_i \leq \frac{(x_i - x_D)(-z_D)}{x_U - x_D} + H_D \;\; ; \; \forall \; \hat{g}_i \in \hat{G}$$

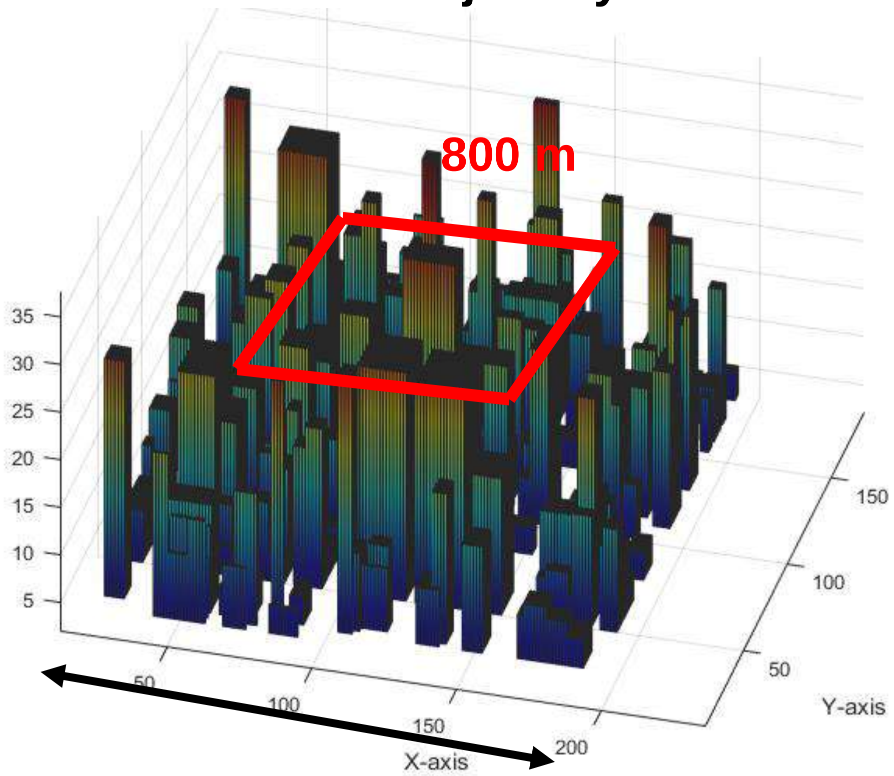
## 2. Probabilistic reconstruction using soft LoS decision

Use soft output from EM-based LoS classification algorithm *Prob*(LoS)



