**A Study on Creating Digital Twin Foliage Representation Through Computer Vision, Aerial Image Analysis and Machine Learning techniques to enhance the Network Planning and Deployment**

Dissertation Proposal

Submitted to National University

National University

in Partial Fulfillment of the

Requirements for the Degree of

DOCTOR OFDATA SCIENCE

by

HASHIM SHAIK

San Diego, California

March 2024

**Table of Contents**

[Chapter 1: Introduction 1](#_Toc161477437)

[Statement of the Problem 3](#_Toc161477438)

[Purpose of the Study 4](#_Toc161477439)

[Introduction to Theoretical or Conceptual Framework 5](#_Toc161477440)

[Introduction to Research Methodology and Design (Nature of the Study) 8](#_Toc161477441)

[Research Questions 10](#_Toc161477442)

[Hypotheses 11](#_Toc161477443)

[Significance of the Study 12](#_Toc161477444)

[Definitions of Key Terms 14](#_Toc161477445)

[Summary 16](#_Toc161477446)

[References 19](#_Toc161477447)

[Appendix A XXX 33](#_Toc161477448)

[Appendix B XXX 34](#_Toc161477449)

**List of Tables**

Begin list of tables here…

**List of Figures**

[**Figure 1** *Smart City Digital Twin: Urban Planning and Green Spaces Integration* 2](#_Toc161477583)

[**Figure 2** *Digital Twin Representation of Foliage - Example* 8](#_Toc161477584)

[**Figure 3** *Flowchart: Digital Twin Representation of Foliage (AI-Driven Foliage Detection Using Machine Learning and Computer Vision)* 9](#_Toc161477585)

# Chapter 1: Introduction

In today’s rapidly advancing telecommunications landscape, the emergence of millimeter-wave (mmW) networks is a pivotal development aimed at fulfilling the surging demand for greater bandwidth, enhanced throughput, and minimized latency (Abdullah et al., 2020; Hong et al., 2021). This progression is vital for the progression of 5G wireless networks to meet the escalating needs of the mobile industry. However, mmW networks are challenged by issues like signal scattering, atmospheric absorption, and the obstruction caused by foliage and building structures; these are critical to navigating the successful roll-out of 5G networks, ensuring optimal coverage and data speeds (Barb et al., 2022; Bose et al., 2024; N. A. Khan & Schmid, 2024; Pradeep et al., 2021; Y. Zhang et al., 2019).

The process of accurately capturing foliage data, crucial (Lai et al., 2023) for the deployment of these high-frequency networks like mmW, has traditionally relied on costly and time-consuming methods such as Light Detection and Ranging (LiDAR) and unmanned aerial vehicles (UAVs) (Q. Chen et al., 2022; X. Deng et al., 2022; Mazzacca et al., 2022; Rogers et al., 2020). To adapt to the dynamic nature of our surroundings, the need for frequent updates of data renders traditional methods less viable for continuous application (Rogers et al., 2020). However, the rise of digital twin technology offers a groundbreaking alternative (Attaran & Celik, 2023; Chang et al., 2021).

Digital twins have become a game-changing strategy with applications spanning urban development and industrial operations, notably in the planning of wireless networks (T. Deng et al., 2021; Gabriele et al., 2023). One of the most compelling uses of digital twin technology is in the detailed modeling of foliage or vegetation. By constructing a virtual representation of the natural environment, focusing on the variety, distribution, and properties of plant life, digital twins afford network planners, environmental experts, and other stakeholders a nuanced understanding of how vegetation influences signal behavior, including path loss and network coverage, in high frequency mmW networks integral to 5G technology (L. U. Khan et al., 2022; Kuruvatti et al., 2022).

The sample image (Figure 1) depicting a digital twin representation of an urban area has been created. It includes 3D models of buildings, streets, and foliage, presenting a clean and simplified city landscape that could be used for architectural visualization or city planning simulation. The design conveys a modern and futuristic tone, indicative of advanced urban planning and smart city concepts (Chang et al., 2021; T. Deng et al., 2021).

**Figure 1**

*Smart City Digital Twin: Urban Planning and Green Spaces Integration*

A city with many tall buildings

Description automatically generated

*Note.* This image was generated with the assistance of Artificial Intelligence (AI).

## Statement of the Problem

Connected devices are becoming more common, and users are demanding higher bandwidth, throughput, and lower latency. This led to the development of millimeter-wave (mmW) networks. The mmW band suffers from scattering, atmospheric absorption, canopy (foliage), and building facades. Implementation of 5G requires mmW band propagation channel optimization (Farooq & Lokam, 2023; Pradeep et al., 2021; Y. Zhang et al., 2019).

Accurate modeling of foliage’s channel propagation is vital for wireless network design, particularly in diverse environments like rural, suburban, and urban settings. The blockage effects of foliage, especially at millimeter-wave frequencies, can be severe because of the comparable size of leaves and branches to the transmitted signal wavelength. Overcoming these challenges is crucial to developing reliable channel propagation models that effectively consider foliage’s impact on wireless communication systems (Anzum, 2021; Chikhale et al., 2022; Lai et al., 2023). Network operators must consider all these factors while deploying mmW technologies (5G, 6G) to improve user coverage and throughput.

Currently, foliage data is acquired using costly methods such as UAVs and LiDAR, requiring substantial physical effort (Q. Chen et al., 2022; Hematang et al., 2022; Mazzacca et al., 2022; Shen et al., 2023; Suhaizad et al., 2023). The continuous growth and transformation of foliage necessitates regular data collection to keep information current. The impracticality of repeating these tasks for regular foliage updates becomes clear because of their high cost, labor, and resource intensity. A more cost-effective and efficient approach involves leveraging Google Street View and satellite images in conjunction with state-of-the-art computer vision and machine learning models for object detection (Aikoh et al., 2023; Sun et al., 2023; Y. Zhao et al., 2023), presenting a promising way forward to address the challenges on collecting foliage or vegetation data.

As foliage is one of the main characteristics impacting the higher frequency like mmW network deployment, this study addresses the problem of providing foliage information by creating a digital twin (DT) of an environment with foliage with which network operators planning to deploy networks with higher frequency can use in their network planning to place the nodes at right locations for better coverage and user experience (Gabriele et al., 2023; Nguyen et al., 2021; Qi & Tao, 2018; Thuvander et al., 2022; D. Zhao et al., 2022).

