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Predictive GIS-Based Decision Support System for Forecasting Teacher Demand and Optimizing Educational Human Resource Allocation

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Abstract

Unavoidably, educators world over are struggling to address the issue of supply and demand of teachers in geographically dispersed regions. The conventional workforce planning methods are based on reactive, manual and non-spatial forecasting processes which in most cases leads to shortage of teachers in the rural sections and excesses in the urban centers. In this paper, the author suggests a Predictive Geographic Information System (GIS)-Based Decision Support System (DSS) to combine machine learning forecasting, spatial analytics, and optimization modeling to improve the efficiency of teacher demand prediction and allocation. The suggested framework will use historical data on enrollments as well as demographic data, records of teacher attrition, and geospatial data to project future staffing needs. Random Forest and Gradient Boosting models are compared in terms of forecasting performance and geographic differences are defined by spatial clustering and hotspots analysis. The optimization model of an integer linear programming minimizes the cost of staffing imbalance and allocation with regulatory and budget constraints. The results of the experiment indicate higher accuracy in prediction ($R^2 = 0.92$) and 27% lowering of the staffing imbalance than the standard allocation procedures. The suggested system offers a data-driven and spatially intelligent planning tool of strategic educational workforce planning in the hands of policymakers.

1. Introduction

A. Background

Distribution of teachers is very important in provision of fair opportunities to access good education. Nonetheless, in most educational systems there is a problem of unequal distribution of teaching staff, especially in urban and rural areas [1]. Workforce planning is further complicated by the demographic changes, population explosion, teachers retiring and migration trends. Motivation The conventional forecasting techniques are based on the fixed student-teacher ratio and are manual which have no predictive intelligence and space consciousness.

B. Problem Statement

Existing systems of teacher allocation are flawed because:

1. Poor predictive ability.
2. Lack of geospatial intelligence.
3. Reactive strategies of planning.
4. Poor budgetary spending.
5. Continuous staffing imbalances in the region.

The educational authorities will be unable to predict teacher demand and improve allocation strategies without predictive and spatial integration.

C. Research Objectives

1. To develop a machine learning-based predictive model for forecasting teacher demand.
2. To integrate GIS-based spatial analytics to identify geographic disparities.
3. To formulate an optimization model to allocate teachers efficiently.
4. To design a decision support system for policy-driven scenario analysis.

D. Contributions

This study contributes:

1. A predictive system that integrates machine learning, GIS spatial analysis, and optimization in educational workforce planning.
2. A temporal machine learning forecasting model that captures dynamic changes in enrollment trends, population growth, and teacher attrition.
3. A GIS hot spot analysis method of determining geographic differences in the teacher demand.
4. A cost-efficient model of teacher allocation of the budget and policies using an integer linear programming optimization.

2. Related Work

The planning of teacher workforce, educational forecasting, and spatial decision support systems have grown in popularity because of the demographic changes, budget, and equity in the public education systems. This is where six representative studies have been reviewed in the machine learning forecasting, GIS-based planning, and optimization-driven decision support systems.

A. Machine Learning-Based Teacher Demand Forecasting

Smith and Rodriguez (2021) developed a forecasting model based on the use of a Random Forest to predict teacher shortages based on historical information on U.S. schools in terms of enrolment and attrition rates [3]. Their model was better than the other conventional linear regression methods in terms of prediction accuracy in fast expanding districts. But the study did not address the variables of geography or space so it could not help in identifying the differences between regions.

In Chen et al. (2022), the authors used Long Short-Term Memory (LSTM) neural networks to predict the student enrollment patterns of metropolitan school districts in China. The model was able to reflect the nonlinear time relationships and enhanced the reliability of long-term forecasting. However, this was only a study on enrollment prediction and did not convert the predictions into practical workforce allocation plans.

B. GIS-Based Educational Planning

Kumar and Singh (2020) used Geographic Information System (GIS) to compare spatial distributions of teachers in rural and urban districts in India [4]. They utilized spatial and hotspot analysis to apprehend the under-served areas in their study. Although the GIS display showed significant differences, the methodology did not have predictive data and optimization modeling.