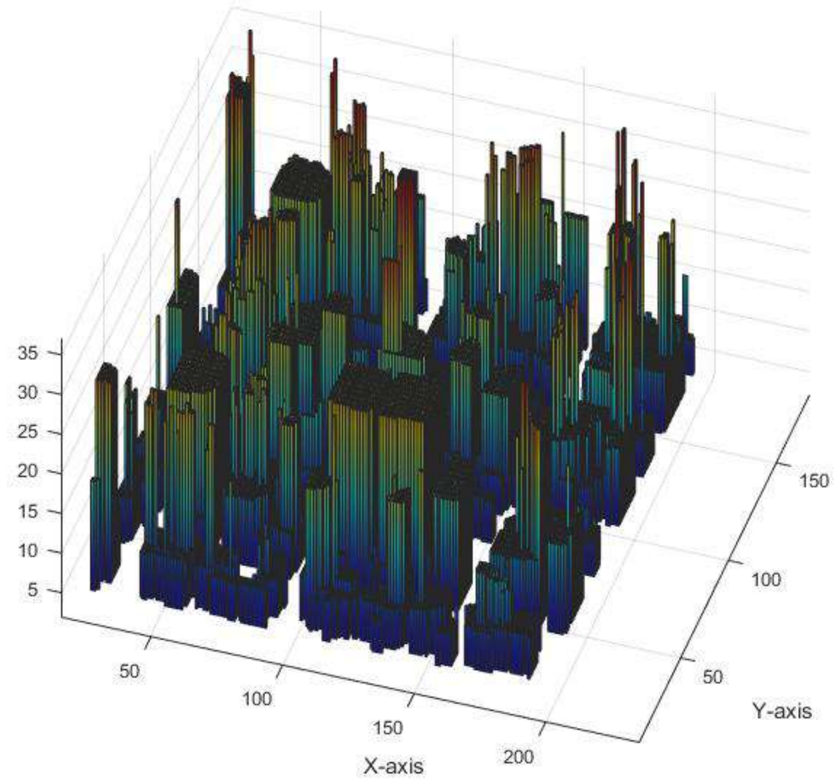
# 3D Reconstruction Performance

**UAV trajectory**




**1km**

**Reconstructed map with 1500 users***

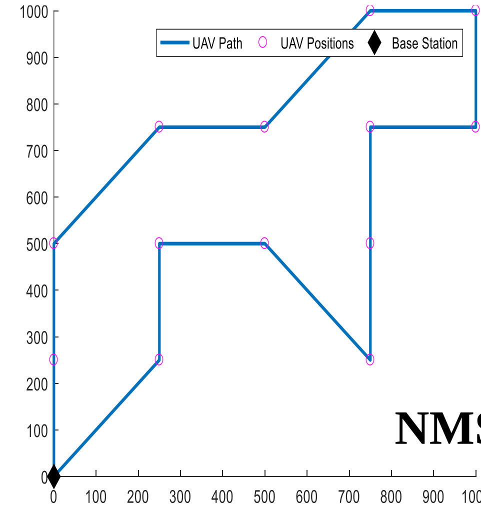



*K=32 UAV locations, spatial smoothing applied

Optimized flying altitude in closed form (Globecom 17)

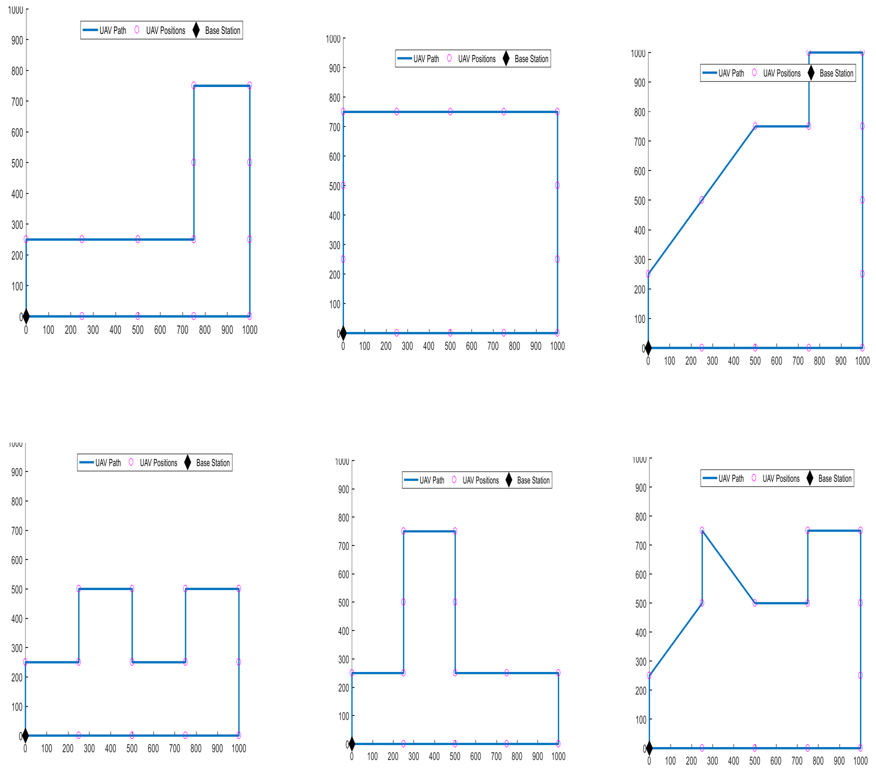
# Optimizing the UAV path for 3D reconstruction

