International Journal of Computational and Experimental Science and ENgineering
(IJCESEN)
Vol. 10-No.4 (2024) pp. 1637-1643
http://www.ijcesen.com
ISSN: 2149-9144

Research Article

5G Network needs estimation & Deployment Plan Using Geospatial Analysis for efficient data usage, Revenue Generation

E. Selvamanju[1*], V. Baby Shalini[2]

[1]Rsearch Scholar, Department of Information Technology, Kalasalingam Academy of Research and Education, Krishnankoil, India
* **Corresponding Author Email:** rselvamanju@gmail.com- **ORCID:** 0009-0002-2622-9615

[2] Professor, Department of Information Technology, Kalasalingam Academy of Research and Education, Krishnankoil, India
Email: v.babyshalini@klu.ac.in- **ORCID:** 0000-0001-8637-3921

Article Info:

DOI: 10.22399/ijcesen.692
Received : 27 November 2024
Accepted : 02 December 2024

Keywords :

Satellite Image processing,
Kernel Density Estimator,
Supervised Classification,
Erdas Imagine & ArcGIS.

Abstract:

Telecom companies can generate more profit by increasing the number of users using 5G mobile internet services. This internet service is widely used by telecom companies by identifying the areas where there is a high number of users. By providing 5G services in the right places first, the existing users can be utilized more and the telecom companies can get more profit. Most telecom companies are initially launching their service in cities and towns but not finding out where the high volume of user demand is located. This research is designed to find out where the most users are, Satellite image processing can be used to identify where there is a high population density. A map generated using supervised classification technology can be easily and accurately identified. Also, the Kernel Density Method can be used to identify where there is a large number of users based on other factors (Educational institutions, companies, etc). When comparing these two technologies, it is necessary to find out where there is a large number of users and provide service there first so that the quality of the service and the needs can be easily met. Separate Algorithm implemented by using Erdas Imagine & ArcGIS Software.

1. Introduction

The fifth generation mobile network called 5G is the first global wireless standard after the 4G mobile network. This standard enables a new kind of mobile network that is designed to connect everything and everyone together, including devices, products, and machines. This 5G network has many advantages such as higher gbps data speed available to increase network capacity. High-quality data service without any lagging in data transmission very less noise. Greater effectiveness and efficiency enable new user experiences and link new industries.

Identifying the locations of people who need high-speed internet service and providing them with fifth-generation mobile internet service will be of great benefit to them. In rural areas, there are people who need high-speed internet service. There are also individuals and educational institutions in rural areas that require a large amount of internet service, but when we compare both rural and urban areas there are different telecom companies in urban areas, they provide mobile broadband service but in rural areas Fiber mobile internet service. There is not much volume of internet service so for them this mobile phone’s 5G Internet service is useful as they know it. Satellite Image Processing & Kernel Density Estimator Algorithms have been used to compare rural and urban areas where people need 5G service. Other educational institutes and software companies require high-speed Internet service and we can find out which locations require high-speed service based on the number of users in that location for this Kernel Density Estimator is very useful. Another important objective of this research is to find out where there are high-speed co-served users in areas where high-speed Internet service is not available, and by providing high-speed service to those areas, users will use it more and thus generate more revenue.

This land use map was created using a LISS III satellite image and the Kernel density estimator was created using the location information of various colleges and also using the location of existing cell phone towers.

Figure 1. *Difference between 5G and earlier mobile network generations*

In general, 5G is utilized by the enormous IoT, mission-critical communications, and improved High-Speed mobile broadband, which is three of the key linked service kinds. One distinguishing feature of 5G is that it is built for forward compatibility, or the flexibility to enable future services that are now unimaginable (figure 1).
The land use map shows how the spread of urban centering varies across rural and urban areas [1]. The Land map from 2000 to 2030 was created to determine how much carbon density there is. [2]. Satellite data from different years were analyzed to find out how polluted and changing the environment is due to urbanization [3]. Satellite data was used to determine the number of waterfalls in which location [4]. Satellite data from different years are also taken and the amount of changes is detected and accurately calculated using the Land map created [5]. Information such as where and what kind of facilities are available is obtained from a map created using plug-ins [6]. Eco-System created services like how the earth was used and how it is being used [7].
Differences between Paul Surd Radar Sat only spot satellite data and generated land use and land cover maps were investigated and it was found that any satellite data provided more accurate information [8]. Differences between land use maps and satellite data and environment were found [9]. Correlations between topography and ecological diversity were explored and a new classification was developed [10]. A geologic map created over a period of time determines what changes there are and defines the relationship between these and the environment [11]. How many road accidents occurred at this place and how many times the road accident occurred at a place was found to be related to the nature of the road at that place [12]. Data such as how many accidents have occurred at the same location, how many problems there are at that location and the cause of the accident is known [13].
Planning is developed to identify the causes of frequent accidents at the same place and take appropriate measures to prevent accidents [14]. The nature of roadways and unsafe places frequented by pedestrians can be identified with multiple barriers, so mobile traffic can often be detected [15]. How many accidents have occurred and at which places have a high number of accidents, the reasons for that are identified, and alternative solutions are developed [16]. Researchers have found kernel density estimator cases to be very good estimations [17]. Identify the cause of high population density in one place and plan to reduce population dispersion [18]. There is so much settlement that what is the significance of the settlement such information is found and for this geographies are created.