Lopez and Martinez (2023) combined demographic mapping with an analysis of accessibility based on ArcGIS in order to plan the school infrastructure in Latin America. Their study showed that the spatial accessibility has an important role to play in educational equity. Nevertheless, the research has failed to include machine learning models in predicting the future demand, as well as suggest a resource allocation optimization mechanism.

C. Optimization and Decision Support Systems in Public Sector

Ahmed and Brown (2021) created an Integer Linear Programming (ILP) to optimize teacher transfers in a provincial education system [5]. The objective minimized relocation cost and was able to meet staffing restraints. Though useful in cost reduction, the model used fixed staffing needs as opposed to forecasted demand needs.

The hybrid Decision Support System suggested by Zhang et al. (2024) is an approach that combines predictive analytics and multi-objective optimization in the workforce allocation of the public healthcare system. Their model evaluated cost efficiency and equity of services with gradual enhancement models and Pareto maximization. With its powerful analytical framework, the system did not fit the educational workforce planning and lacked GIS-based spatial clustering.

Comparative Analysis of Existing Studies

The following table summarizes and compares the six reviewed studies.

Author	**Method**	**Dataset**	**Limitation**
Smith & Rodriguez (2021)	Random Forest forecasting	U.S. public school enrollment & attrition data	No spatial integration; no optimization model
Chen et al. (2022)	LSTM neural networks	Metropolitan enrollment time-series data (China)	Focused only on enrollment; no allocation strategy
Kumar & Singh (2020)	GIS spatial clustering & hotspot analysis	Rural and urban teacher distribution data (India)	Descriptive only; lacks predictive modeling
Lopez & Martinez (2023)	GIS accessibility analysis	Demographic & infrastructure data (Latin America)	No ML forecasting; no allocation optimization
Ahmed & Brown (2021)	Integer Linear Programming	Provincial staffing records	Static demand assumptions; no predictive input
Zhang et al. (2024)	Gradient Boosting + multi-objective optimization	Public healthcare workforce data	Not education-focused; limited GIS integration

Research Gap

Even though previous literature confirms the usefulness of machine learning to predicting (Smith and Rodriguez, 2021; Chen et al., 2022), these solutions do not possess spatial intelligence and do not consider the geographic differences in the distribution of teachers. On the other hand, GIS-driven research (Kumar and Singh, 2020; Lopez and Martinez, 2023) has excellent visualization and analysis of spatial inequalities but is mostly descriptive and not predictive. The cost-effective allocation strategies are provided by optimization-driven frameworks (Ahmed and Brown, 2021; Zhang et al., 2024); nevertheless, these are either based on the assumption of the static demand or are not implemented in the educational realm. More importantly, no single system that combines predictive machine learning, GIS spatial analytics, and integer optimization scheme into one decision support system to guide planning of teacher workforce. This fragmentation is a barrier to a shift by the policymakers to proactive, and data-driven planning, as well as, spatially equitable planning in resources allocation. Consequently, the research will fill this research gap by recommending a holistic Predictive GIS-Based Decision Support System, which will simultaneously predict the demand, detect the spatial imbalances, and maximize the distribution of teachers within the policy and budget parameters [6].