**Dynamic Programming Optimized Path**

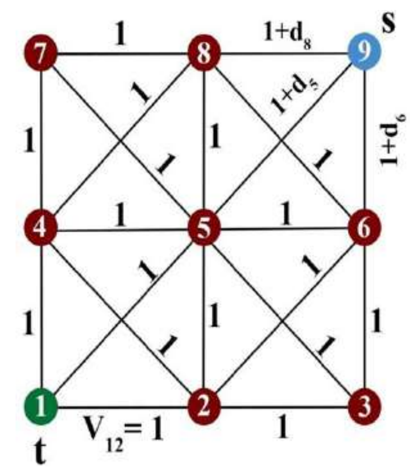



**NMSE = 0.2488**

## Arbitrary Paths



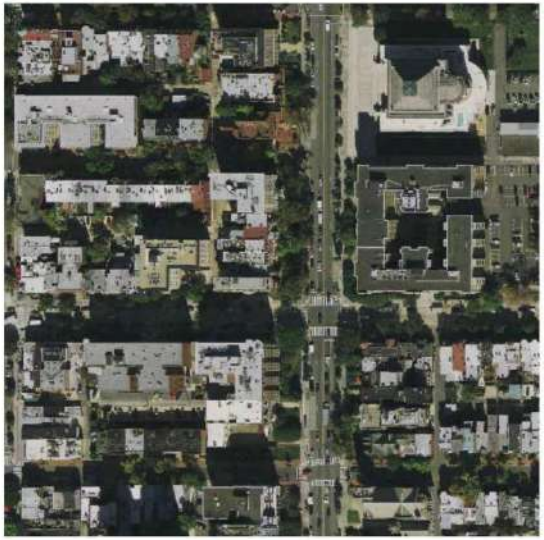
**NMSE = 0.343 (averagr across arbitray paths)**



