THE HONG KONG POLYTECHNIC UNIVERSITY
香港理工大學

FACULTY OF ENGINEERING
工程學院
WHERE CONCEPTS BECOME REALITY

2025/26 Interdepartmental Final Year Project Interim Report

Intelligent UAV Systems for GNSS-Based Remote Sensing on Vegetation

[AAE] ZHOU Jiayi (22099961D)

[AAE] MAHMUD Md Sahat (22097159D)

[EEE] GAMAGE Sashenka (22097129D)

[ME] TAN Qing Lin (22101126D)

Chief Supervisor: [AAE] Prof. Guohao ZHANG

Co-Supervisor: [AAE] Prof. Li-Ta HSU

Date of Submission: 2026 January 18

Contents

1 Abstract

Placeholder text

2 Introduction

Vegetation is a critical asset to the environment and the human civilization. Not only does vegetation produce essential societal resources, but its distribution and productivity also greatly impacts the terrestrial ecosystems and the global climate [1]. Therefore, the continuous and accurate monitoring of vegetation is essential for sustainable resource management [2], ecosystem preservation [3], and climate change modeling [1].

Traditionally, methods of vegetation monitoring involved manual field assessments of site characteristics, extracting vegetation condition indicators such as species composition, geometrical structure, and biochemical activities [4]. However, the accuracy and efficiency of such monitoring methods are highly dependent on the available expertise and resources, as the site assessments often required the assessor to possess reasonable levels of field knowledge prior to surveying [5]. To address the limitations of manual assessments and to accommodate for the increasing large-scale monitoring demands, remote sensing systems emerged as an essential tool for ecological monitoring [6].

Remote sensing refers to the acquisition of an object's information through measurements obtained without coming into direct contact with said object, effectively minimizing the need for manual involvement on-site [7]. Specifically, remote sensing relies on information derived from different measurements of energy reflected from the object of interest [7]. In the context of surveying terrestrial vegetation, the remote sensing methods could be classified into two categories based on the distance between the target object and the measurement sensor: 1) space-borne and 2) airborne remote sensing. Space-borne remote sensing involves the use of instruments onboard orbiting satellites, including spectral and hyperspectral cameras [8], synthetic aperture radar (SAR) [9], and space-borne Light Detection And Ranging (LiDAR) sensors [10]. Due to the wide coverage and availability of space-borne data, large-scale terrestrial changes over time could be captured, enabling the continuous monitoring of macro-scale ecosystems [11]. Compared to space-borne systems, airborne remote sensing can provide significantly improved spatial resolution and assessment flexibility through the integration of sensors onboard manned aircraft or unmanned aerial vehicles (UAVs) [11]. Although limited by coverage area, airborne remote sensing can provide timely information for addressing regional emergencies such as pest [12] or wildfire [13] outspreads since the systems could be deployed on-demand. In UAV-based remote sensing particularly, this temporal flexibility is further complemented with the benefit of low operational cost, rendering it an ideal platform for monitoring regional and urban vegetation [14].

Conventionally, UAV remote sensing platforms carry similar instruments to that of other remote sensing systems, including radar, LiDAR, and multi-spectral or hyperspectral imagery sensors [14]. However, while imaging instruments are susceptible to the influence of lighting and weather [15], LiDAR devices tend to face difficulties penetrating through dense canopy [16]. Therefore, it is critical to explore a robust sensing technique that is suitable for UAVs in terms of payload and power consumption to complement the existing instruments. Recently, the technique of Global Navigation Satellite System Reflectometry (GNSS-R) is receiving increasing interest in the field of remote sensing. GNSS-R exploits the L-band signals transmitted from Global Navigation Satellite Systems (GNSS) that are then scattered on different terrain surfaces of the Earth [17]. Then, the reception of reflected GNSS signals can provide information regarding the properties of the signal reflector on land [17]. As signals of opportunity conventionally dedicated to Positioning, Navigation, and Timing (PNT) applications, GNSS is capable of providing real-time measurements regardless of time, location, and weather [17]. Additionally, as a bi-static system where signal transmitters are separated from receivers, GNSS-R is exempt from the need of dedicated transmitter-receiver instruments that are crucial to mono-static radar systems [18]. Instead, any consumer-grade receivers capable of receiving reflected GNSS signals could be used for GNSS-R remote sensing, further demonstrating GNSS-R's applicability onboard low-cost remote sensing systems such as an UAV.