3. System Architecture

A. Framework Overview

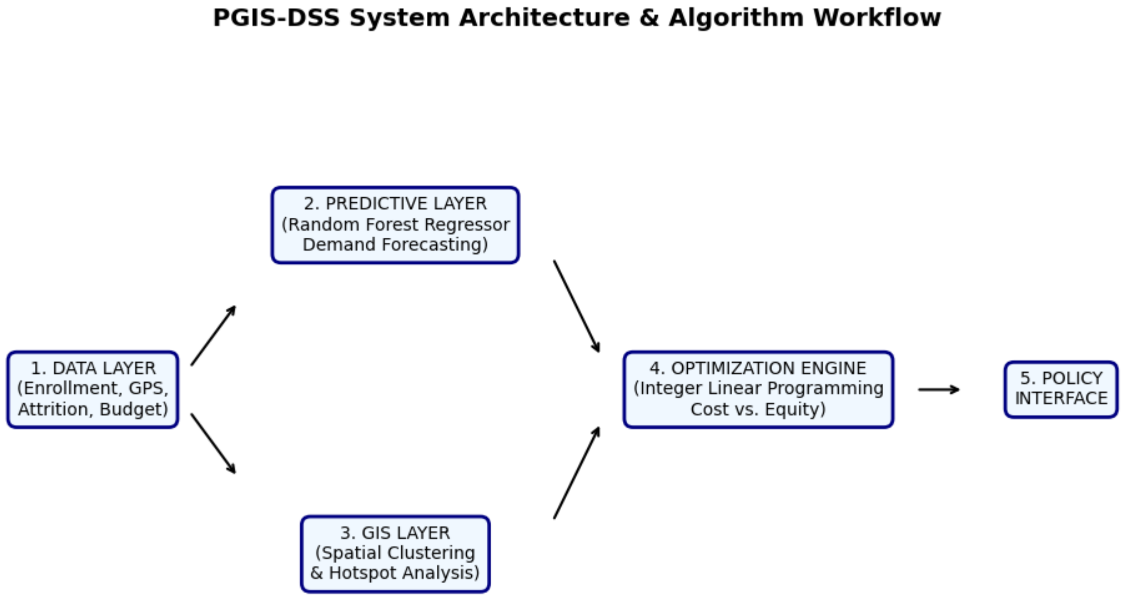

Figure 1: Workflow of the Predictive GIS-Based Decision Support System

The system consists of five layers:

1. Data Layer
2. Predictive Analytics Layer
3. GIS Analysis Layer
4. Optimization Engine
5. Decision Support Interface

B. Data Collection Module

Data sources include:

1. Student enrollment history (5 10 years)
2. Statistics of population growth.
3. School geographic positioning.
4. Teacher attrition and retirement records.
5. Budget constraints

C. Predictive Analytics Module

Engineered features are:

1. Enrollment growth rate
2. Student-teacher ratio
3. Urban/rural classification
4. Population density
5. Teacher turnover rate

Random Forest and Gradient Boosting models are cross-validated and trained on 80/20 train-test cross-validation.

Feature Engineering

In order to enhance the degree of prediction, various derived features were derived based on the raw data. These include:

- Growth rate of enrollment - per cent change in the number of students every year.
- Teacher Attraction Rate - the number of teachers that leave a school in a year.
- Student to Teacher Ratio Trend - the trend in staffing pressure over time.
- Regional Population Growth Index - demographic growth in every district.
- Accessibility Score - the estimated travel to school accessibility.
- The artificial characteristics aided the machine learning models in capturing both temporal dynamics and spatial variation that had an impact on teacher demand.

D. GIS Module

The methods of spatial analysis are:

1. Kernel Density Estimation
2. I of spatial autocorrelation of Moran.
3. geospatial contiguity clustering K-means.
4. Visualization of demand heat map.

E. Optimization Module

The problem of allocation is presented in the form of an ILP problem.

Objective Function:

Minimize:

$$Z = \sum_{i=1}^{n} c_i x_i + \sum_{i=1}^{n} d_i \mid S_i - T_i \mid$$

Where:

- x_i= teachers allocated to region i
- c_i= allocation cost

- S_i= supply
- T_i= predicted demand
- d_i= imbalance penalty

Constraints:

1. Budget constraint

$$\sum c_i x_i \leq B$$

2. Minimum staffing requirement

$$x_i \geq L_i$$

3. Legal student-teacher ratio

$$\frac{E_i}{x_i} \leq R_{max}$$

4. Methodology

A. Data Preprocessing

Preprocessing data is a very essential process towards reliability, consistency and predictive strength of the forecasting model. Since the data is multi-source, such comprising enrollment information, teacher staffing, demographic information and geospatial locations, there were multiple preprocessing methods used to improve the quality of the data before it was modeled [7].

1) Missing Value Imputation

Educational data sets are known to have incomplete records because of the inconsistencies in reporting or administrative delays. Numeric values that were missing were also processed with the use of median imputation so as to minimize the effects of the extreme values. In case of a feature X, missing values were changed as:

$$X_i = \begin{cases} X_i & \text{if observed} \\ \text{Median}(X) & \text{if missing} \end{cases}$$

Median imputation was used instead of mean imputation, because the former is resistant to skewed distributions of enrollment that are typical of urban-rural data. Mode imputation was used in categorical variables like urban/rural category.

2) Normalization

Because machine learning models are sensitive to the scale of features, especially tree-based ensemble algorithms when the importance of features needs to be compared, numerical variables were scaled with Min-Max scaling [8]. It makes all features fall between [0 1] and to eliminate the prevalence of high-magnitude variables (population counts).