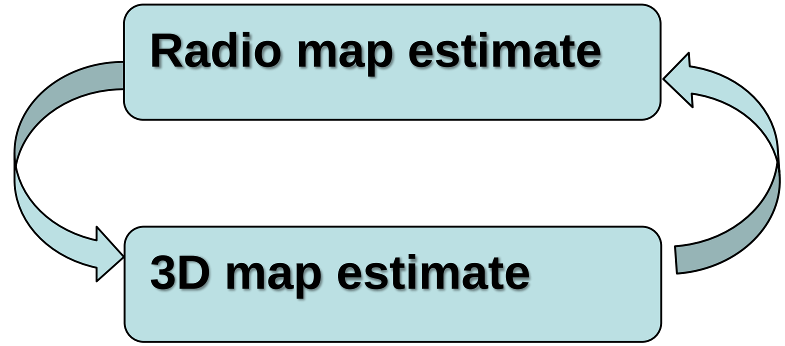

**Refinement Graph**

*[Esrafilian, Gesbert, 2017]*

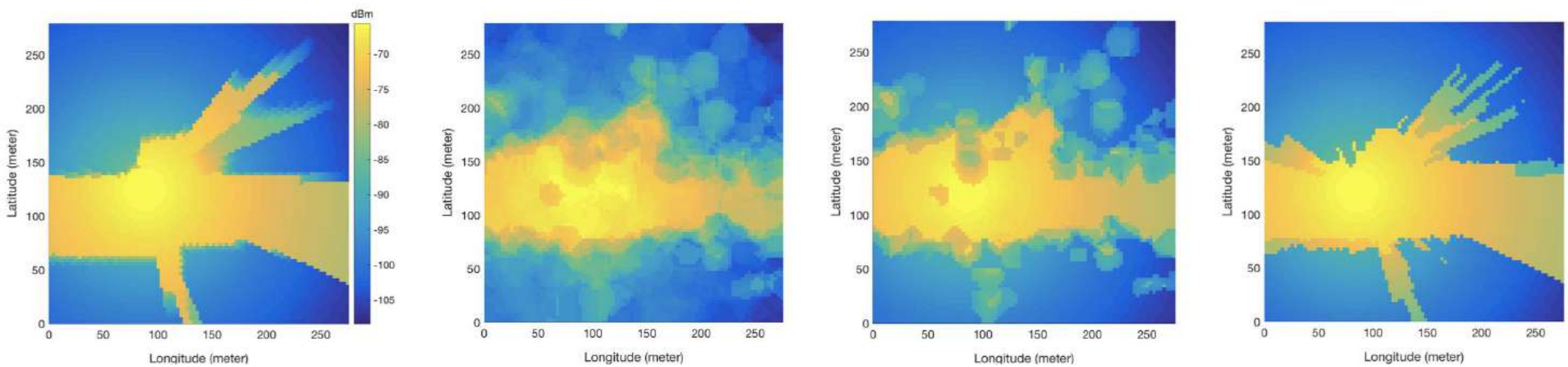
# Joint 3D and radio map reconstruction



An orthoimagery of
an area at center
Washington DC, USA




Radio map
reconstruction




(a) True radio map (b) KNN (c) Direct reconstruction [8] **Joint approach**

*[Chen, Esrafilian, Gesbert, Mitra, Robotics, Science and Systems, MIT, 2017]*

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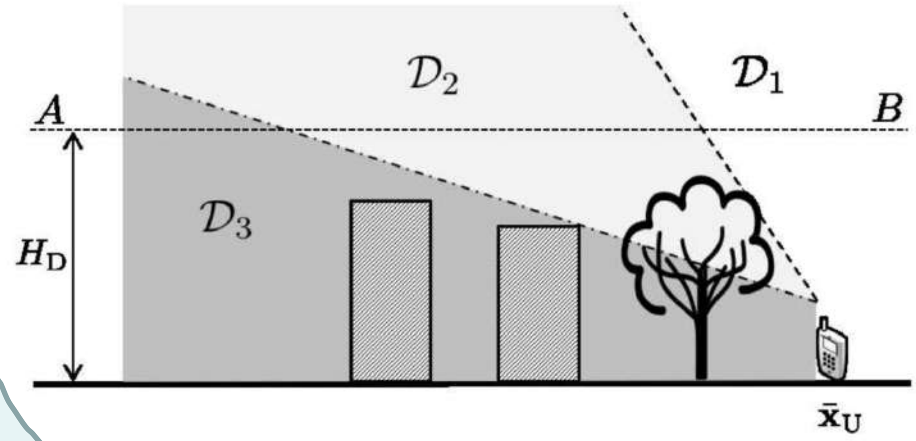
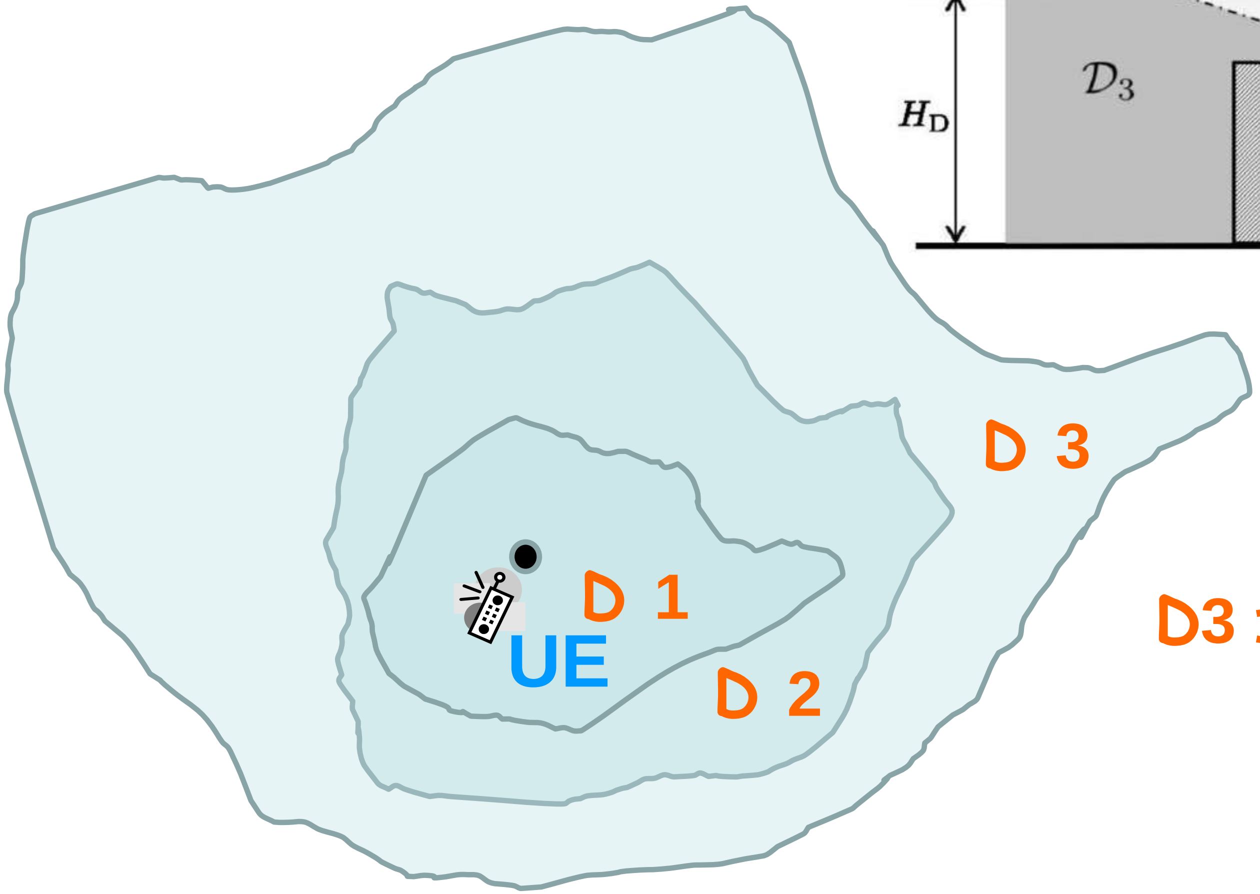
# Nested Propagation Segment Property