2. Material and Methods

2.1 Methodology & Problem Statement

Figures 2 and figure 3 explain the entire research process. There are 4 analyses that will execute by using different software, tools & Algorithms.

- Settlement Area Identification
- Population Density Estimation
- Signal Strength Identification
- Bulk user identification

2.2 Settlement Area Identification

Settlement area indication can be used to find out which place has the highest population density. A satellite image called LISS III was used for this type of research, Different types of satellite images are available with different spatial & spectral resolutions. This Landuse Map, created with Erdas Imagine software, is able to determine exactly where the population is located and how many acres of land there are. This research was completed using a supervised classification method and a maximum likelihood estimator.
A supervised classification used pixels enclosed in polygons to identify known, defined classes (for instance, land-use type) to construct the signature file. Clusters, not classes, are derived from the statistical characteristics of the pixels in an unsupervised classification. Classifying all of the pixels in a digital image into various land use/land cover categories is the goal of image classification. There are two forms of classification, depending on how the computer and interpreter interact during the process.

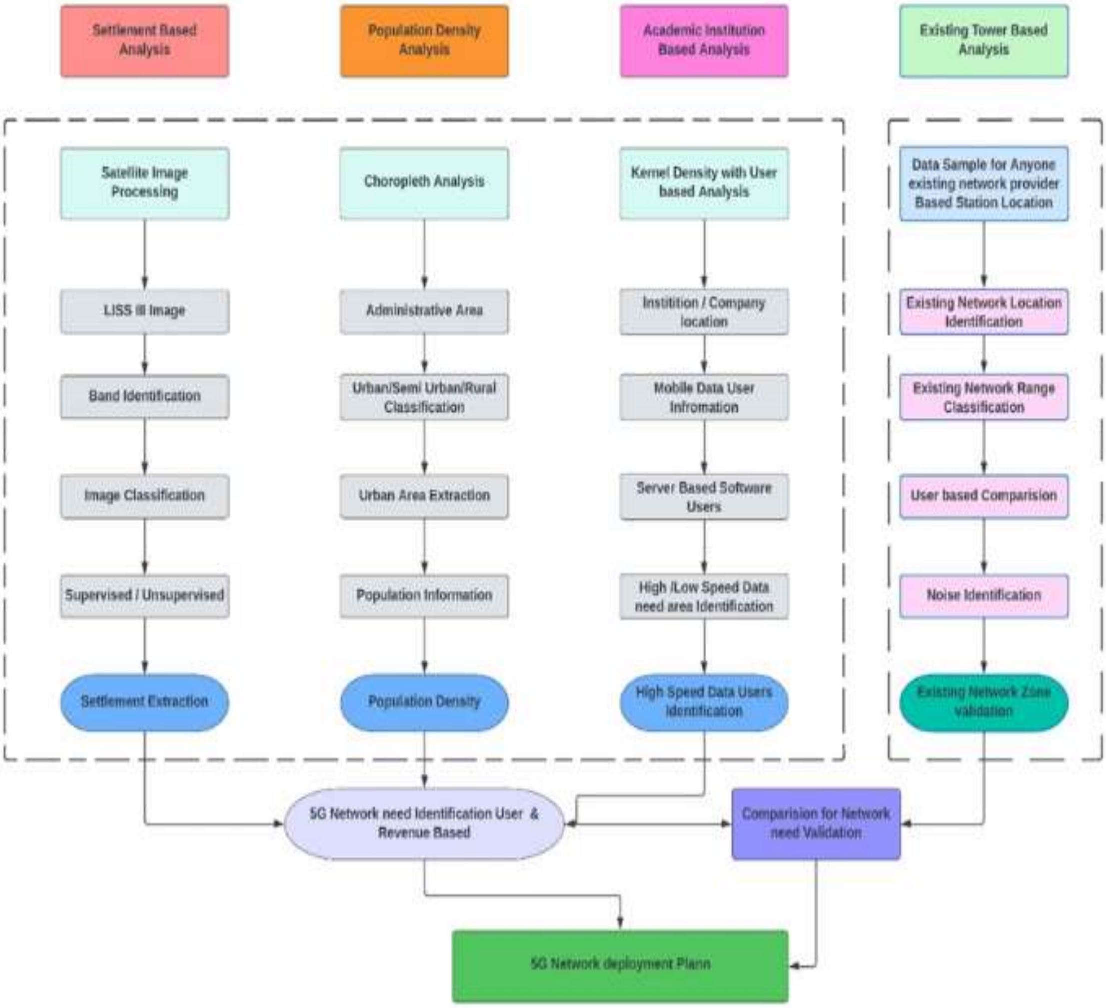

Figure 2. *Methodology*

S.No	1	2	3	4
Analysis	Settlement Area Identification	Population Density Estimation	Signal Strength Identification	bulk User Identification
Software/ Programming language	ERDAS	Leaflet / java Script	Leaflet / java Script	Leaflet / java Script
Tool	Supervised Classification	Choropleth	Kernel Density	Kernel Density (Weightage)
Input Data	Satellite Image	Ward Area with population data	Mobile Tower Location Details	Schools, Colleges & Companies, etc location with Population