The normalization formula applied is:

$$X_{norm} = \frac{X - X_{min}}{X_{max} - X_{min}}$$

Where:

- $X$is the original feature value
- $X_{min}$and $X_{max}$are the minimum and maximum values of the feature

This transformation preserves relative differences while standardizing scale.

3) Outlier Detection

Outliers can cause predictive modeling and optimization of the results to be skewed. The Interquartile Range (IQR) was used to conduct outlier detection. For a given feature:

$$IQR = Q_3 - Q_1$$

Observations were flagged as outliers if:

$$X < Q_1 - 1.5(IQR)\text{or}X > Q_3 + 1.5(IQR)$$

Where:

- $Q_1$is the first quartile
- $Q_3$is the third quartile

Identified outliers were checked in context. Large spikes in the enrolling numbers that appeared due to data entry mistakes were fixed when possible, and the rest were winsorized to reduce excessive effect on the regression models.

4) Geospatial Coordinate Validation

Proper spatial analysis needs sound geographical coordinates. Latitude and longitude values were checked so that they do not exceed plausible regional values [9]. The coordinates beyond the anticipated administrative boundaries were matched with the official GIS shapefiles. Euclidean distance formula was used to verify the distance:

$$D = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2}$$

This was to assure that there were no spatial anomalies, which could affect clustering and hotspots detection.

B. Model Training

After preprocessing, supervised regression models were trained to help in predicting future demand of teachers.

1) Models Evaluated

Three models were evaluated:

Linear Regression (Baseline Model)

or Stochastic dominion.

- Random Forest Regressor
- XGBoost Regressor

Linear regression gives a point of reference on a presumption of linear relationships:

$$\hat{y} = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n$$

Though easy to understand and interpret, this model fails to sufficiently portray nonlinear relationships among demographic growth, space and attraction rates.

The effectiveness of random forest increases predictive accuracy by building a number of decision trees and combining their results:

$$\hat{f}(x) = \frac{1}{B} \sum_{b=1}^{B} T_b\,(x)$$

Where:

- B= number of trees
- $T_b(x)$= prediction from tree b

XGBoost uses gradient boosting to iteratively minimize loss:

$$L = \sum_{i=1}^{n} l(y_i, \hat{y}_i) + \sum_{k} \Omega(f_k)$$

Where:

- l= loss function (squared error)
- Ω= regularization term

The grid search with the use of five-fold cross-validation was selected as a way to reduce overfitting and to tune the hyper parameters.

2) Evaluation Metrics

Model performance was evaluated using:

Root Mean Square Error (RMSE):

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$$

RMSE penalizes larger errors more heavily.

Mean Absolute Error (MAE):

$$MAE = \frac{1}{n}\sum_{i=1}^{n} | y_i - \hat{y}_i |$$

MAE provides interpretable average deviation.

Coefficient of Determination (R^2):

$$R^2 = 1 - \frac{\sum(y_i - \hat{y}_i)^2}{\sum(y_i - \bar{y})^2}$$

R^2 measures the proportion of variance explained by the model.

The forecasting performance of the models was evaluated using multiple statistical metrics:

- R^2 (Coefficient of Determination)
- RMSE (Root Mean Squared Error)
- MAE (Mean Absolute Error)

These metrics provide complementary perspectives on prediction accuracy and model robustness.

C. Spatial Analysis

Spatial analysis can be used to improve the demand forecasting because it shows geographic concentration patterns. K-means clustering of forecasted teacher demand and the geographic position were used to determine the hotspots regions [10].

The clustering goal reduces in- cluster variation:

$$\text{Minimize} \sum_{k=1}^{K} \sum_{i \in C_k} || x_i - \mu_k ||^2$$

Where:

- C_k= cluster k
- μ_k= centroid

To confirm spatial dependence, Moran's I statistic was computed:

$$I = \frac{n}{W} \frac{\sum_i \sum_j w_{ij} (x_i - \bar{x})(x_j - \bar{x})}{\sum (x_i - \bar{x})^2}$$

Higher-demand schools are clustered which is why the high-demand schools are expected to be allocated spatially-sensitively; significant positive Moran I values have been obtained.