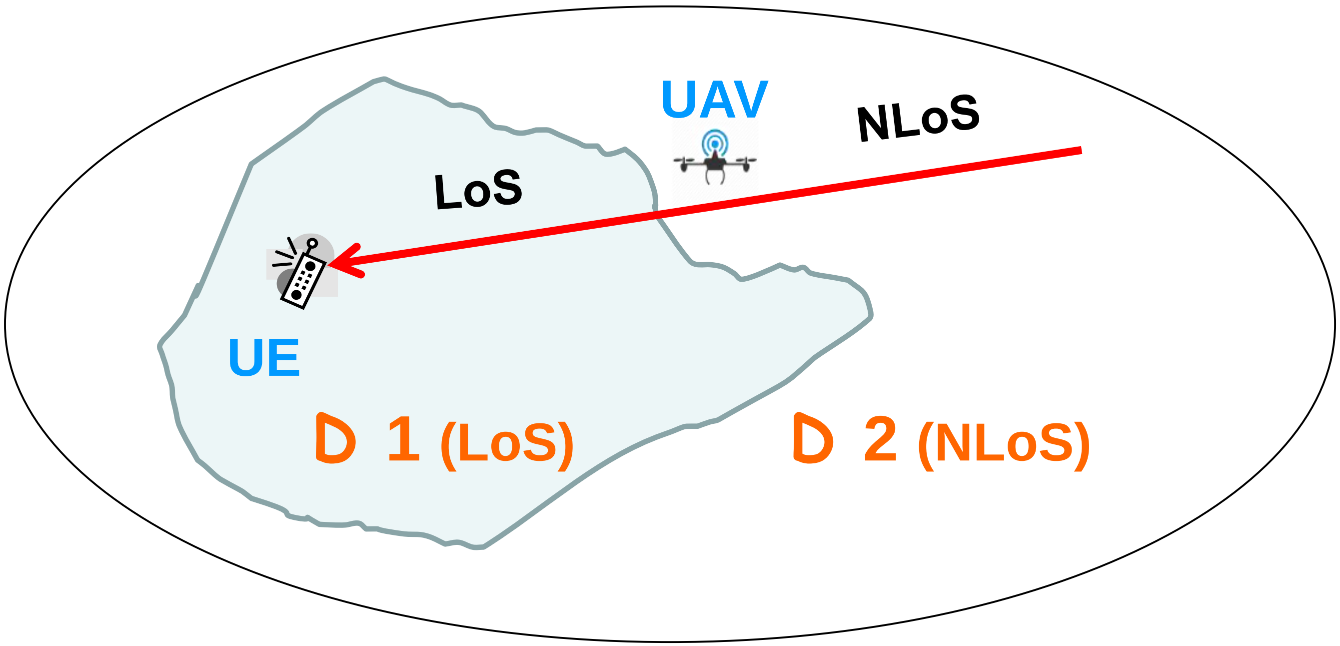



D3 ⊃ D2 ⊃ D1

# Nested Propagation Segment Property (K=2)

- Two regions only: LoS and Nlos
- LoS “**irreversibility**”



