University of East Anglia

UAV-Facilitated 3D Signal Propagation Mapping using Temporal-Spatial Neural Networks

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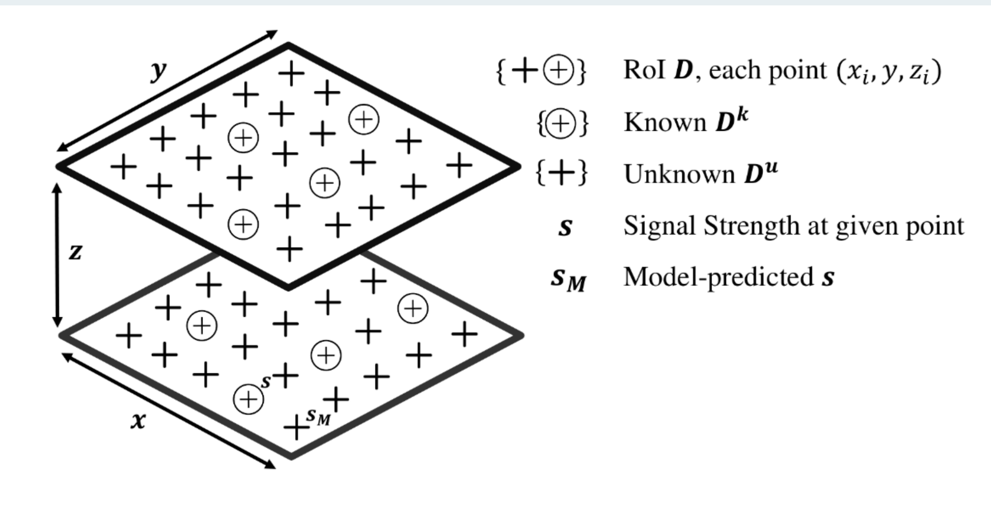
INTRODUCTION

The shift to drone-based services in 6G environments demands robust, altitude-aware cellular connectivity. However, existing 2D coverage models fail to capture signal variability in 3D space. This poses safety and reliability issues for UAV operations. The paper addresses these challenges by developing a method to generate 3D signal strength maps using drone-collected data, feature engineering, and neural networks to enable more scalable and efficient signal prediction across complex environments.

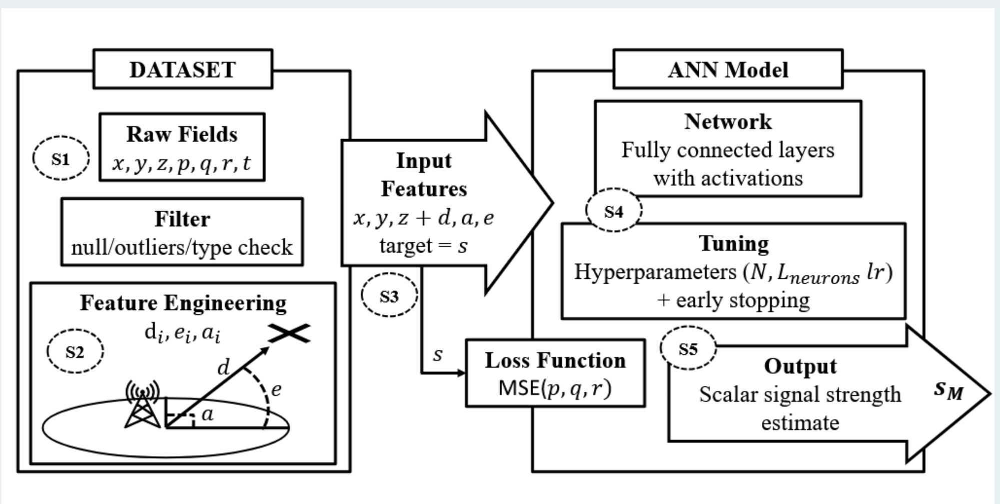


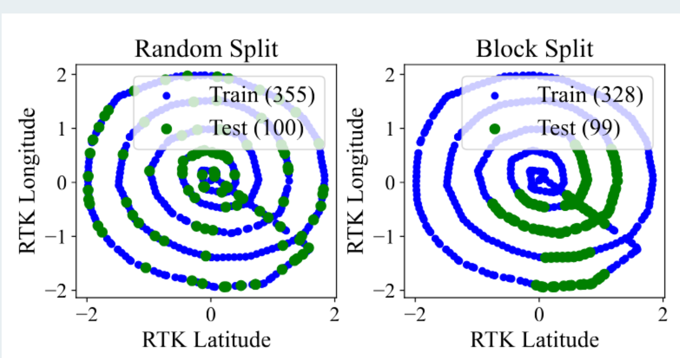
METHODS

Two datasets were collected using drones flying pre-defined paths (Rows and Spiral) around a controlled 5G transmitter. Signal metrics (RSSI, SINR), GPS coordinates, and tower metadata were recorded.