## Purpose of the Study

The purpose of this study is to develop a sophisticated digital twin that mirrors the physical environment, particularly integrating detailed foliage information (Lai et al., 2023; Pradeep et al., 2021; Y. Zhang et al., 2019). The digital twin will serve as a critical tool for network operators, enabling them to estimate the path loss attributed to foliage within the context of high frequency mmW network planning (Lai et al., 2023). Such estimations are pivotal for optimizing network performance and reliability in environments where vegetation can significantly impact signal propagation (Farooq & Lokam, 2023; Pradeep et al., 2021; Y. Zhang et al., 2019).

In order to accomplish this, a machine learning model based on computer vision will be used, which will be meticulously trained on a large dataset of foliage imagery. This model will employ advanced instance semantic segmentation techniques to identify and categorize foliage or vegetation within images. Through a combination of image segmentation, classification, and object detection methodologies, the study will dissect images into precise regions or objects (J. Chen et al., 2021; He et al., 2018; Sun et al., 2023; Y. Zhao et al., 2023).

This approach enables a pixel-level analysis of each scene, facilitating a deeper understanding of the vegetative elements within the digital twin environment (Jiang et al., 2023; Savelonas et al., 2022). The study will explore the nuanced interactions between vegetation and signal propagation, offering network operators a robust framework for mitigating the adverse effects of foliage on mmW network signals (De Beelde et al., 2023; Pradeep et al., 2021; Y. Zhang et al., 2019). This comprehensive approach representing foliage in a DT aims to bridge the gap between theoretical network planning and the practical challenges posed by natural vegetation, fostering more resilient and efficient communication networks in the face of environmental obstacles.

The study will utilize aerial and street view imagery from broad geographic areas in Philadelphia alongside LiDAR or UAV datasets (Research Natural Areas, 2023; OCM Partners, 2024; Philadelphia Lidar - LAS Files 2022 {2022} - Big Ten Academic Alliance Geoportal, 2022) for validating the model via grid-based assessments and Mean Intersection over Union (MIoU) for segmentation accuracy evaluation (Rezatofighi et al., 2019).

## Introduction to Theoretical or Conceptual Framework

The theoretical framework for employing digital twin technology in enhancing millimeter-wave (mmW) network planning and deployment pivots around the Cross-Industry Standard Process for Data Mining (CRISP-DM) process model (Blume et al., 2020; Hayat Suhendar & Widyani, 2023). This framework is specifically tailored to address the unique challenges posed by foliage in urban and suburban environments, which can significantly impact mmW signal propagation due to its high frequency and susceptibility to attenuation by physical obstacles, such as trees and dense vegetation (Barb et al., 2022; De Beelde et al., 2023; Rogers et al., 2020). The digital twin representation of foliage, built upon the CRISP-DM framework, serves as a foundational tool for simulating and analyzing the interaction between mmW signals and urban foliage, facilitating optimized network infrastructure placement and configuration. This initial phase is crucial for delineating the scope and objectives of the mmW network planning project, with a specific emphasis on understanding how foliage impacts signal integrity and network performance (Lai et al., 2023). The aim is to leverage the digital twin to simulate real-world scenarios, thus enabling network engineers to preemptively identify and mitigate potential signal interference or blockage caused by vegetation. Identifying the specific needs, such as improving telecommunications infrastructure, enhancing urban green spaces, or optimizing environmental conservation efforts, will dictate the direction of the subsequent phases.

The second phase involves an initial data collection and familiarization process. For foliage digital twins, this entails gathering high-resolution aerial and street view imagery (Aikoh et al., 2023), LiDAR data, and any available UAV survey data (Q. Chen et al., 2022). Understanding the types, densities, and heights of foliage within the proposed network area is essential for assessing potential mmW signal attenuation or reflection issues. The following Data collection phase is Data preparation. This phase prepares the data for analysis, which may involve cleaning, selecting subsets, constructing data sets, annotating, and formatting data to suit the modeling needs (Dutta & Zisserman, 2019). Given the complexity of urban environments and the diverse data sources involved, this stage is critical for ensuring that the inputs to the machine learning models are of high quality and appropriately structured for detecting and analyzing foliage (J. Chen et al., 2021; He et al., 2018; Sun et al., 2023; J. Zhang et al., 2021; Y. Zhao et al., 2023). With the data prepared, various modeling techniques are applied to extract patterns and generate the digital twin representation. In the case of foliage, machine learning models such as convolutional neural networks (CNNs) or Mask R-CNN are employed to identify, classify, and analyze foliage from the aerial or street view imagery (J. Chen et al., 2021; He et al., 2018; Sun et al., 2023). This involves training models on annotated datasets, selecting the most effective models, and tuning parameters to optimize accuracy and performance (Rezatofighi et al., 2019).

Before proceeding to full-scale deployment, the models and their representations need to be evaluated against predefined success criteria, such as accuracy, reliability, and usability in practical applications (Rezatofighi et al., 2019). This could involve comparing the digital twin outputs with ground-truth data from LiDAR or UAV surveys and assessing the model's ability to represent foliage in various urban scenarios accurately. The final phase involves integrating the digital twin into the mmW network planning and deployment workflow. This enables planners and engineers to visualize signal propagation in the context of urban foliage, identify optimal equipment placement, and anticipate potential maintenance or signal-boosting requirements. The deployment also includes mechanisms for updating the digital twin with new data, ensuring it remains a relevant and effective tool for mmW network optimization (Rogers et al., 2020). By focusing on the unique challenges of mmW network planning in environments with significant vegetation, the CRISP-DM-based digital twin represents a targeted approach to enhancing network reliability and performance. Through detailed simulation and analysis of foliage interactions with mmW signals, network planners can make informed decisions that optimize coverage and capacity while minimizing interference and attenuation, thereby ensuring robust, high-speed wireless connectivity in urban and suburban settings.