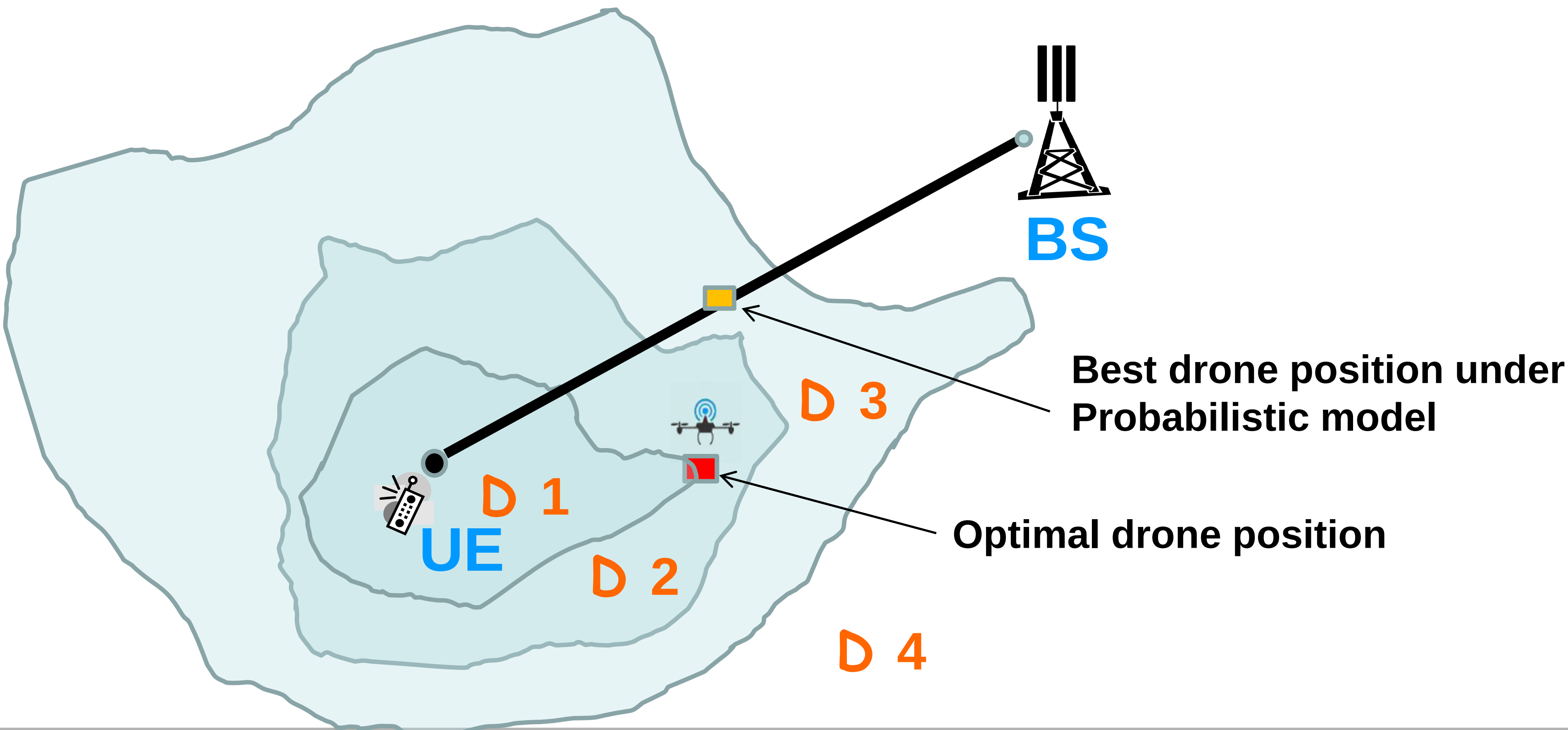
# Big building hole breaks LoS irreversibility

**CCTV Building**
**Beijing, China**

-

# Distance minimization vs. segment optimization

**Proposition [J Chen & D. Gesbert 2017]:**
*"The optimal single-UAV relay position is found either (i) on the BS-UE axis, or (ii) on the boundary of segment D k for one of the D k segments k=1,..K-1"*



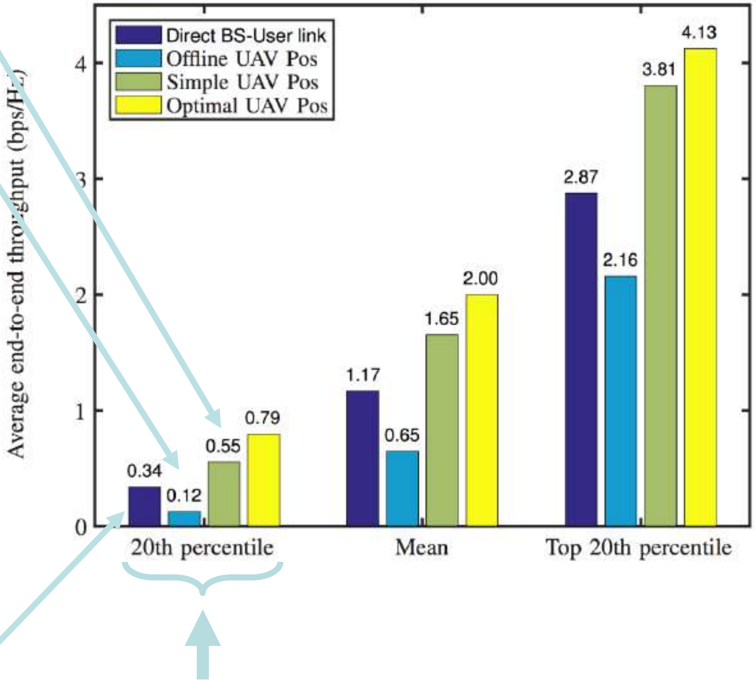
# UAV-induced capacity gains

**10,000 random user locations, buildings 5 - 45 meters, UAV 50 meter height**
**Decode-and-Forward Relaying**

**Simple UAV positioning: Only search over the BS-user line segment**

**Probabilistic UAV positioning:**

$$\mathbf{P}(\mathrm{LOS}, \theta) = \left[1 + a \exp(-b[\theta - a])\right]^{-1}$$