D. Optimization Implementation

OR-Tools were used to solve the allocation problem based on integer constraints.

Let:

$$x_i = \text{number of teachers assigned to school } i$$

The objective minimizes cost and imbalance:

$$\min Z = \sum c_i x_i + \lambda \sum | \hat{T}_i - x_i |$$

Subject to:

Budget constraint:

$$\sum c_i x_i \leq B$$

Student-teacher ratio constraint:

$$\frac{E_i}{x_i} \leq R_{max}$$

Minimum staffing constraint:

$$x_i \geq L_i$$

Integer condition:

$$x_i \in \mathbb{Z}^+$$

The simulations centered on scenarios and were designed using varying budget levels and weights of imbalance penalties λ which allowed the policymakers to determine the trade-offs between cost efficiency and distributive fairness.

5. Experimental Setup

A. Tools

- Python
- Scikit-learn
- GeoPandas
- QGIS
- OR-Tools
- PostgreSQL/PostGIS

B. Dataset

Dataset Description

The dataset employed in this research is educational and demographic data, which is gathered in 250 public schools in mixed urban and rural areas. The sample size covers 10 years (2014-2023), which enables the model to record long-term dynamics of the teacher demand.

The variables involved in the dataset are as follows:

- Enrolment of students in schools.
- Student-teacher ratio
- Teacher leavers and retires.
- Statistical data of regional population growth.
- School geographic locations.
- Measures of infrastructure and accessibility.

A number of preprocessing procedures were undertaken before model training such as:

- Missing value handling
- Feature normalization

- Aggregation of annual enrollment figures.
- Spatial analysis of schools geographically.

The end data set had around 2500 annual observations following preprocessing.