Analysis	Satellite Image processing	Population in ward wise analysis	Existing Signal Strength Analysis	School, Colleges & Companies location based Analysis
Finding & Solution	Satellite data can be used to find high population density areas and provide internet services there	Find a high population density Place and prioritize internet service there	provide internet services - Compare with exiting network Provider information	provide internet services- Educational Institutions & Companies

Figure 3. *Problem Statement – Implementation Planning (Technological & Functional)*

The terms "supervised" and "unsupervised" refer to the two basic categories used to produce a categorized output. When an analyst has extensive expertise in the field, supervised classification—one of the two main approaches of picture classification—is typically selected. These "training sites" are subsequently utilized by the software, which then applies them to the full image. The spectral signature identified in the training set is used in supervised classification. In supervised classification, a variety of methods are employed, including the maximal maximum likelihood estimator.

2.3 Maximum likelihood Estimation

Maximum likelihood estimation (MLE) is a statistical technique for estimating the parameters of the distribution of probabilities that have been assumed given some observed data. This is accomplished by maximizing a likelihood function to make the observed data possible as possible given the presumed statistical model.

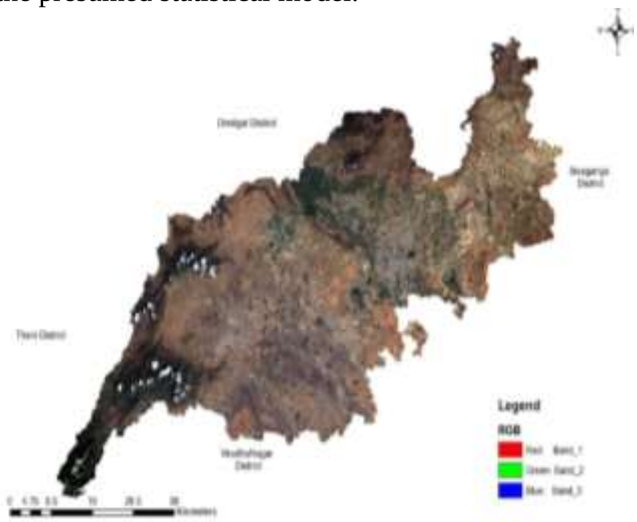

Figure 4. *Raw Satellite Image*

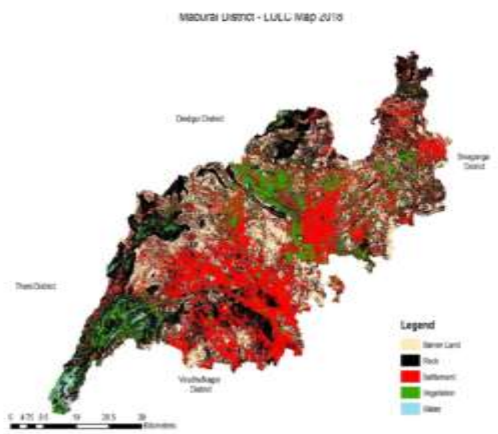

Figure 5. *Processed Satellite Image*

Figure 4 and figure 5 shows the raw satellite image and processed satellite image, Sample Satellite image of the Madurai district was downloaded from GLCF and processed using Erdas Imagine Software. For concept testing purposes only use this image. Various satellite image provides various accuracy.

This Analysis easily identifies the accurate settlement area, Identification Quality depends upon spatial & Spectral resolution.

