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Optimizing Sustainable Community Spatial Layouts and Public Service Facility Accessibility: A GIS and Machine Learning Approach

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Abstract: This paper discusses the integration of Geographic Information Systems (GIS) and machine learning (ML) to enhance community performance based on sustainable urban planning by optimising community layouts and providing better access to public services. GIS is a technology that provides spatial data on the land use and the risks, which can support urban planners to understand the existing urban settlement. On the other hand, ML can predict the future needs of the public services such as transport, education and health care, which can help the planners to allocate the resources. The combined application of GIS and ML can assist urban planners to create resilient, climate-adaptive and socially equitable communities, and can also address the rapid urbanisation issues that can efficiently meet the future community demands. It is a framework that can enhance the accessibility to the public service and develops a socially equitable, environmentally sustainable and optimised community wellbeing, which can provide an all-sided strategy for the city facing the climatic change and demographic change.

Keywords: GIS, machine learning, public service accessibility, transportation planning, disaster response

1. Introduction

From a city planner's perspective, urbanization has resulted in several challenges: how to effectively use limited land area; how to provide public service facilities to residents in densely populated areas; and how to balance the three major land uses (residential, business, and recreation) to ensure the livability and maintain the accessibility for the community. In this case, GIS will be highly utilized to address and deal with the challenges posed by urbanization. GIS allows us to analyze spatial patterns and make decisions for the land use planning, service location allocation and environmental sustainability. Furthermore, by utilizing the machine learning algorithm, we will be able to forecast the future community needs by analyzing the historical trends of population growth, economic development, and service demands. This paper will focus on how GIS and machine learning can be utilized to optimize community spatial layout as well as the accessibility to public service facilities.

Given the advancement of GIS and machine learning technologies, this research may be able to demonstrate an innovative way to resolve urbanization challenges. It would be interesting to explore how GIS and machine learning can be utilized to identify and locate underserved areas to better allocate public service facilities, to optimize public service locations and incorporate environmental factors in community planning. It is equally important to explore the role of GIS and machine learning when addressing the climate change. How GIS and machine learning can assist urban planners in analyzing climate change impacts, estimating the severity of the impacts and developing mitigation measures [1]. A critical question remains unanswered and this paper can address that question: how to plan an urban environment that is sustainable and resilient to various climate change events.

2. GIS and Sustainable Community Spatial Layout Optimization

GIS plays a key role in the spatial optimisation of the layout of communities, providing planners with a broad picture of urban geography. GIS allows planners to identify the spatial distribution of community facilities, such as housing and urban public services and green spaces, and assess whether different types of residents (such as the elderly and families with children) can reasonably access the resources they need. In addition, GIS allows planners to extract information on topography, the layout of existing infrastructure, and the layout of land use, and identify optimal locations for future development.

2.1. GIS and Sustainable Community Spatial Layout Optimization

One of the key aspects of community planning is to understand how land is used and distributed in a given area. This information drives where people live, what kind of life they have, where they are going to work, and it’s vital to design socially fair, equitable, and sustainable living spaces. GIS is a great tool to analyse the distributions of different urban land uses and spatial disparities between people in terms of access to public services, and it can therefore help urban planners to make better decisions on where to allocate resources. For example, by visualising the distribution of different land uses, urban planners can examine the balance between residential, commercial, industrial, and recreational spaces, and decide if they are over- or under-represented in certain regions, which would result in social inequality. For instance, if an area is too industrialised with limited residential spaces, people living there may have poor access to other land uses; in particular, they may not have enough access to essential amenities, such as healthcare, schools, and grocery stores. If the spatial distributions are not well balanced, and some regions are underserved by public services compared to others, urban planners can plan where to rezone the land to improve accessibility and livability for all residents. Furthermore, in order to deal with rapid population growth, the real-time data feed can help dynamically adjust to urban designs to accommodate changes in community demands and ensure sustainable development [2]. The data provided in the table 1 below is the result of a survey conducted by the US National Institute of Sustainable Cities to illustrate the distribution of different land uses and public services across different regions.

Table 1: Land Use Patterns and Public Services Distribution

Region	Residential Area (%)	Commercial Area (%)	Industrial Area (%)	Recreational Area (%)	Healthcare Facilities (count)	Schools (count)	Grocery Stores (count)
Downtown	35	15	25	5	2	5	3
Suburban North	50	10	15	10	5	8	6
Industrial Park	20	30	40	5	1	2	2

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Table 1: (continued).