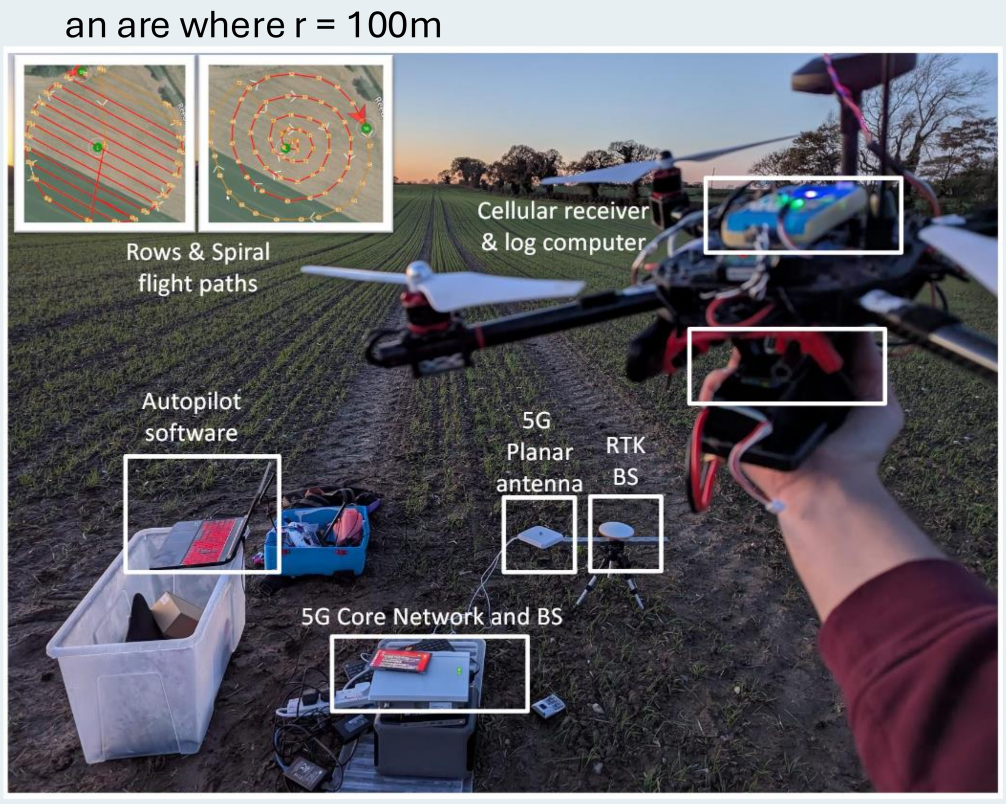
The proposed pipeline included:

- Preprocessing and filtering of raw data.
  - Drone telemetry - [Lat, Lon, Altitude]
  - Network data - [**rssi**, sinr, rsrq, rsrp]
- Feature engineering to calculate distance, azimuth, and elevation from the tower.
- A feedforward Artificial Neural Network (ANN) trained on spatial and contextual features.
- The model was evaluated using various dataset splits (random, block, temporal) to test generalisation.





- Above is a test train split example. Below is the dataset we recorded across multiple planes, over an area where r = 100m