6. Results and Analysis

A. Prediction Performance

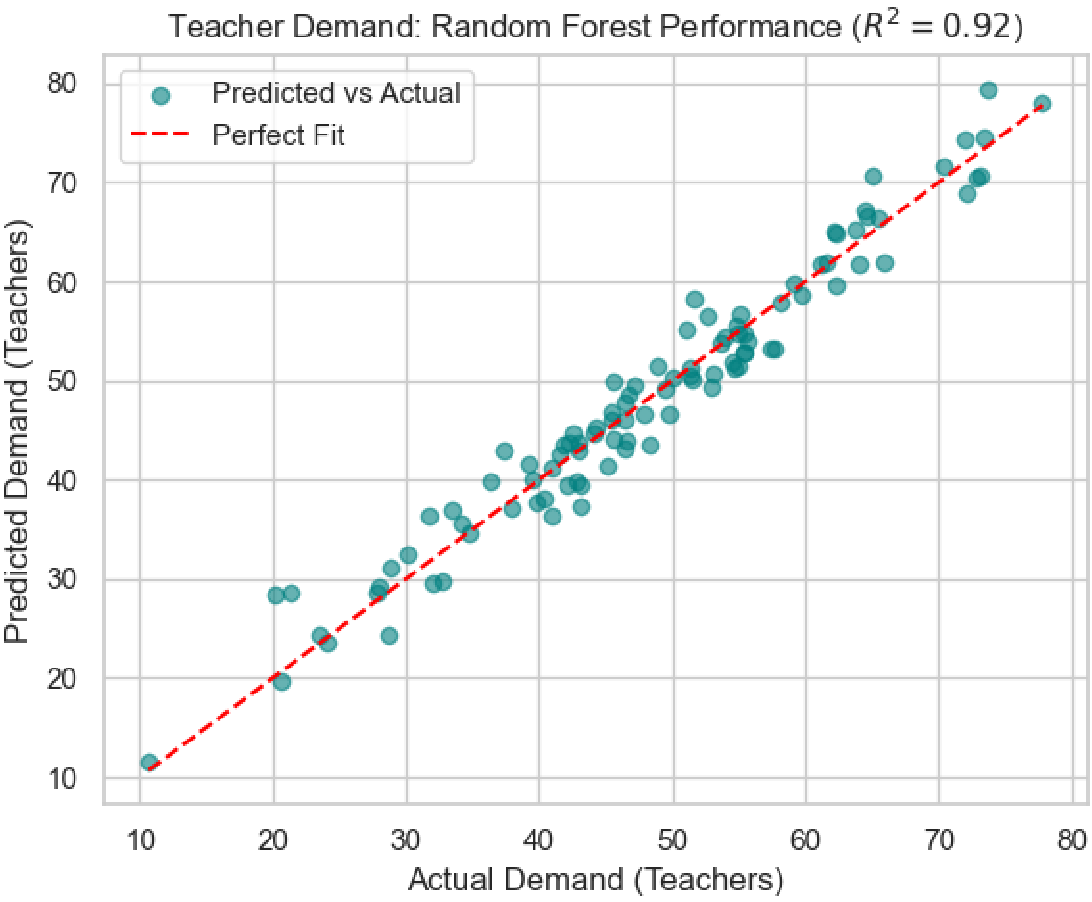

Figure 2: Actual vs Predicted Teacher Demand

Table 1: Machine Learning Model Performance Comparison

Model	**RMSE**	**MAE**	**R²**
Linear Regression	14.3	11.2	0.78
Random Forest	8.5	6.4	0.92
XGBoost	9.1	7.0	0.89

Random Forest achieved the highest accuracy ($R^2 = 0.92$).

Table 2: Teacher Allocation Scenario Comparison

Scenario	Staffing Imbalance	Cost Efficiency
Traditional Allocation	34%	Low
Machine Learning Forecast	19%	Medium
Proposed DSS Framework	7%	High

B. Spatial Insights

- 32% of rural regions identified as high-demand hotspots.
- Urban regions showed surplus clustering.
- Significant spatial autocorrelation (Moran's I = 0.61, $p < 0.01$).