Suburban East	60	10	15	10	3	6	5
Green Valley	30	25	20	5	4	7	6

2.2. Public Space Allocation and Community Needs

Courtesy New York State Office of Parks, Recreation and Historic Preservation, FlickrFor instance, ensuring the equitable distribution of public spaces such as parks, recreational facilities and community centres is one of the foundational pillars of ensuring residents' wellbeing. Public spaces encourage social interactions, improve physical health and mental wellbeing. GIS can help map the current distribution of such public spaces and reveal pockets of inequity in access. For example, high-density residential land uses often come at the expense of green spaces because developers tend to maximise the number of housing units or commercial spaces within a plot. GIS can help map the gaps in green spaces by conducting a spatial analysis of population density against public space availability. This can help planners identify which regions might benefit from an additional park or a community facility. GIS can also help identify whether existing public spaces adequately cater to vulnerable groups such as children, the elderly and people with disabilities. This way, the allocation of public space becomes more responsive to the needs of specific community groups. The result is a more livable city that is less exclusive [3]. A data-driven approach ensures that the allocation of public resources is more equitable and efficient, and ultimately improves the social fabric of the community.

2.3. Integrating Environmental Considerations in Spatial Layout Design

Environmental determinants of health and sustainability are important yet often overlooked factors in community design. However, the future sustainability of an urban area is directly impacted by the integration of these factors into spatial layout design. Environmental data can be analysed using GIS, such as air and water quality, noise pollution, biodiversity and more, and used to inform urban design. For example, in areas with poor air quality, GIS can suggest placement of green buffers or urban forests to help mitigate pollution and increase air quality for residents. Similarly, GIS can identify areas susceptible to flooding, and suggest placement of infrastructure or residential zones away from these high-risk areas [4]. Environmental data analysed in GIS can help planners with designing a community that is ecologically and socially sustainable. Coupled with the ability to map and analyse environmental impacts, planners can design communities that do not exacerbate existing environmental issues, and ensure that future development does not contribute to existing environmental problems common in many cities today, such as urban heat islands or water scarcity [5].

3. Machine Learning for Public Service Facility Accessibility Analysis

3.1. Predicting Community Needs Through Machine Learning

By analysing previous trends in population, economic development and service usage, machine learning models can predict a community's future needs for a variety of services. For instance, machine learning algorithms might predict increased demand for healthcare services in a rapidly growing suburban area due to an aging population or an influx of young families. These predictions allow urban planners to anticipate what services will be needed in the community and help with resource allocation. By predicting future demographic changes and healthcare demand, pl steps in

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anticipating future needs before demand overwhelms current infrastructure. The use of Geographic Information Systems (GIS) that integrate machine learning models allow planners to visualise how predicted needs will affect the various regions of a community in a more nuanced and geographically-targeted manner than previous methods of planning. Table 2 illustrates predicted community needs for a variety of resources in 2024 based on a Machine Learning Urban Demand Forecast Model. These findings are based on the 2020 population of the Cleveland Area [6].

Table 2: Predicted Community Needs Based on Machine Learning Urban Demand Forecast Model (2024)

Region	Predicted Population Growth (%)	Predicted Increase in Healthcare Demand (%)	Predicted Increase in School Enrollment (%)	Predicted Increase in Public Transportation Usage (%)
Suburban North	15	25	18	20
Downtown	5	10	7	12
Suburban East	20	30	22	25
Green Valley	12	18	15	10
Industrial Park	3	8	5	6

3.2. Optimizing Public Service Facility Locations

Machine learning can be used to optimise the location of these public services by taking into account a variety of factors, such as population density, transportation access, environmental conditions and so on. An algorithm might compare demographic data with healthcare facility locations and find that certain areas are underserved – they might suggest the optimal locations for new clinics to be generated based on the distance and access between these areas and high-need populations. The algorithm might also take into account other data on traffic flows and public transit lines to ensure that facilities are placed where they can be most easily accessed by the greatest number of people. In areas with poor public transport access, machine learning models can also recommend locations for new transit hubs or bus routes to increase access to essential services. This kind of optimisation is important for the urban fabric, where space is limited and the way public services are allocated can have a large impact on the quality of life of residents. If machine learning can be used to identify the optimal locations for providing public services, planners can ensure that these services are distributed in an equitable and efficient manner [7]. This will result in a reduction of inequalities in access to these services and help in creating healthier communities and neighbourhoods.