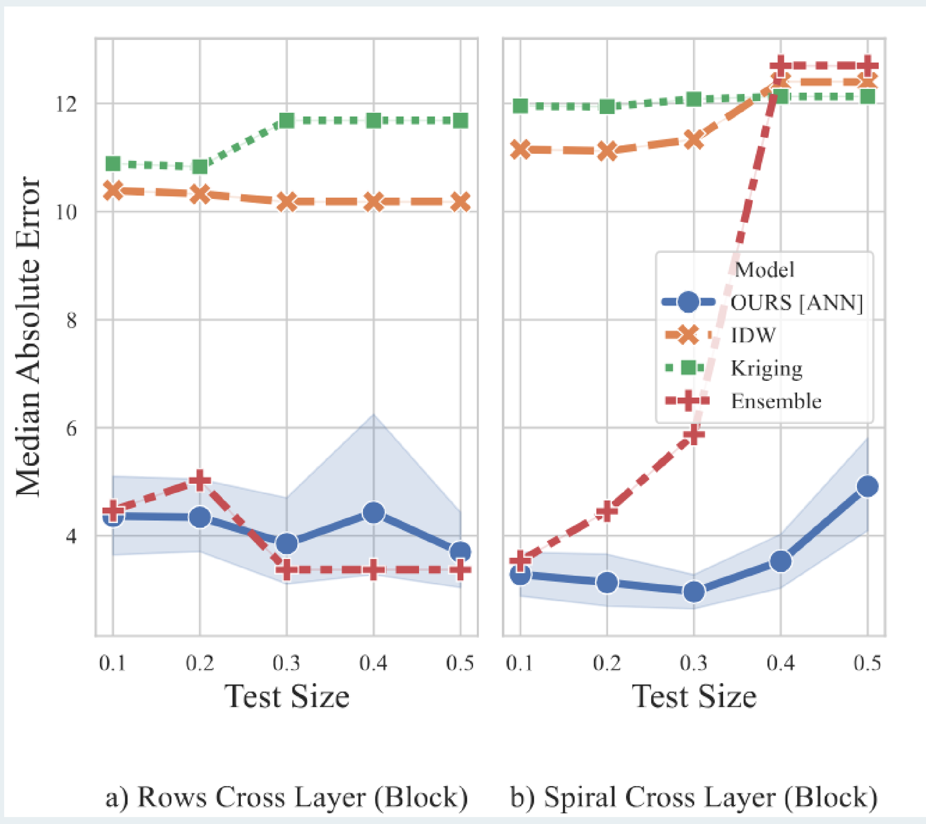
RESULTS

ANN consistently outperformed traditional methods (IDW, Kriging, Ensemble) across block, cross-layer, and time-series tests.

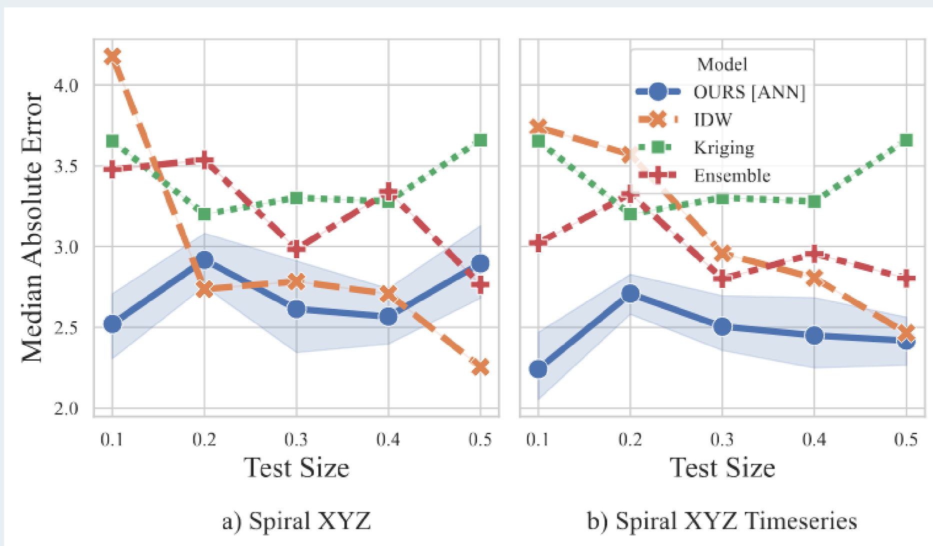
Median Absolute Error (MAE) remained lowest in ANN, especially in sparse or unseen areas.

Feature inclusion (distance, azimuth, elevation) significantly improved cross-layer predictions.

ANN showed resilience to input reduction and generalised well across different spatial and temporal splits.