May need some intro for path planning and lidar here. The above is from Louise's project proposal, so need further editing. (Also need to mention the full name of SLAM somewhere)

In this project, the technique of GNSS-R will be integrated onto an UAV platform to achieve an intelligent and structured remote sensing system for vegetation monitoring. The main objectives of this project are as follows:

1. To introduce an autonomous path planning framework onboard the UAV platform for optimized GNSS-R remote sensing.
2. To analyze and model the correlations between signal propagation parameters retrieved through GNSS-R and ground vegetation conditions.
3. To classify signals reflected by vegetation and predict vegetation parameters based on raw GNSS data using machine learning-based approach.
4. To establish a detailed 3D canopy map using LiDAR-based SLAM, providing a spatial validation reference for the 2D vegetation features detected by GNSS-R.

This report is structured as follows: Section 3 reviews contemporary research in UAV path planning, GNSS-R, machine learning, and LiDAR SLAM, while Section 4 outlines the project's methodologies. The subsequent sections cover the experiments conducted (Section 5), a discussion of current results (Section 6), and the project conclusions (Section 7). Finally, Section 8 explores future work, and Section 9 summarizes project management details.

3 Literature Review

To achieve the project objectives, this literature review comprehensively examines the contemporary research in four domains, each associated with one project objective. First, existing path planning methodologies are reviewed to ... Subsequently, the existing techniques of GNSS-R are explored, with a focus on its prior applications in vegetation parameter retrieval. Then, machine learning ... Finally, LiDAR-based SLAM techniques ... Consequently, this review identifies the existing gaps in each domain for the objective of vegetation monitoring, which will inform the integrated project methodologies.

3.1 Path Planning

Placeholder text

3.2 GNSS-R

The concept of using GNSS-R for remote sensing was first proposed in 1993, where the correlation between direct and scattered GNSS signals were proven promising for the application of ocean altimetry [19]. Today, apart from the originally proposed application, GNSS-R techniques has been extensively used for Earth observations and land information retrieval, including ocean salinity, soil moisture, and ice thickness [20]. However, research on vegetation parameter retrieval remains limited to preliminary analyses [21].

In a previous study, the capabilities of monitoring vegetation through GNSS-R were demonstrated through a theoretical simulation of GNSS scattering characteristics [22]. Furthermore, this study revealed that the sensitivity of GNSS-R signals can be influenced by incidence angle, soil parameters, and tree size, while signals with lower elevation angles and RL polarization (transmission of right-hand circular polarization (RHCP) signal, reception of left-hand circular polarization (LHCP) signal) appeared to be ideal for forest monitoring [22]. In another study, the polarization scattering properties of GNSS-R signals in forest canopies were modeled, where simulations revealed that tree trunk scattering effects would dominate total scattering response, while satellite azimuth angles are significantly correlated to the signal polarization [23].

Aside from simulated approaches, empirical or semi-empirical studies regarding GNSS-R remote sensing of vegetation were also reviewed. In a study by Yueh et al., GNSS-R data onboard the Cyclone GNSS (CYGNSS) satellite were analyzed against the vegetation water content estimated through the satellite-derived Normalized Difference Vegetation Index (NDVI) [24]. The results demonstrated near-linear relationship between vegetation water content and GNSS-R signal attenuation, while the CYGNSS data also suggested the existence of volume scattering within complex forest components [24]. Similarly, another study analyzing GNSS-R data from TechDemoSat-1 demonstrated reduced sensitivity to soil moisture retrieval due to vegetation attenuation, which could be effectively compensated using NDVI data, indicating a correlation between signal attenuation and vegetation water content [25]. Additionally, the interference pattern between direct and reflected GNSS signals from the Earth's surface was used in estimating vegetation height and land topography [20]. Through using a Soil Moisture Interference-pattern GNSS Observations at L-band (SMIGOL) reflectometer, the instantaneous power of the direct and reflected signals were coherently added, in which the resulting power oscillations present notches that are correlated to vegetation layer thickness and the reflection geometry [20]. As a result, an RMSE of 3-5 cm in estimating the height of vegetation with simple geometrical structures (barley and wheat) could be achieved [20]. Yet, despite the effort in prior studies, the use of GNSS-R techniques in vegetation remote sensing and monitoring is far from developed. Most importantly, existing research relies heavily on space-borne or static ground-based platforms, while the use of high spatial resolution and flexibility platforms - such as an UAV - remains underexplored. Therefore, it is critical to develop a systematic framework for an UAV-based GNSS-R system, in which correlations between GNSS-R signal features and vegetation condition parameters are comprehensively assessed and modeled. Additionally, with adequate dataset size, the GNSS-R framework could be complemented by machine learning-based modelling approaches, further enhancing the system robustness. Connection to ML part

3.3 Machine Learning

Placeholder text

3.4 LiDAR SLAM

Placeholder text

4 Methodology

Placeholder text

4.1 UAV Platform

Placeholder text

4.2 System Architecture

Placeholder text

4.3 Path Planning

Placeholder text

4.4 GNSS-R

The GNSS-R framework takes in raw GNSS data collected from the onboard receivers and runs the data through the steps of GNSS measurement extraction, Fresnel zone analysis, and GNSS measurement level modelling.