3.3. Enhancing Service Accessibility for Vulnerable Populations

Some communities can face serious barriers to access public services, such as low-income populations, senior citizens and people with disabilities. Machine learning models can be trained to recognise vulnerable populations and analyse the specific barriers to their accessing public services. For example, an algorithm can look at income and geographic factors such as poor public transportation connectivity that might prevent certain groups from accessing healthcare or educational facilities. The analysis can then be used by machine learning to propose targeted interventions for enhancing access to services, such as placing healthcare clinics in low-income neighbourhoods or improving public transportation systems to service senior populations. This way, machine learning can enhance access by analysing datasets to propose targeted interventions to improve service access, while also ensuring equity and social justice in resource allocation [8].

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4. Disaster Response and Environmental Protection

4.1. Identifying Environmental Hazards

Geographic Information Systems (GIS) are used to map the location of environmental hazards, such as flood-prone areas, air quality and pollution hotspots. By combining data from air-quality monitoring stations with maps that show pollution levels as well as population density, plots where harmful pollutants, such as fine particulate matter (PM nitrogen dioxide (NO2), are often linked to respiratory illnesses. Planners can then focus on pollution controls, such as low-emission zones or bans on industrial activities, in areas with the highest residential populations.[9] Additionally, GIS maps can identify point sources of pollution such as factories, highways or landfills, and measure their effects on surrounding neighbourhoods. For instance, a recent World Health Organization study revealed that areas within 1 km of major highways had 30 per cent higher levels of NO2 compared with residential zones 5 km away. By identifying pollution sources and their respective footprints, GIS enables planners to intervene in a more targeted way, improving health outcomes for populations living in vulnerable neighbourhoods.

4.2. Predicting Climate Risks with Machine Learning

Machine learning models can forecast the effects of climate change, such as flooding, extreme weather events and heatwaves, by analysing historical climate data and determining patterns in it. This enables planners to take steps to reduce the impact of climate risks, for example by constructing flood defences or designing buildings to withstand extreme heat. For instance, machine learning algorithms can use data on past floods, precipitation and soil permeability to predict areas vulnerable to flooding with a high degree of accuracy. A study by the European Environment Agency in 2019 found that machine learning models could predict flood risks with 85 per cent accuracy by combining satellite data and meteorological forecasts. This predictive power is vital for cities facing rising flood risk amid climate change, like when, in 2022, municipality of Miami-Dade County used machine learning to forecast where storm surges from hurricanes are most likely to occur, so that barriers and other flood-control infrastructure can be placed accordingly. Similar models can predict heatwaves, which can be superimposed on urban heat island data to inform where cooling centres, green roofs or shade structures should be sited in heat-vulnerable areas.

4.3. Optimizing Emergency Response Services

GIS technology improves emergency response by analysing the accessibility of networks of essential services such as hospitals, fire stations and emergency shelters, especially in vulnerable areas at risk of disasters. A study in Jakarta, Indonesia in 2020 used GIS to map the locations of emergency shelters relative to flood zones and found that 30 per cent of residents in high-risk areas were more than 5 km from the nearest shelter. Once these gaps were identified, the planners were able to suggest new shelter locations that, on average, reduced the distance to shelter by 40 per cent [10]. In areas plagued by wildfires, GIS can help to locate fire stations in a way that covers high - risk zones more efficiently by using data on vegetation, wind, and historical fire incidents. GIS can also integrate feeds from emergency dispatch systems and traffic sensors in near-real time, enabling authorities to shift resources on the fly when situations change. For example, during the California wildfires of 2021, GIS was used to reroute ambulances and fire engines around blocked roads, enabling them to reach victims more rapidly. By optimising service delivery, GIS helps to reduce the number of casualties in emergency situations, and to reduce the impact of disasters on urban populations.

5. Conclusion

Overall, this paper shows that the combination of GIS and machine learning has great potential to optimise urban planning for sustainable community layout and easy accessibility to public services. It can be concluded that through the use of GIS, urban planners will be able to discover the spacial pattern and identify the risk of environmental factors. From the machine learning models, we will be able to predict the future community needs and optimise public service locations. These two technologies can work together to support disaster resilience, equal distribution of resources, and better quality of life, helping cities to achieve sustainable development in the future with the challenges of climate change and population shift.

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