## Introduction to Research Methodology and Design (Nature of the Study)

This section describes the research methodology and design for the study relating to the study problem, purpose, and research questions in constructing a Digital Twin Representation of Foliage. The constructive research design aims to bridge the gap between theoretical computer vision techniques and practical applications in digital twin technology for foliage representation. A constructive research design for the “Digital Twin Representation of Foliage” problem ensures a systematic approach to creating a practical solution that addresses the challenges of accurate foliage representation in digital twin models. Below (Figure 2) is a sample of a Digital twin representation of foliage (Z. Li et al., 2023; S. Song & Qin, 2022; Wilk et al., 2022).

**Figure 2**

*Digital Twin Representation of Foliage - Example*

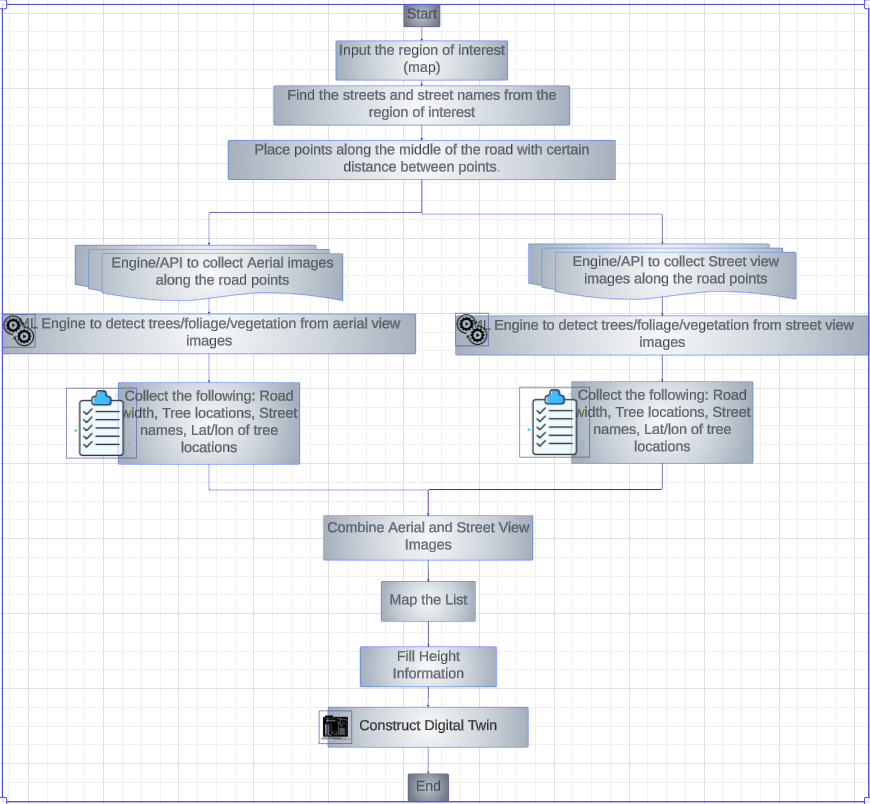
A city with trees and buildings

Description automatically generated

*Note.* This image was generated with the assistance of Artificial Intelligence (AI).

**Figure 3**

*Flowchart: Digital Twin Representation of Foliage (AI-Driven Foliage Detection Using Machine Learning and Computer Vision)*



For future implementation

The current approach focuses on constructing a digital twin model to represent foliage in various environments, leveraging cutting-edge computer vision and machine learning techniques. The flowchart in Figure 3 outlines the process for constructing a Digital Twin model of foliage, starting with the region of interest as the initial input.

## Research Questions

The research questions aim to drive innovation and practical applications in the field of digital twin technology for foliage representation, fostering interdisciplinary collaboration and knowledge exchange among researchers, practitioners, and stakeholders. By addressing these research questions and hypotheses, the study aims to evaluate the feasibility, accuracy, and practicality of using digital twin technology for foliage representation, offering valuable insights for future research and practical applications in wireless network planning and environmental monitoring.

### RQ1

How can a digital twin effectively represent the spatial distribution and characteristics of foliage in natural environments?

### RQ2

How can the integration of image analysis of street view and aerial view images, coupled with computer vision techniques, provide a cost-effective alternative for obtaining foliage information compared to traditional methods?

### RQ3

How are the accuracy and performance of digital twin models for foliage representation compared to traditional methods such as LiDAR and UAV datasets, and what factors influence their effectiveness?

### RQ4

How can digital twin models incorporating foliage representation contribute to more effective urban planning, environmental monitoring, and wireless network optimization in smart city environments?

## Hypotheses

With the use of computer vision-based machine learning methods and image analysis techniques on images collected through aerial (satellite) and street view images, DT models can be generated that provide information about foliage so that mmW networks can be deployed more intelligently and efficiently with better information about foliage.

### H10

The DT generated through computer vision and image analysis approaches do not provide foliage information levels comparable to those obtained through more expensive LiDAR or UAV methods.

### H1a

The DT generated through computer vision and image analysis approach provides foliage information levels comparable to those obtained through more expensive LiDAR or UAV methods.

### H20

The DT generated through the integration of image analysis of aerial view and street view images, along with computer vision techniques, is not a cost-effective alternative for obtaining foliage information.

### H2a

The DT generated through the integration of image analysis of aerial view and street view images, along with computer vision techniques, is a cost-effective alternative for obtaining foliage information.

### H30

The accuracy of the digital twin is comparable to or worse than traditional methods like LiDAR or UAV datasets.

### H3a

The digital twin offers an accurate and dependable representation of various types of foliage, comparable to or at the level of precision achieved by traditional methods.

### H40

The Accurate foliage representation does not significantly contribute to more efficient and intelligent network planning.

### H4a

The digital twin's accurate foliage representation enhances the efficiency and intelligence of network planning, especially in high-frequency scenarios like 5G.

## Significance of the Study

The significance of this study on the digital twin representation of foliage primarily revolves around its pivotal role in advancing network planning and deployment strategies, especially pertinent to the challenges posed by urban environments on telecommunications infrastructure. This research is critical as it provides a novel approach to understanding and mitigating the impact of urban foliage on signal propagation, a significant concern for the deployment of high-frequency networks such as 5G and beyond (Barb et al., 2022; De Beelde et al., 2023; Lai et al., 2023; Pradeep et al., 2021; Y. Zhang et al., 2019). By creating virtual replicas of urban landscapes that accurately reflect the spatial distribution and physical characteristics of foliage (Attaran & Celik, 2023; Chang et al., 2021; L. U. Khan et al., 2022; Kuruvatti et al., 2022), network engineers and planners can simulate and analyze how vegetation impacts network performance, leading to more informed decision-making and optimized network designs.