4.4.1 GNSS Measurement Extraction

Two major GNSS measurements are extracted from the collected data: carrier to noise ratio (C/N_0) and pseudorange error.

Carrier to Noise Ratio

Carrier to noise ratio refers to the power of received carrier signal relative to the noise power per unit bandwidth, usually expressed in decibel-Hertz (dB-Hz) [26]. C/N_0 can be readily obtained from the receiver, and it is calculated using the following equation:

$$C/N_0 = C - (N - BW) \tag{1}$$

where C refers to the carrier power in dBm or dBW; N refers to the noise power in dBm or dBW; and BW refers to the bandwidth of the observation in Hz.

Pseudorange Error

In GNSS, pseudorange refers to the "apparent" distance between a satellite and a receiver, which includes the true geometric range plus various biases and delays. For the ith satellite, its pseudorange ρ^i could be expressed as the following [27]:

$$\rho^i = R^i + \Delta t_r + \Delta t_s^i + I^i + T^i + \epsilon^i \tag{2}$$

where R^i refers to the true geometric distance between the satellite and the receiver; Δt_r refers to the receiver clock bias; Δt_s^i refers to the satellite clock bias; I^i refers to the ionospheric delay; T^i refers to the tropospheric delay; and ϵ^i refers to the pseudorange error, which is mainly introduced through signal reflections. Among all the signals received at a given instant, a satellite m with the highest elevation angle is selected as the master satellite, where the assumption that the master satellite is free of reflections is applied [28]:

$$\rho^m = R^m + \Delta t_r + \Delta t_s^m + I^m + T^m. \tag{3}$$

Assuming Δt_s^i and Δt_s^m can be effectively removed by satellite-broadcasted parameters, I^i and I^m can be effectively removed by the Klobuchar model, and T^i and T^m can be effectively removed by the Saastamoinen model, the pseudorange equations can be approximated as [27]:

$$\rho^i = R^i + \Delta t_r + \epsilon^i, \tag{4}$$

$$\rho^m = R^m + \Delta t_r. \tag{5}$$

Finally, taking the difference between (4) and (5) and rearranging the equation will result in the pseudorange error:

$$\epsilon^i = \rho^i - \rho^m - R^i + R^m. \tag{6}$$

4.4.2 Fresnel Zone Analysis

Placeholder text

4.4.3 GNSS Measurement Level Model

Placeholder text

4.5 Machine Learning

Placeholder text

4.6 LiDAR SLAM

Placeholder text

5 Experiments

Placeholder text

5.1 Experiment Workflow

Placeholder text

5.2 Summary of Experiments Conducted

Placeholder text

5.3 Key Experiment 1

Placeholder text

5.4 Key Experiment 2

Placeholder text

6 Results and Discussion

Placeholder text

6.1 Path Planning

Placeholder text

6.2 GNSS-R

Placeholder text

6.3 Machine Learning

Placeholder text

6.4 LiDAR SLAM

Placeholder text

7 Conclusion

Placeholder text

8 Future Works

Placeholder text

8.1 Path Planning

Placeholder text

8.2 GNSS-R

Placeholder text

8.3 Machine Learning

Placeholder text

8.4 LiDAR SLAM

Placeholder text

9 Project Management

Placeholder text

9.1 Gantt Chart

Placeholder text

9.2 Project Difficulties and Solutions

Placeholder text

9.2.1 Path Planning

Placeholder text

9.2.2 GNSS-R

Placeholder text

9.2.3 Machine Learning

Placeholder text

9.2.4 LiDAR SLAM

Placeholder text

Appendix

Placeholder text

References

[1] A. D. Richardson, T. F. Keenan, M. Migliavacca, Y. Ryu, O. Sonnentag, and M. Toomey, "Climate change, phenology, and phenological control of vegetation feedbacks to the climate system," *Agricultural and Forest Meteorology*, vol. 169, p. 156–173, Feb. 2013. [Online]. Available: http://dx.doi.org/10.1016/j.agrformet.2012.09.012