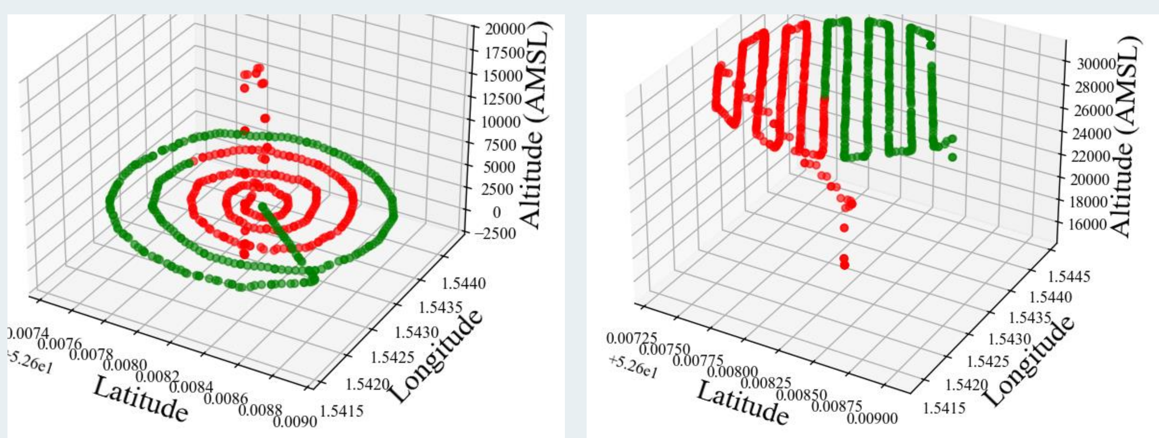
a) Rows Cross Layer (Block) b) Spiral Cross Layer (Block)



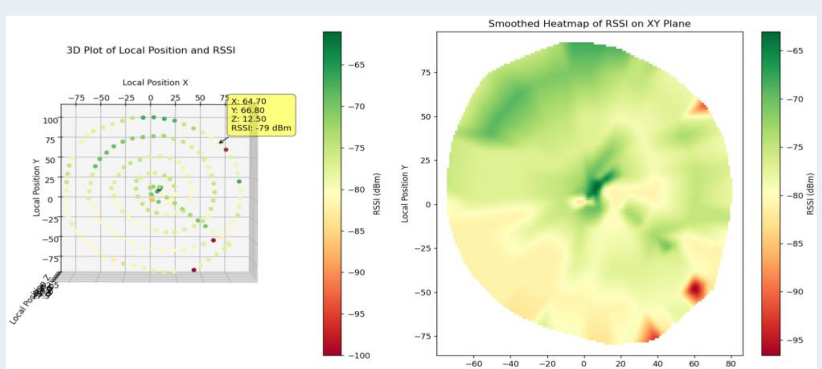
a) Spiral XYZ b) Spiral XYZ Timeseries

CONCLUSION

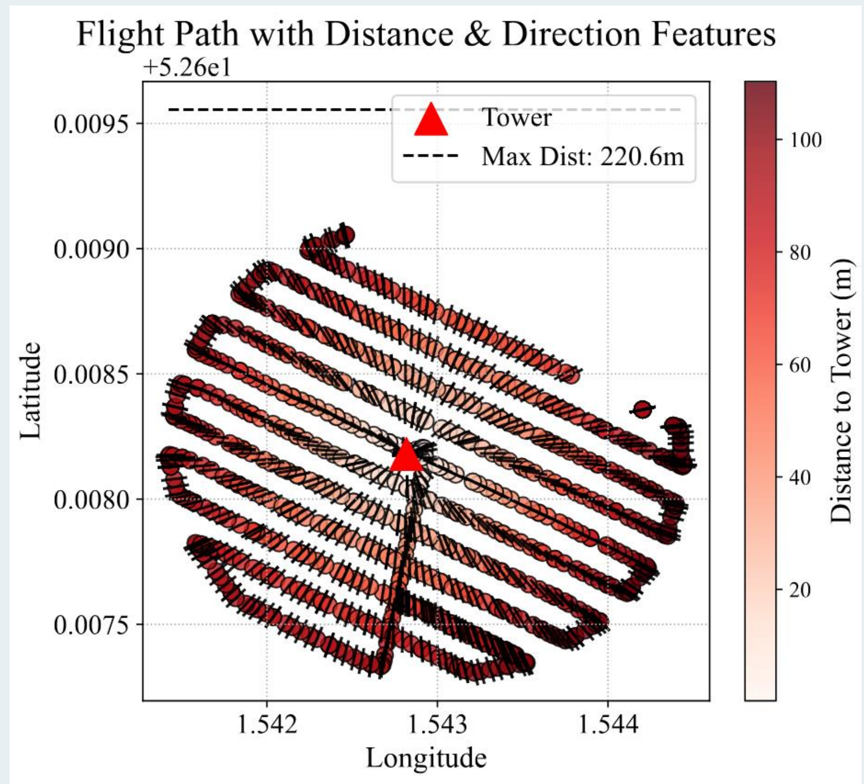
This work introduces a neural network-based approach for 3D signal mapping using drone-collected data. By integrating spatial-temporal learning and engineered features, the model achieves accurate predictions with sparse data. Future directions include exploring alternative NN architectures and adaptive flight paths to enhance scalability and accuracy in real-time drone operations.