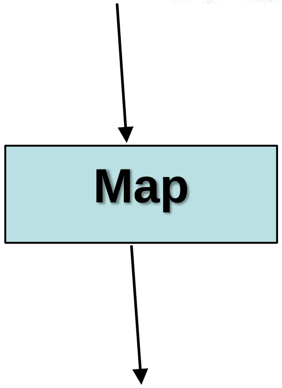

**Direct BS-user link: Directly BS → user transmission without UAV relaying**

# Map-based placement for multi-user case

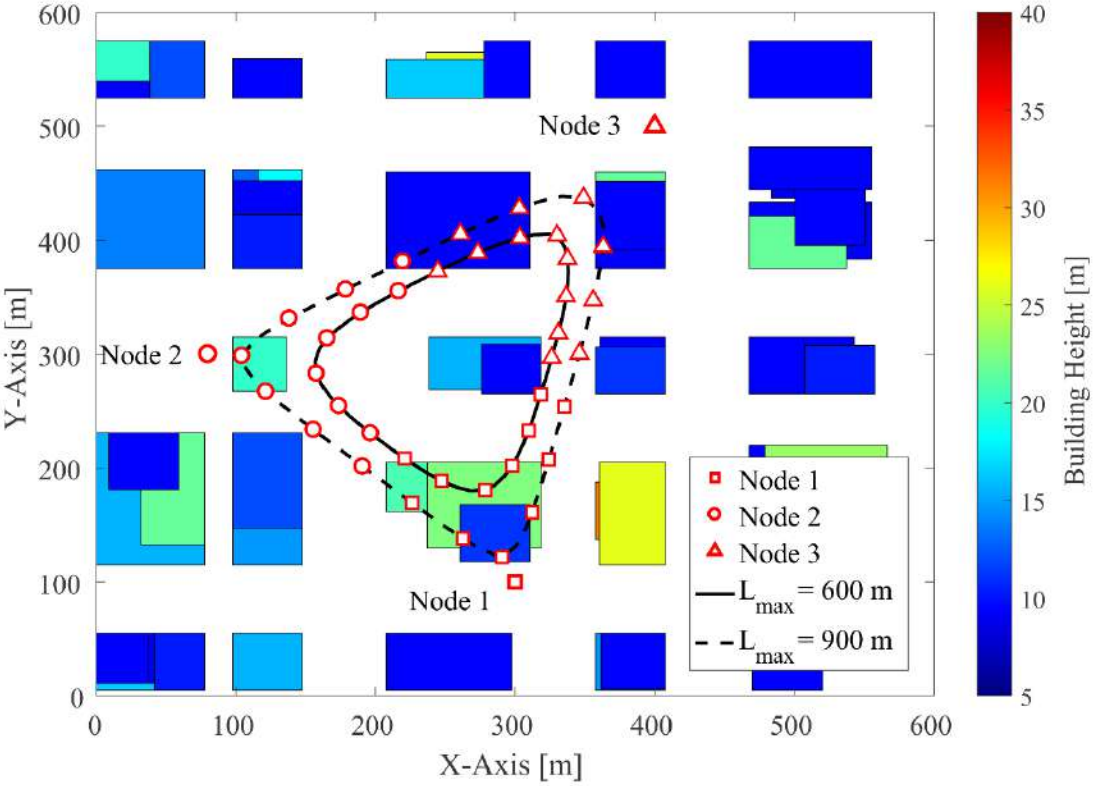
- **Overcoming non-differentiability:**
  - *Map Compression [Esrafilian-Gangula-Gesbert 2018]*

**Global Probability model**

$$\mathbf{P}(\mathrm{LoS}, \theta) = \frac{1}{1 + a\exp\left(-b[\theta - a]\right)}$$




**Local Probability model P(LoS,θ, user m)**



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# DroneFor5GLab @ EURECOM

- **LTE license**
- **Outdoor (EURECOM SophiaTech Campus)**
- **Integrated autonomous UAV-base station with full LTE functionality -> World’s first?**
  - OpenAirInterface for communication layer
  - On-line learning for placement