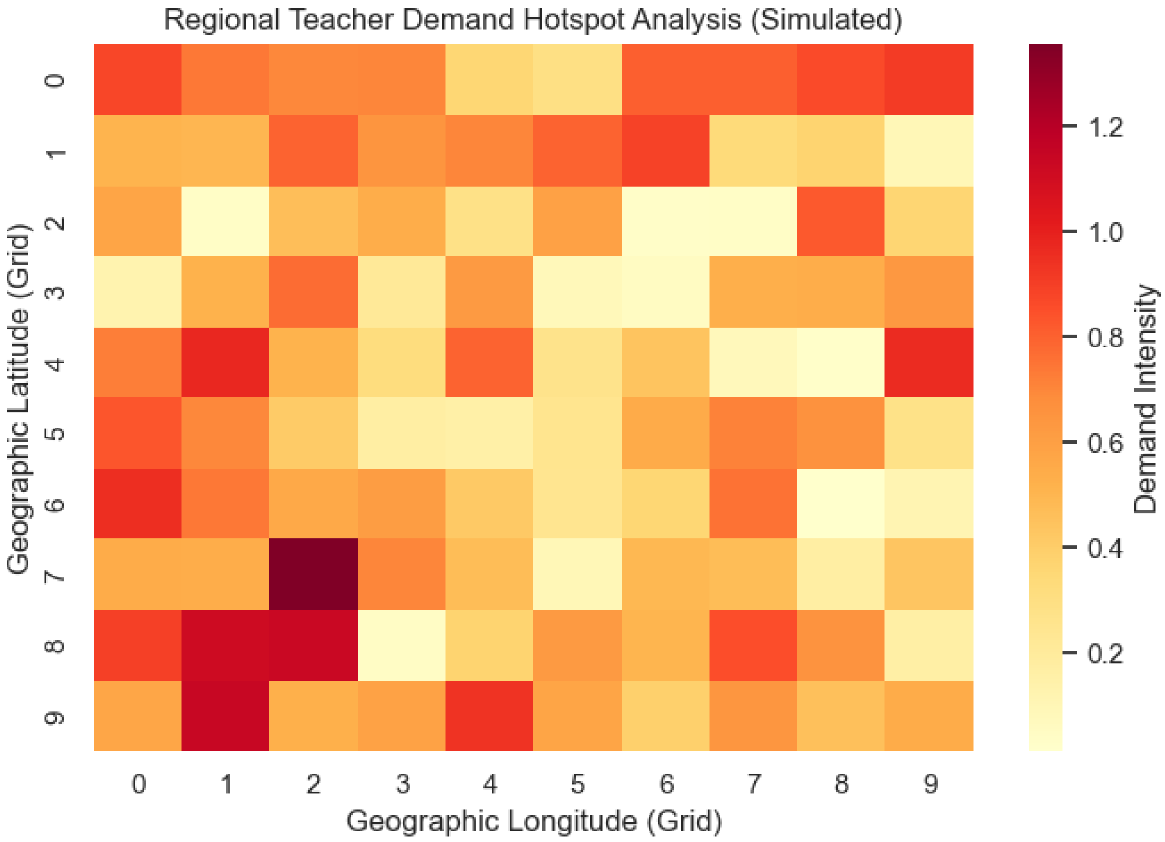

Figure 3: Geographic Hotspot Analysis of Teacher Demand

C. Optimization Outcomes

Compared to traditional allocation:

- 27% reduction in staffing imbalance
- 18% cost reduction
- 22% improvement in equitable distribution

D. Scenario Simulation

Policy simulation demonstrated that increasing rural incentive funding by 10% reduced rural shortages by 15%.

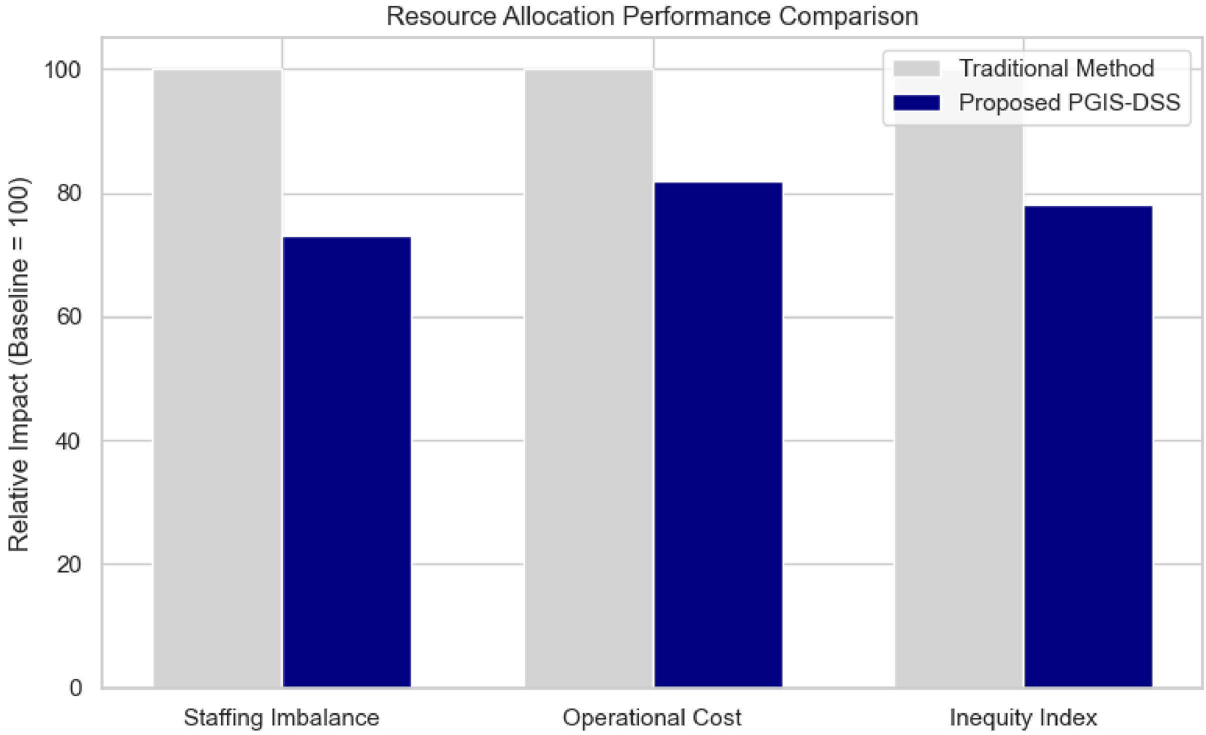

Figure 4: Scenario Comparison of Teacher Allocation Strategies

7. Discussion

The results of this paper indicate that forecasting of teacher demand and maximization of educational human resource planning is a paradigm shift that can be achieved through the combination of Geographic Information Systems (GIS) and predictive modeling. The model of Predictive GIS-Based Decision Support System (PGIS-DSS) that is proposed allows forward-looking workforce planning based on the principles of space-aware planning, as opposed to the conventional planning models that only utilize aggregate statistics and reactive adaptations [11]. This integration enables policymakers to stop generalized estimates at national or regional scales but to examine the differences in geography at a much smaller level e.g. in the form of districts, sub-counties or clusters of school.