In the realm of network planning and deployment, this study contributes by offering a data-driven framework that enhances the accuracy of predicting signal interference caused by foliage (Abdullah et al., 2020; Pradeep et al., 2021; Y. Zhang et al., 2019). The research methodically applies machine learning and computer vision to create digital twins that serve as a sandbox for testing various network configurations and their interactions with urban greenery. This approach not only improves the reliability of network services in densely vegetated areas but also assists in identifying ideal locations for network infrastructure, minimizing environmental disruption and costs associated with physical trials (Rogers et al., 2020).

Moreover, the study highlights the potential for digital twins to contribute to more sustainable urban development practices (Attaran & Celik, 2023; Chang et al., 2021; T. Deng et al., 2021; Kuruvatti et al., 2022). By understanding the interplay between network infrastructure and urban green spaces, planners can devise strategies that preserve and enhance vegetation while ensuring technological advancement. This balance is crucial for the future of smart cities, where connectivity needs to harmonize with environmental conservation and urban aesthetics (Pradeep et al., 2021; Y. Zhang et al., 2019). The research enriches the data science literature by highlighting an innovative application of digital twins, grounded in rigorous data analysis and modeling. It advances the telecommunications field by providing a novel tool for addressing one of the key challenges in network deployment (Bose et al., 2024; Pradeep et al., 2021), offering insights that are directly applicable to the design and optimization of next-generation wireless networks.

## Definitions of Key Terms

Here are definitions of key terms for the current study:

### Cross Industry Standard Process for Data Mining (CRISP-DM)

CRISP-DM provides a structured approach to data mining projects, ensuring that all necessary steps are followed to achieve successful outcomes (Blume et al., 2020; Hayat Suhendar & Widyani, 2023)

### Digital Twin (DT)

A virtual representation of a physical asset that closely mimics its real-world counterpart, including detailed information about its design, materials, components, and behavior (Angin et al., 2020; Attaran & Celik, 2023; Azad et al., 2019).

### Geospatial Data:

Data that provides information about the geographic location or spatial characteristics of objects, features, or events is typically represented by latitude and longitude coordinates (Cureton & Hartley, 2023; Rogers et al., 2020; Suhaizad et al., 2023).

### Hypothesis Testing

A statistical process is used to assess the validity of research hypotheses by evaluating whether observed data is consistent with the proposed hypotheses.

### Lidar (Light Detection and Ranging)

A remote sensing technology that uses laser light to measure distances, providing highly accurate 3D information about the terrain, objects, and surfaces it interacts with (Q. Chen et al., 2022; X. Deng et al., 2022; Mazzacca et al., 2022).

### Machine Learning Model

A computational system is trained to perform specific tasks or make predictions based on data, often utilizing algorithms that improve their performance over time (Hayat Suhendar & Widyani, 2023; Kapteyn & Willcox, 2020).

### Mask RCNN

A type of machine learning model, specifically a convolutional neural network, is used, for instance, in segmentation in computer vision tasks. It segments objects in images by delineating their boundaries (He et al., 2018; Sun et al., 2023; J. Zhang et al., 2021).

### Precision, Recall, F1-Score, and Intersection Over Union (IoU)

Performance metrics are used to evaluate the accuracy and effectiveness of machine learning models. Precision measures the proportion of true positive predictions, recall measures the ability to identify actual positives, the F1-score is a harmonic mean of precision and recall, and IoU measures the overlap between predicted and actual objects in segmentation tasks (Rezatofighi et al., 2019; J. Song et al., 2022).

### Quality Assurance and Validation

Ensuring data integrity, accuracy, and reliability through systematic checks and validation procedures to confirm that the collected data and results are trustworthy.

### Statistical Analysis

Applying statistical techniques and tests to analyze and interpret data, identify patterns, and draw meaningful conclusions from datasets.

### Spatial Analysis

Examining the spatial distribution, relationships, and patterns of geographic features or data, often using geographic information system (GIS) tools and methods.

### UAV (Unmanned Aerial Vehicle)

An aircraft without a human pilot onboard is often equipped with cameras or other data collection and remote sensing sensors (Q. Chen et al., 2022; Hematang et al., 2022; Luo et al., 2023; Suhaizad et al., 2023; D. Zhao et al., 2022).

### Visualization

Visual aids, such as charts, maps, graphs, or diagrams, can be used to represent and communicate data and analysis results in a comprehensible and informative manner.

## Summary

This constructive research design aims to bridge the gap between theoretical computer vision techniques and practical applications in digital twin technology for foliage representation. This multidisciplinary approach, combining remote sensing, computer vision, machine learning, and digital twin technology, offers a comprehensive method for accurately representing foliage in digital models, which is essential for the effective planning and deployment of next-generation wireless networks. The study seeks to offer a cost-effective, scalable, and accurate tool for urban planners and network engineers (Alkhateeb et al., 2023; Fett et al., 2023; Kuruvatti et al., 2022; Lehtola et al., 2022). The approach is grounded in rigorous data analysis, ethical considerations, and a clear acknowledgment of its scope and limitations, setting a foundation for future advancements in digital twin technology and its applications in smart city development and environmental monitoring.

The current research significance of digital twin representation of foliage, utilizing computer vision image analysis methods, compared to traditional approaches like LiDAR and UAV, stems from its capacity to overcome inherent challenges and constraints in conventional methodologies. Traditional techniques such as LiDAR and UAV surveys are often cost-prohibitive (Rogers et al., 2020), labor-intensive, and require extensive human involvement for data collection and processing (X. Deng et al., 2022; H. Li et al., 2021). Moreover, these methods could be more extensive in their coverage, resolution, and ability to maintain up-to-date information. In contrast, the digital twin representation of foliage harnesses advanced computer vision, AI, and machine learning techniques to analyze aerial and street view imagery. This approach offers several advantages, including cost-effectiveness, scalability, and the potential for real-time or near-real-time data updates (Attaran & Celik, 2023; Mylonas et al., 2021).