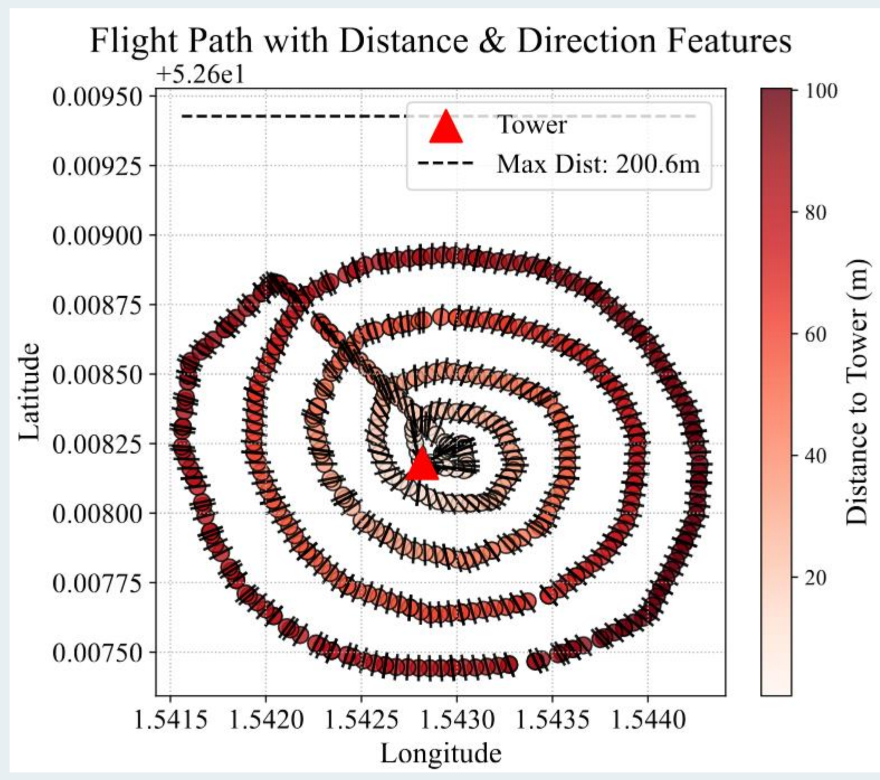


Above shows how we may attempt to predict readings for remaining flight paths based on known data. This can be applied to drone delivery or surveying methods where paths need to be updated depending on a variety of factors. Next, we will explore windowed training data or autocorrelation. This will help when developing real time signal prediction for applications such as drone delivery networks or dynamic mapping. We may also use this new information update predicted maps as pictured below.



Spiral Vs Rows sets

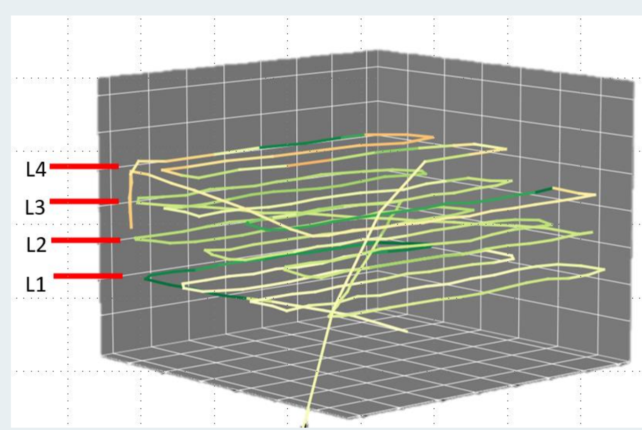




DISCUSSION

Traditional geospatial interpolation struggles in vertical or sparse environments. The ANN model demonstrated adaptability to 3D, directional signal characteristics, enabling reliable extrapolation. Simpler models faltered in unobserved regions or with reduced input features. The feature-engineered ANN approach proved more robust and scalable, particularly valuable for real-world 6G UAV applications where dense measurements are impractical.

We saw interesting relationships emerge between coordinate-based prediction of tower property-based predictions. In the future we would like to explore how these relationships may affect accuracy, such as which features are more important in predicting RSSI. This will require additional datasets.



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