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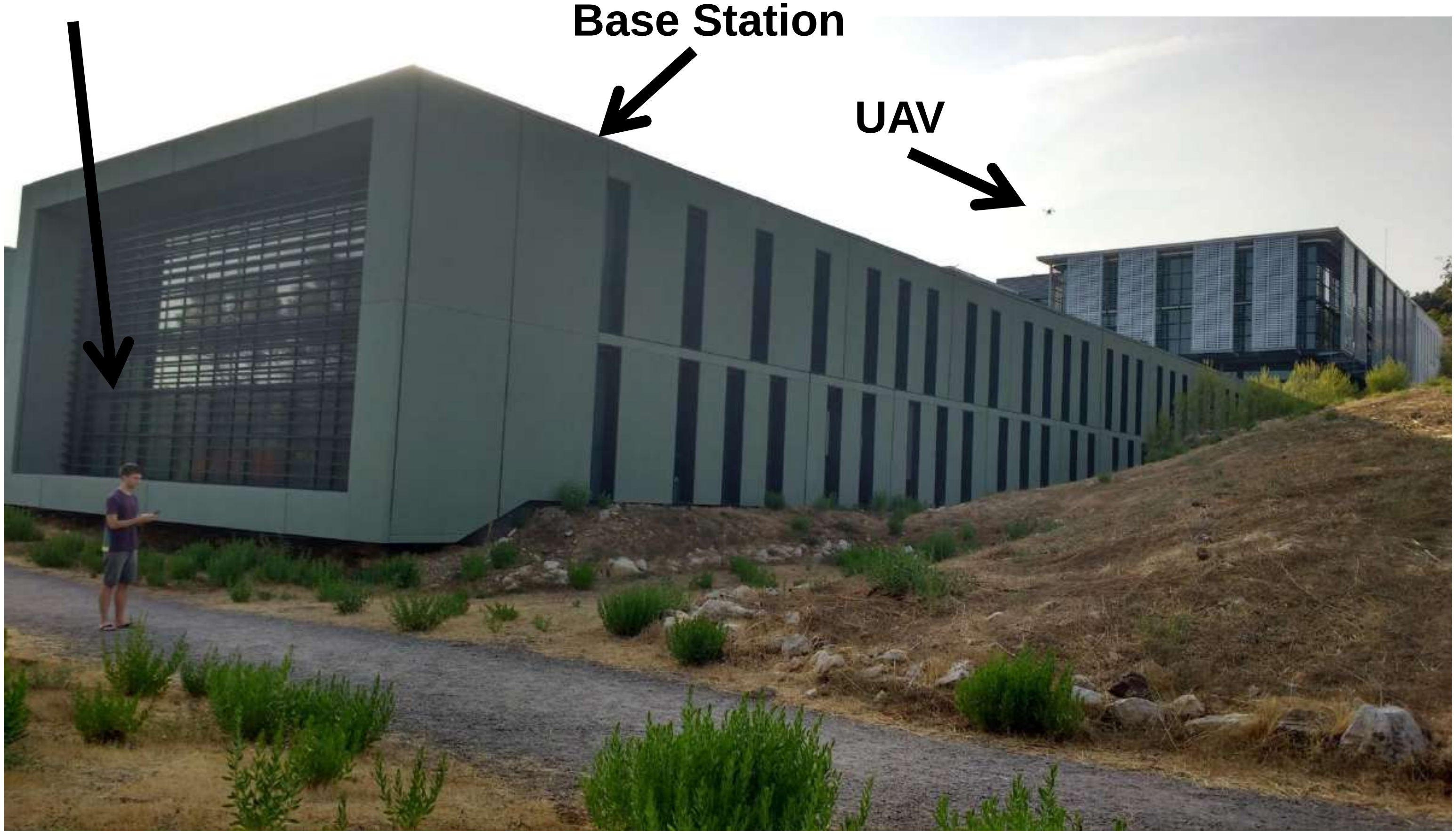
# DroneFor5GLab @ EURECOM

**Video of demo available: www.youtube.com/watch?v=GI_lOsg_qmQ**



# Perspectives

## UAV-aided networks: Promising technology

- Brings data contents closer to the user
- Ultra-flexible
- Low cost (?)

## Plenty of hard problems (theoretical/experimental)

- Optimally combining 3D map and radio map reconstruction
- Map compression for many user case
- Coordinated multi-UAV setting
- Onboard RF/antenna design
- Networking issues (UAV and terrestrial co-existence)
- Onboard vs. offboard computing