By automating foliage detection and analysis, digital twin representation enables swift and accurate data collection, facilitating more efficient network planning, urban development, and other applications. The impetus behind developing a DT representation of foliage arises from the escalating demand for precise and current foliage information across diverse sectors, encompassing telecommunications, urban planning, and environmental conservation. Industry reports and white papers underscore the critical role of digital twin technology in optimizing telecommunications infrastructure and enhancing service quality (Alkhateeb et al., 2023; L. U. Khan et al., 2022; Kuruvatti et al., 2022). Additionally, government initiatives aimed at sustainable urbanization and environmental stewardship emphasize the value of digital twins in informing data-driven decision-making processes (Angin et al., 2020; Chang et al., 2021; T. Deng et al., 2021; Mylonas et al., 2021).

In summary, digital twins will significantly advance over traditional methods like LiDAR and UAVs in urban and city planning. They offer improved data integration, faster iterations, sustainability, and smart city applications. The development of digital twins, driven by AI and computer vision, is a response to the challenges and limitations of traditional methods, promising more efficient, cost-effective, and scalable solutions for urban planning, and development.

# References

Abdullah, Q., Abdullah, N., Balfaqih, M., Shah, N. S. M., Anuar, S., Almohammedi, A. A., Salh, A., Farah, N., & Shepelev, V. (2020). Maximising system throughput in wireless powered sub-6 GHz and millimetre-wave 5G heterogeneous networks. *Telkomnika*, *18*(3), 1185–1194. https://doi.org/10.12928/TELKOMNIKA.v18i3.15049

Aikoh, T., Homma, R., & Abe, Y. (2023). Comparing conventional manual measurement of the green view index with modern automatic methods using Google Street View and semantic segmentation. *Urban Forestry & Urban Greening*, *80*, 127845. https://doi.org/10.1016/j.ufug.2023.127845

Alkhateeb, A., Jiang, S., & Charan, G. (2023). Real-time digital twins: Vision and research directions for 6G and beyond. *IEEE Communications Magazine*, *61*(11), 128–134. https://doi.org/10.1109/MCOM.001.2200866

Angin, P., Anisi, M. H., Göksel, F., Gürsoy, C., & Büyükgülcü, A. (2020). AgriLoRa: a digital twin framework for smart agriculture. *Journal of Wireless Mobile Networks, Ubiquitous Computing, and Dependable Applications (JoWUA)*, *11*(4), 77–96. https://doi.org/10.22667/JOWUA.2020.12.31.077

Anzum, R. (2021). Factors that affect LoRa Propagation in Foliage Medium. *Procedia Computer Science*, *194*, 149–155. https://doi.org/10.1016/j.procs.2021.10.068

Attaran, M., & Celik, B. G. (2023). Digital Twin: Benefits, use cases, challenges, and opportunities. *Decision Analytics Journal*, *6*, 100165. https://doi.org/10.1016/j.dajour.2023.100165

Azad, M. M., Carla, C. M., & Scott, D. L. (2019). Leveraging Digital Twin Technology in Model-Based Systems Engineering. *Systems*, *7*(1), 7. https://doi.org/10.3390/systems7010007

Barb, G., Danuti, F., Ouamri, M. A., & Otesteanu, M. (2022, November). *Analysis of vegetation and penetration losses in 5G mmwave communication systems*. 2022 International Symposium on Electronics and Telecommunications (ISETC) Electronics and Telecommunications (ISETC), 2022 International Symposium on. :1-5 Nov, 2022. https://doi.org/10.1109/ISETC56213.2022.10009963

Blume, C., Blume, S., Thiede, S., & Herrmann, C. (2020). Data-Driven Digital Twins for Technical Building Services Operation in Factories: A Cooling Tower Case Study. *Journal of Manufacturing Materials Processing*, *4*(4), 97. https://doi.org/10.3390/jmmp4040097

Bose, T., Chatur, N., Mukherjee, M., Verma, S., & Adhya, A. (2024). Traffic-Aware Optimal Multi-Beam Resource Allocation in 5G Networks Impaired by Rain and Foliage. *IEEE Communications Letters*, 1. https://doi.org/10.1109/LCOMM.2024.3357174

Capecchi, I., Borghini, T., & Bernetti, I. (2023). Automated urban tree survey using remote sensing data, Google Street View images, and plant species recognition apps. *European Journal of Remote Sensing*, *56*(1), 2162441. https://doi.org/10.1080/22797254.2022.2162441

Chang, T. H., Chunho, Y., & Ehab, S. (2021). *City Digital Twin Potentials: A Review and Research Agenda*. https://doi.org/10.3390/su13063386

Chen, J., Wang, G., Luo, L., Gong, W., & Cheng, Z. (2021). Building Area Estimation in Drone Aerial Images Based on Mask R-CNN. *IEEE Geoscience and Remote Sensing Letters*, *18*(5), 891–894. https://doi.org/10.1109/LGRS.2020.2988326

Chen, Q., Gao, T., Zhu, J., Wu, F., Li, X., Lu, D., & Yu, F. (2022). Individual Tree Segmentation and Tree Height Estimation Using Leaf-Off and Leaf-On UAV-LiDAR Data in Dense Deciduous Forests. *Remote Sensing*, *14*(12), 2787. https://doi.org/10.3390/rs14122787

Chikhale, D., Munde, M., & Deosarkar, S. (2022). Atmospheric effects and behavior of electromagnetic signals in the millimeter wave range wireless communication. *International Journal of Microwave & Optical Technology*, *17*(2), 115–125.