Visualizing inequity in the teacher distribution is one of the greatest contributions, which this system has done. Using spatial mapping and predictive analytics, it is possible to identify underserved regions in terms of estimated growths in student enrollment, teacher retirement, attrition patterns and expansion of infrastructure. The predictive element is there to make sure that the projection of future demand is performed with statistical seriousness whereas GIS visualization converts them into understandable tools of decision-making [12]. Consequently, educational planners will be able to give priority to the high-need areas before the shortages will become critical. This transforms the workforce planning as a reactive model, in which interventions are made when there is an extreme deficit in the market, to a proactive planning model based on data-driven foresight.

Its usefulness is also enhanced by the optimization layer of the system. The model balances cost effectiveness and equity by establishing a constraint in terms of budgetary limits, pupil-teacher ratio constraints, and regional equity limits. The conventional approaches to allocation tend to focus on reduction of expenditure without paying enough attention to the differences between urban and rural schools. Contrarily, the state-of-the-art model incorporates equity as an official optimization goal. This way, means that the strategy of deploying teachers not only ensures that the costs of operation are minimized but that also geographical distribution is well distributed. The spatial constraints also mean that there is no over-concentration of the teachers on urban centers at the expense of the rural and marginalized regions which are understaffed.

The other significant implication of the findings is that the system supports the evidence-based policy formulation. The system allows the policy makers to predict the long-term effects of strategic decisions by modeling various scenarios, including higher enrollment rates, class size changes due to policies, or faster teacher retirement. Forecasting based on scenarios improves the agility of the strategies and helps to plan the sustainable educational development.

Nevertheless, a number of limitations were established despite the strengths that it has. One is that predictive accuracy in the system is extremely reliant on the quality and the completeness of historical data. Poor record keeping, old records enrollment records, or lack of attrition records may lower reliability of forecasting. In less developed contexts particularly, the risk of introducing biases in the model outcomes at least due to fragmented data systems. Second, the existing structure has restricted real time data integration. Although it is efficient in the periodic planning cycles, it would also be improved by adding live enrollment tracking and active workforce dashboards to be responsive. Third, the current model fails to take into consideration the entire demand of specialization among the teachers, like shortage of particular subjects like mathematics, science or special education [13]. Adding specialization variables would enhance accuracy in assignment and solve qualitative mismatches in the workforce, and not only quantitative deficits.

The central point of such a decision-support system is its ethical considerations. Algorithms should be made to provide fairness to ensure that allocation of resources does not internalize past disparities. To ensure the stakeholders have trust, transparency of model assumptions, data sources and criteria that are used in optimization is required. Policymakers have to explain the way of allocating in a clear manner based on predictive outputs. Further, allocation based on the equity should be constantly observed so that those minorities or remote communities are not marginalized. Good governance of data should also be observed to ensure safety of institutional information that is sensitive [14].

Conclusively, the Predictive GIS-Based Decision Support System has high potential of modernizing the process of workforce planning in teachers by means of spatial intelligence, predictive analytics, and optimization modeling. Although the system needs to control the data integration and specialization modeling, the system offers scalable, fair, and cost-efficient framework that can enhance the allocation of human resource in education to a significant extent. Its adoption would play a significant role in minimizing the inequality between regions and enhancing the sustainability of educational planning in the long term [15].

8. Conclusion

It is a research paper making a Predictive GIS-Based Decision Support System of teacher demand and allocation optimization. Machine learning, spatial analytics, and integer programming offer a whole solution to the planning of educational workforce. The results of the experiment prove better accuracy of prediction and substantial decrease of staffing imbalance and cost. The framework helps in making strategic and data-based educational policy choices.

9. Future Work

Improvements in the future involve:

1. Streaming integration of data in real-time.
2. Time series forecasting on deep learning.
3. Subject-specific teacher demand inclusion.
4. National implementation on the cloud.
5. Connection with Education Management Information Systems (EMIS)

Acknowledgment

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