[2] J. Wallace, G. Behn, and S. Furby, "Vegetation condition assessment and monitoring from sequences of satellite imagery," *Ecological Management & Restoration*, vol. 7, no. s1, May 2006. [Online]. Available: http://dx.doi.org/10.1111/j.1442-8903.2006.00289.x

[3] Y. Zeng, D. Hao, A. Huete, B. Dechant, J. Berry, J. M. Chen, J. Joiner, C. Frankenberg, B. Bond-Lamberty, Y. Ryu, J. Xiao, G. R. Asrar, and M. Chen, "Optical vegetation indices for monitoring terrestrial ecosystems globally," *Nature Reviews Earth & Environment*, vol. 3, no. 7, p. 477–493, May 2022. [Online]. Available: http://dx.doi.org/10.1038/s43017-022-00298-5

[4] P. Gibbons and D. Freudenberger, "An overview of methods used to assess vegetation condition at the scale of the site," *Ecological Management & Restoration*, vol. 7, no. s1, May 2006. [Online]. Available: http://dx.doi.org/10.1111/j.1442-8903.2006.00286.x

[5] D. Parkes, G. Newell, and D. Cheal, "Assessing the quality of native vegetation: The 'habitat hectares' approach," *Ecological Management & Restoration*, vol. 4, no. s1, Feb. 2003. [Online]. Available: http://dx.doi.org/10.1046/j.1442-8903.4.s.4.x

[6] L. Li, X. Xin, J. Zhao, A. Yang, S. Wu, H. Zhang, and S. Yu, "Remote sensing monitoring and assessment of global vegetation status and changes during 2016–2020," *Sensors*, vol. 23, no. 20, p. 8452, Oct. 2023. [Online]. Available: http://dx.doi.org/10.3390/s23208452

[7] J. Campbell and R. Wynne, *Introduction to Remote Sensing, Fifth Edition*. Guilford Publications, 2011. [Online]. Available: https://books.google.com.hk/books?id=NkLmDjSS8TsC

[8] S. Qian, “Overview of hyperspectral imaging remote sensing from satellites,” p. 41–66, Nov. 2022. [Online]. Available: http://dx.doi.org/10.1002/9781119687788.ch2

[9] C. Hu, Y. Li, Z. Chen, F. Liu, Q. Zhang, A. V. Monti-Guarnieri, S. Hobbs, A. Anghel, and M. Datcu, “Distributed spaceborne sar: A review of systems, applications, and the road ahead,” *IEEE Geoscience and Remote Sensing Magazine*, vol. 13, no. 2, p. 329–361, Jun. 2025. [Online]. Available: http://dx.doi.org/10.1109/MGRS.2025.3535412

[10] K. M. Bergen, S. J. Goetz, R. O. Dubayah, G. M. Henebry, C. T. Hunsaker, M. L. Imhoff, R. F. Nelson, G. G. Parker, and V. C. Radeloff, “Remote sensing of vegetation 3-d structure for biodiversity and habitat: Review and implications for lidar and radar spaceborne missions,” *Journal of Geophysical Research: Biogeosciences*, vol. 114, no. G2, Jun. 2009. [Online]. Available: http://dx.doi.org/10.1029/2008JG000883

[11] M. N. Khan, Y. Tan, A. A. Gul, S. Abbas, and J. Wang, “Forest aboveground biomass estimation and inventory: Evaluating remote sensing-based approaches,” *Forests*, vol. 15, no. 6, p. 1055, Jun. 2024. [Online]. Available: http://dx.doi.org/10.3390/f15061055

[12] M. A. Wulder, C. C. Dymond, J. C. White, D. G. Leckie, and A. L. Carroll, “Surveying mountain pine beetle damage of forests: A review of remote sensing opportunities,” *Forest Ecology and Management*, vol. 221, no. 1–3, p. 27–41, Jan. 2006. [Online]. Available: http://dx.doi.org/10.1016/j.foreco.2005.09.021

[13] L. A. Arroyo, C. Pascual, and J. A. Manzanera, “Fire models and methods to map fuel types: The role of remote sensing,” *Forest Ecology and Management*, vol. 256, no. 6, p. 1239–1252, Sep. 2008. [Online]. Available: http://dx.doi.org/10.1016/j.foreco.2008.06.048