Clancy, R., O’Sullivan, D., & Bruton, K. (2023). Data-driven quality improvement approach to reducing waste in manufacturing. *The TQM Journal*, *35*(1), 72. https://doi.org/10.1108/TQM-02-2021-0061

Cureton, P., & Hartley, E. (2023). City Information Models (CIMs) as precursors for Urban Digital Twins (UDTs): A case study of Lancaster. *Frontiers in Built Environment*, *9*. https://doi.org/10.3389/fbuil.2023.1048510

De Beelde, B., Plets, D., & Joseph, W. (2023). Characterization of Vegetation Loss and Impact on Network Performance at V-Band Frequencies. *IEEE Antennas and Wireless Propagation Letters*, *22*(3), 596–600. https://doi.org/10.1109/LAWP.2022.3219556

Deng, T., Zhang, K., & Shen, Z.-J., (Max). (2021). A systematic review of a digital twin city: A new pattern of urban governance toward smart cities. *Journal of Management Science and Engineering*, *6*(2), 125–134. https://doi.org/10.1016/j.jmse.2021.03.003

Deng, X., Tang, G., & Wang, Q. (2022). A novel fast classification filtering algorithm for LiDAR point clouds based on small grid density clustering. *Geodesy and Geodynamics*, *13*(1), 38–49. https://doi.org/10.1016/j.geog.2021.10.002

Dutta, A., & Zisserman, A. (2019). *The VIA Annotation Software for Images, Audio, and Video*. https://doi.org/10.1145/3343031.3350535

Farooq, U., & Lokam, A. (2023). Performance analysis of mmWave/sub-terahertz communication link for 5G and B5G mobile networks. *Frequenz*, *77*(11/12), 599–606. https://doi.org/10.1515/freq-2023-0024

Fett, M., Wilking, F., Goetz, S., Kirchner, E., & Wartzack, S. (2023). A Literature Review on the Development and Creation of Digital Twins, Cyber-Physical Systems, and Product-Service Systems. *Sensors (Basel, Switzerland)*, *23*(24). https://doi.org/10.3390/s23249786

Gabriele, M., Cazzani, A., Zerbi, C. M., & Brumana, R. (2023). DIGITAL TWIN TO MONITOR, UNDERSTAND AND PRESERVE THE COMPLEXITY OF MULTI-SCALE NATURAL, AGRICULTURAL, DESIGNED LANDSCAPES AND ARCHITECTURE: BIODIVERSITY CONSERVATION, TRANSFORMATION AND DECLINE AT VILLA ARCONATI SITE AT CASTELLAZZO OF BOLLATE (MI). *International Archives of Photogrammetry, Remote Sensing & Spatial Information Sciences*, *48*(M/2), 613–620. https://doi.org/10.5194/isprs-archives-XLVIII-M-2-2023-613-2023

*Google for developers Maps Static API*. (n.d.). Google for Developers. https://developers.google.com/maps/documentation/maps-static/start

*Google for developers Street View Static API overview*. (n.d.). Google for Developers. https://developers.google.com/maps/documentation/streetview/overview

Hayat Suhendar, M. T., & Widyani, Y. (2023, September 7–8). *Machine Learning Application Development Guidelines Using CRISP-DM and Scrum Concept* [Conference session]. 2023 IEEE International Conference on Data and Software Engineering (ICoDSE), Toba, Indonesia, Indonesia. https://doi.org/10.1109/ICoDSE59534.2023.10291438

He, K., Gkioxari, G., Dollár, P., & Girshick, R. (2018). Mask R-CNN. *arXiv.org*. https://doi.org/10.48550/arXiv.1703.06870

Hematang, F., Murdjoko, A., Hendri, H., & Tokede, M. (2022). Application of Unmanned Aerial Vehicle (UAV) For Estimation of Tree Height in Heterogeneous Forest. *Biosaintifika: Journal of Biology & Biology Education*, *14*(2), 168–179. https://doi.org/10.15294/biosaintifika.v14i2.35637

Hong, W., Jiang, Z. H., Yu, C., Hou, D., Wang, H., Guo, C., Hu, Y., Kuai, L., Yu, Y., Jiang, Z., Chen, Z., Chen, J., Yu, Z., Zhai, J., Zhang, N., Tian, L., Wu, F., Yang, G., Hao, Z., & Zhou, J. Y. (2021). The Role of Millimeter-Wave Technologies in 5G/6G Wireless Communications. *IEEE Journal of Microwaves*, *1*(1), 101–122. https://doi.org/10.1109/JMW.2020.3035541

Hu, W., Fang, J., Zhang, T., Liu, Z., & Tan, J. (2023). A new quantitative digital twin maturity model for high-end equipment. *Journal of Manufacturing Systems*, *66*, 248–259. https://doi.org/10.1016/j.jmsy.2022.12.012

Jahnke, N., & Otto, B. (2023). Data Catalogs in the Enterprise: Applications and Integration. *Datenbank Spektrum*, *23*(2), 89–96. https://doi.org/10.1007/s13222-023-00445-2

Jiang, B., An, X., Xu, S., & Chen, Z. (2023). Intelligent Image Semantic Segmentation: A Review Through Deep Learning Techniques for Remote Sensing Image Analysis. *Journal of the Indian Society of Remote Sensing*, *51*(9), 1865–1878. https://doi.org/10.1007/s12524-022-01496-w

Kapteyn, M. G., & Willcox, K. E. (2020). From physics-based models to predictive digital twins via interpretable machine learning. *arXiv preprint arXiv:2004.11356*. https://doi.org/10.48550/arXiv.2004.11356

Khan, L. U., saad, W., Niyato, D., Han, Z., & Hong, C. S. (2022). Digital-Twin-Enabled 6G: Vision, Architectural Trends, and Future Directions. *IEEE Communications Magazine*, *60*(1), 74–80. https://doi.org/10.1109/MCOM.001.21143

Khan, N. A., & Schmid, S. (2024). AI-RAN in 6G Networks: State-of-the-Art and Challenges. *IEEE Open Journal of the Communications Society*, *5*, 294–311. https://doi.org/10.1109/OJCOMS.2023.3343069

Kuruvatti, N. P., Habibi, M. A., Partani, S., Han, B., Fellan, A., & Schotten, H. D. (2022). Empowering 6G communication systems with digital twin technology: A comprehensive survey. *IEEE Access*, *10*, 112158–112186. https://doi.org/10.1109/ACCESS.2022.3215493

Lai, C., Senic, D., Gentile, C., Senic, J., & Golmie, N. (2023). Raytracing Digital Foliage at Millimeter-Wave: A Case Study on Calibration Against 60-GHz Channel Measurements on Summer and Winter Trees. *IEEE Access*, *11*, 145931–145943. https://doi.org/10.1109/ACCESS.2023.3345248

Lehtola, V. V., Koeva, M., Elberink, S. O., Raposo, P., Virtanen, J.-P., Vahdatikhaki, F., & Borsci, S. (2022). Digital twin of a city: Review of technology serving city needs. *International Journal of Applied Earth Observation and Geoinformation*, *114*, 102915. https://doi.org/10.1016/j.jag.2022.102915

