Calssifing Buildings Based from Drone Aerial Imagery

Connor Williams
Brigham Young University
Department of Civil and Construction Engineering
Provo, Utah 8460

Gregory Macfarland
Brigham Young University
Department of Civil and Construction Engineering
Provo, Utah 8460

Kaylen Turley
Brigham Young University
Department of Civil and Construction Engineering
Provo, Utah 8460

***Abstract*—This document is a template demonstrating the Ieee-conference format.**

***Index Terms*—template; demo**

I. Introduction

Travel forecasting models are based heavily on data provided by government statistical agencies, such as the US Census Bureau and the Bureau of Labor Statistics. In countries where statistical agencies are not as reliable, travel forecasting models are generally not developed or have data gaps. The data needed for modeling includes household statistics such as humber of adults, income level, etc.

With the rise of commercially availible and affordable aerial drones, the ability to capture remote sensing data such as high quality aerial imagery has become signifigantly easier. This leads to the question "can remote sensing data be used to develop land use data to supplement or replace data from statistical agencies?"

This paper presents a model that recongizes and categorizes building types based off remote sensing data and estimates household statistics for a general area.

II. Related Literature

[1] - Uses RGB images, road length and desnity, and distance from populations to estimate populations in rural areas. Density of Roads is correlated to population.

[2] -Night time light from vehicles to predict car travel between cities on highways

[3] - Used deep learning to estimate population characteristics and location of human made structures. Area, volume, and inhabitant number was estimated from AI model trained on GeoDenmark, lidar data, and population data.

[4] - Discusses ethical and safety concerns when using drone data. Public data can slide into private data if specific people can be identified.

[5] - Opensource hardware and software for drone use.

[6] - Night time Light data is strongly correlated with social economic varibles such as population, GDP and electric power consumption.

[7] - Developing proxy economic activity from daytime imagery for periods without the data. And AI model was developed to assist in teh analysis.

[8] -Using AI model YOLO, object detection deep learning was used to extract building footprints.

[9] - Extracting building footprints from point cloud data. Building were classified before extracting the footprints.

[10] - Inventoried residential structures based off microsoft building footprint data, lidar, and point of interest data. When from census level data to annomynized individual house holds.

[11] -remote sensing data to classify land use in China. Estimated landscape patterns and building functions, divided vegitation, water, and hard surfaces, categorized the buildings.

III. Methodolgy

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IV. Results

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V. Discussion

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1) Subsubsection Heading Here: Subsubsection text here.

VI. Conclusion

The conclusion goes here.

VII. Acknowledgment

The authors would like to thank. . .

VIII. Bibliography styles

Here are two sample references: [**barrington2017osm**, **Dirac1953888**].

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