[14] L. Tang and G. Shao, “Drone remote sensing for forestry research and practices,” *Journal of Forestry Research*, vol. 26, no. 4, p. 791–797, Jun. 2015. [Online]. Available: http://dx.doi.org/10.1007/s11676-015-0088-y

[15] J. Wu, Y. Zhang, P. Hu, and Y. Wu, “A review of the application of hyperspectral imaging technology in agricultural crop economics,” *Coatings*, vol. 14, no. 10, p. 1285, Oct. 2024. [Online]. Available: http://dx.doi.org/10.3390/coatings14101285

[16] J. G. Su and E. W. Bork, “Characterization of diverse plant communities in aspen parkland rangeland using lidar data,” *Applied Vegetation Science*, vol. 10, no. 3, p. 407–416, Jul. 2007. [Online]. Available: http://dx.doi.org/10.1111/j.1654-109X.2007.tb00440.x

[17] S. Jin, A. Camps, Y. Jia, F. Wang, M. Martin-Neira, F. Huang, Q. Yan, S. Zhang, Z. Li, K. Edokossi, D. Yang, Z. Xiao, Z. Ma, and W. Bai, “Remote sensing and its applications using gnss reflected signals: advances and prospects,” *Satellite Navigation*, vol. 5, no. 1, May 2024. [Online]. Available: http://dx.doi.org/10.1186/s43020-024-00139-4

[18] S. Jin and A. Komjathy, “Gnss reflectometry and remote sensing: New objectives and results,” *Advances in Space Research*, vol. 46, no. 2, p. 111–117, Jul. 2010. [Online]. Available: http://dx.doi.org/10.1016/j.asr.2010.01.014

[19] M. Martín-Neira, “A pasive reflectometry and interferometry system (paris) application to ocean altimetry,” 1993. [Online]. Available: https://api.semanticscholar.org/CorpusID:210311905

[20] N. Rodriguez-Alvarez, A. Camps, M. Vall-llossera, X. Bosch-Lluis, A. Monerris, I. Ramos-Perez, E. Valencia, J. F. Marchan-Hernandez, J. Martinez-Fernandez, G. Baroncini-Turricchia, C. Perez-Gutierrez, and N. Sanchez, “Land geophysical parameters retrieval using the interference pattern gnss-r technique,” *IEEE Transactions on Geoscience and Remote Sensing*, vol. 49, no. 1, p. 71–84, Jan. 2011. [Online]. Available: http://dx.doi.org/10.1109/TGRS.2010.2049023

[21] Y. Jia and Y. Pei, *Remote Sensing in Land Applications by Using GNSS-Reflectometry*. InTech, Jul. 2018. [Online]. Available: http://dx.doi.org/10.5772/intechopen.72901

[22] P. Ferrazzoli, L. Guerriero, N. Pierdicca, and R. Rahmoune, “Forest biomass monitoring with gnss-r: Theoretical simulations,” *Advances in Space Research*, vol. 47, no. 10, p. 1823–1832, May 2011. [Online]. Available: http://dx.doi.org/10.1016/j.asr.2010.04.025

[23] X. Wu and S. Jin, “Gnss-reflectometry: Forest canopies polarization scattering properties and modeling,” *Advances in Space Research*, vol. 54, no. 5, p. 863–870, Sep. 2014. [Online]. Available: http://dx.doi.org/10.1016/j.asr.2014.02.007

[24] S. H. Yueh, R. Shah, M. J. Chaubell, A. Hayashi, X. Xu, and A. Colliander, “A semiempirical modeling of soil moisture, vegetation, and surface roughness impact on cygnss reflectometry data,” *IEEE Transactions on Geoscience and Remote Sensing*, vol. 60, p. 1–17, 2022. [Online]. Available: http://dx.doi.org/10.1109/TGRS.2020.3035989

[25] A. Camps, H. Park, M. Pablos, G. Foti, C. P. Gommenginger, P.-W. Liu, and J. Judge, “Sensitivity of gnss-r spaceborne observations to soil moisture and vegetation,” *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, vol. 9, no. 10, p. 4730–4742, Oct. 2016. [Online]. Available: http://dx.doi.org/10.1109/JSTARS.2016.2588467

[26] A. Joseph, “Gnss solutions: Measuring gnss signal strength. insidegnss,” 2010.

[27] E. D. Kaplan and C. Hegarty, *Understanding GPS/GNSS: principles and applications*. Artech house, 2017.

[28] L.-T. Hsu, “Analysis and modeling gps nlos effect in highly urbanized area,” *GPS solutions*, vol. 22, no. 1, p. 7, 2018.