Li, H., Ye, C., Guo, Z., Wang, L., Wei, R., & Li, J. (2021). A Fast Progressive TIN Densification Filtering Algorithm for Airborne LiDAR Data Using Adjacent Surface Information. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, *14*, 12492–12503. https://doi.org/10.1109/JSTARS.2021.3131586

Li, Z., Wu, B., Li, Y., & Chen, Z. (2023). Fusion of aerial, MMS and backpack images and point clouds for optimized 3D mapping in urban areas. *ISPRS Journal of Photogrammetry & Remote Sensing*, *202*, 463–478. https://doi.org/10.1016/j.isprsjprs.2023.07.010

Luo, S., Liang, Y., Luo, Z., Liang, G., Wang, C., & Wu, X. (2023). Vision-Guided Object Recognition and 6D Pose Estimation System Based on Deep Neural Network for Unmanned Aerial Vehicles towards Intelligent Logistics. *Applied Sciences*, *13*(1). https://doi.org/10.3390/app13010115

Mazzacca, G., Grilli, E., Cirigliano, G. P., Remondino, F., & Campana, S. (2022). Seeing among foliage with lidar and machine learning: Towards a transferable archaeological pipeline. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, *XLVI-2-W1-2022*, 365–372. https://doi.org/10.5194/isprs-archives-XLVI-2-W1-2022-365-2022

*MWC23 – Intelligent 5G mmWave network planning*. (2023, February 27). Wireless Technology & Innovation | Mobile Technology | Qualcomm. https://www.qualcomm.com/videos/mwc23-intelligent-5g-mmwave-network-planning

Mylonas, G., Kalogeras, A., Kalogeras, G., Anagnostopoulos, C., Alexakos, C., & Muñoz, L. (2021). Digital twins from smart manufacturing to smart cities: A survey. *IEEE Access*, *9*, 143222–143249. https://doi.org/10.1109/ACCESS.2021.3120843

National Academies of Sciences, Engineering, and Medicine. (2023). *Foundational research gaps and future directions for digital twins*. The National Academies Press. https://doi.org/10.17226/26894

Nguyen, H. X., Trestian, R., To, D., & Tatipamula, M. (2021). Digital Twin for 5G and beyond. *IEEE Communications Magazine*, *59*(2), 10–15. https://doi.org/10.1109/MCOM.001.2000343

*Northern Research Station | Research Natural Areas. U.S. Department of Agriculture, Forest Service, Northern Research Station.* (2023, September 22). ArcGIS StoryMaps. https://storymaps.arcgis.com/stories/5b1cfad1e7bd49058b2e570ecdc3b50a

*OCM Partners, 2024: 2022 City of Philadelphia Lidar DEM: Philadelphia, PA*. (2024, January 10). Welcome to NOAA | NOAA Fisheries. https://www.fisheries.noaa.gov/inport/item/70174

*Philadelphia LiDAR - LAS files 2022 {2022} - Big Ten academic alliance Geoportal*. (2022). Big Ten Academic Alliance Geoportal. https://geo.btaa.org/catalog/pasda-7154

*Policies for aerial view API*. (n.d.). Google for Developers. https://developers.google.com/maps/documentation/aerial-view/policies

*Policies for street view static API*. (n.d.). Google for Developers. https://developers.google.com/maps/documentation/streetview/policies

Pradeep, T., Shukla, N. K., Animesh, T., & Shiv, P. (2021). *Investigating the Effect of Rain, Foliage, Atmospheric Gases, and Diffraction on Millimeter (mm) Wave Propagation for 5G Cellular Networks*. https://doi.org/10.1007/978-981-16-3346-1\_42

QGIS Development Team. (2021). *QGIS Geographic Information System* [Computer software]. QGIS Association. http://www.qgis.org

Qi, Q., & Tao, F. (2018). Digital Twin and Big Data Towards Smart Manufacturing and Industry 4.0: 360 Degree Comparison. *IEEE Access*, *6*, 3593. https://doi.org/10.1109/ACCESS.2018.2793265

Rezatofighi, H., Tsoi, N., Gwak, J., Sadeghian, A., Reid, I., & Savarese, S. (2019). *Generalized Intersection over Union: A Metric and A Loss for Bounding Box Regression*. http://arxiv.org/abs/1902.09630

Rogers, S. R., Manning, I., & Livingstone, W. (2020). Comparing the Spatial Accuracy of Digital Surface Models from Four Unoccupied Aerial Systems: Photogrammetry Versus LiDAR. *Remote Sens.*, *12*(17). https://doi.org/10.3390/rs12172806

Saravanan, S. K., Muthusenthil, B., & Gurusubramani, S. (2022). *A review of digital twin leveraging technology, concepts, tools, and industrial applications*. 2022 1st International Conference on Computational Science and Technology (ICCST) Computational Science and Technology (ICCST). https://doi.org/10.1109/ICCST55948.2022.10040359

Savelonas, M. A., Veinidis, C. N., & Bartsokas, T. K. (2022). Computer Vision and Pattern Recognition for the Analysis of 2D/3D Remote Sensing Data in Geoscience: A Survey. *Remote Sensing*, *14*(23), 6017. https://doi.org/10.3390/rs14236017

Sharma, A., Kosasih, E., Zhang, J., Brintrup, A., & Calinescu, A. (2022). Digital Twins: State of the art theory and practice, challenges, and open research questions. *Journal of Industrial Information Integration*, *30*. https://doi.org/10.1016/j.jii.2022.100383

Shen, Y., Huang, R., Hua, B., Pan, Y., Mei, Y., & Dong, M. (2023). Automatic Tree Height Measurement Based on Three-Dimensional Reconstruction Using Smartphone. *Sensors 2023*, *23*(16), 7248. https://doi.org/10.3390/ s23167248

Somanath, S., Naserentin, V., Eleftheriou, O., Sjölie, D., Wästberg, B. S., & Logg, A. (2023, May 3). *On procedural urban digital twin generation and visualization of large scale data*. From Oaister®, Provided by the OCLC Cooperative. http://arxiv.org/abs/2305.02242