An essential nonparametric method for estimating density from line-based or point-based data is kernel density estimation. It has been extensively utilized for many different things, including various hot spot detection, network range mapping, and smoothing of line or point data. Each observation (line or point) is given a kernel function before being dispersed across the proposed kernel window. Usually, the output of kernel density estimation is a density surface, where each and every cell is drawn using the kernel density calculated at the cell center. The choice of kernel bandwidth or kernel function, with the latter having a bigger impact, could have a significant impact on the advanced kernel density estimation outcome.

Since the majority of widely-used standard kernels are constrained to one unit of distance, they are typically scaled to account for the data and allow the observation point to be spread farther or closer. Assume that a scaled kernel Kh (d) is

$$K_h(d) = \frac{1}{h}K\left(\frac{d}{h}\right) \tag{1}$$

Where K is the baseline kernel to scale and h is the smoothing or bandwidth parameter that regulates the degree of kernel scaling. It can be proved that the integral of K_h also equals 1.

Three types of analysis were executed by using a kernel density estimator.

1. Population Density – Local area based
2. Educational Institution Density
3. Existing tower Location Density

Population density estimation is done by finding out how much population there is in the wards of a City or a village and finding out how much population there is per square km area. This estimation was done using an open-source Coimbatore Corporation ward map available on the internet. Also, the density of schools and colleges in the Coimbatore district was determined by location. The location of an existing cell phone tower gives a rough estimate of how many users are located where. Through the three types of density estimation found, we can determine which location has the highest number of users and which location we should provide co-service. Figure 6 is the population density estimation and figure 7 is educational institution location kernel density analysis.

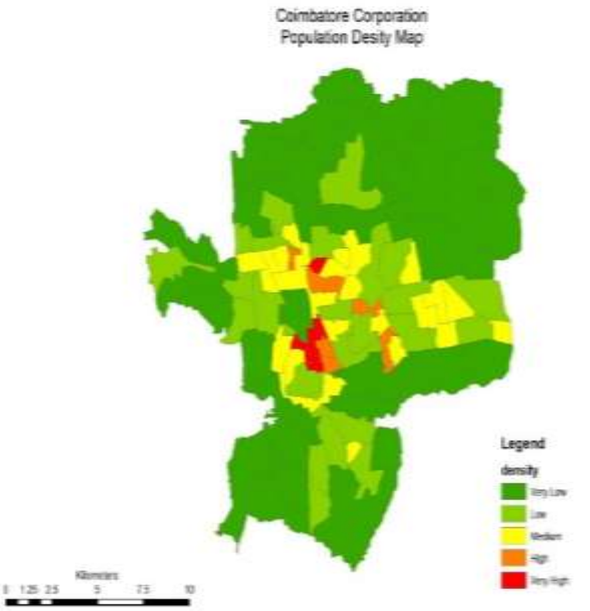

Figure 6. *Population Density Estimation*

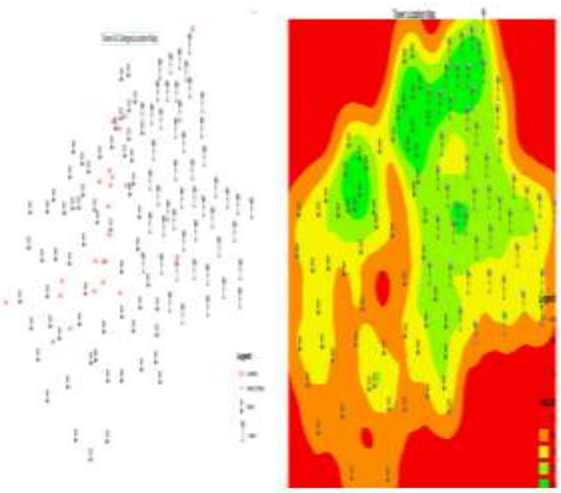

Figure 7. *Educational Institution Location Kernel Density Analysis*

4. Conclusions

Through a program developed using such technology, we can provide 5G services for high volumes of travel and directly to users who require high volumes of 5G services. This research through research paper is conducted to ensure that the method we develop can be used in real life. We can bring our project to a large number of users when implementing a project created using such geospatial data. It would be more beneficial for organizations and users to provide 5G services where software companies have a large number of academic institutions rather than using population density to destroy co-services. There are some similar works reported in the literature [19-33].

Author Statements:

- **Ethical approval:** The conducted research is not related to either human or animal use.
- **Conflict of interest:** The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper
- **Acknowledgement:** The authors declare that they have nobody or no-company to acknowledge.
- **Author contributions:** The authors declare that they have equal right on this paper.
- **Funding information:** The authors declare that there is no funding to be acknowledged.
- **Data availability statement:** The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

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