Song, J., Zhao, Y., Song, W., Zhou, H., Zhu, D., Huang, Q., Fan, Y., & Lu, C. (2022). Fisheye Image Detection of Trees Using Improved YOLOX for Tree Height Estimation. *Sensors*, *22*, 3636. https://doi.org/10.3390/s22103636

Song, S., & Qin, R. (2022). A NOVEL INTRINSIC IMAGE DECOMPOSITION METHOD TO RECOVER ALBEDO FOR AERIAL IMAGES IN PHOTOGRAMMETRY PROCESSING. *ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, *V-2-2022*, 23–30. https://doi.org/10.5194/isprs-annals-V-2-2022-23-2022

Suhaizad, L. S., Khalid, N., & Abu Sari, M. Y. (2023). Tree Height and Crown Extraction From UAV-Based Multispectral Imagery. *International Journal of Geoinformatics*, *19*(5), 61–68. https://doi.org/10.52939/ijg.v19i5.2661

Sun, Z., Xue, B., Zhang, M., & Schindler, J. (2023). *An Improved Mask R-CNN for Instance Segmentation of Tree Crowns in Aerial Imagery*. 2023 38th International Conference on Image and Vision Computing New Zealand (IVCNZ), Image and Vision Computing New Zealand (IVCNZ). https://doi.org/10.1109/IVCNZ61134.2023.10343827

Thuvander, L., Somanath, S., & Hollberg, A. (2022). PROCEDURAL DIGITAL TWIN GENERATION FOR CO-CREATING IN VR FOCUSING ON VEGETATION. *International Archives of Photogrammetry, Remote Sensing & Spatial Information Sciences*, *48*(4/W5), 189–196. https://doi.org/10.5194/isprs-archives-XLVIII-4-W5-2022-189-2022

Tran, B.-H., Aussenac-Gilles, N., Comparot, C., & Trojahn, C. (2022). Semantic Integration of Raster Data for Earth Observation on Territorial Units. *ISPRS International Journal of Geo-Information*, *11*(2), 149. https://doi.org/10.3390/ijgi11020149

Trevisan, L. R., Brichi, L., Gomes, T. M., & Rossi, F. (2023). Estimating Black Oat Biomass Using Digital Surface Models and a Vegetation Index Derived from RGB-Based Aerial Images. *Remote Sens*, *15*(5). https://doi.org/10.3390/rs15051363

Wang, W., Xiao, L., Zhang, J., Yang, Y., Tian, P., Wang, H., & He, X. (2018). Potential of Internet street-view images for measuring tree sizes in roadside forests. *Urban Forestry & Urban Greening*, *35*, 211–220. https://doi.org/10.1016/j.ufug.2018.09.008

Waqar, A., Othman, I., Almujibah, H., Khan, M. B., Alotaibi, S., & Elhassan, A. A. M. (2023). Factors Influencing Adoption of Digital Twin Advanced Technologies for Smart City Development: Evidence from Malaysia. *Buildings*, *13*(3). https://doi.org/10.3390/buildings13030775

Weil, C., Bibri, S. E., Longchamp, R., Golay, F., & Alahi, A. (2023). Urban Digital Twin Challenges: A Systematic Review and Perspectives for Sustainable Smart Cities. *Sustainable Cities and Society*, *99*, 104862. https://doi.org/10.1016/j.scs.2023.104862

Wilk, Ł., Mielczarek, D., Ostrowski, W., Dominik, W., & Krawczyk, J. (2022). SEMANTIC URBAN MESH SEGMENTATION BASED ON AERIAL OBLIQUE IMAGES AND POINT CLOUDS USING DEEP LEARNING. *International Archives of the Photogrammetry, Remote Sensing & Spatial Information Sciences*, (B2), 485–491. https://doi.org/10.5194/isprs-archives-XLIII-B2-2022-485-2022

Yang, E., Wang, M., Cheng, H., Liu, R., & Chen, F. (2022). *A Method to Improve the Precision of 2-Dimensioanl Size Measurement of Objects through Image Processing*. 2022 21st International Symposium on Distributed Computing and Applications for Business Engineering and Science (DCABES) DCABES Distributed Computing and Applications for Business Engineering and Science (DCABES), 2022 21st International Symposium on, DCABES, 197–200. https://doi.org/10.1109/DCABES57229.2022.00010

Zhang, J., Cosma, G., & Watkins, J. (2021). Image Enhanced Mask R-CNN: A Deep Learning Pipeline with New Evaluation Measures for Wind Turbine Blade Defect Detection and Classification. *Journal of Imaging*, *7*(3). https://doi.org/10.3390/jimaging7030046

Zhang, Y., Anderson, C. R., Michelusi, N., Love, D. J., Baker, K. R., & Krogmeier, J. V. (2019). Propagation Modeling Through Foliage in a Coniferous Forest at 28 GHz. *IEEE Wireless Communications Letters*, *8*(3), 901–904.

Zhao, D., Li, X., Wang, X., Shen, X., & Gao, W. (2022). Applying Digital Twins to Research the Relationship Between Urban Expansion and Vegetation Coverage: A Case Study of Natural Preserve. *Frontiers in Plant Science*, *13*, 840471. https://doi.org/10.3389/fpls.2022.840471

Zhao, W., Persello, C., & Stein, A. (2023). Semantic-aware unsupervised domain adaptation for height estimation from single-view aerial images. *ISPRS Journal of Photogrammetry and Remote Sensing*, *196*, 372–385. https://doi.org/10.1016/j.isprsjprs.2023.01.003

Zhao, Y., Cheng, D., Shen, S., Cai, D., & Lyu, X. (2023). *Improved Mask R-CNN for Disturbed Area Extraction in Construction Projects from High-Resolution Satellite Imagery*. 2023 6th International Conference on Artificial Intelligence and Big Data (ICAIBD), Artificial Intelligence and Big Data (ICAIBD). https://doi.org/10.1109/ICAIBD57115.2023.10206407

# 

# Appendix A XXX

Insert Appendix A content here…

Note that you are required to include your Programming Modules and or the final standalone (if applicable here), an alternative that I would definitely propose is to include the link to your personal GitHub webpage and include all modules and the data you worked with there.

You should include here a link that is static and ensure that the GitHub page stays live.

# Appendix B XXX

Insert/type Appendix n content here…