Journal of Human Resource and Sustainability Studies, 2024, 12, 803-810
https://www.scirp.org/journal/jhrss
ISSN Online: 2328-4870
ISSN Print: 2328-4862

The Estimating of Public Service Delivery Using Fuzzy Base

Ser-Od Bayaraa[1], Khurelbaatar Batjargal[2*], Tuul Ser-Od[3]

[1]School of Applied Sciences, Mongolian University of Science and Technology, Ulaanbaatar, Mongolia
[2]Business School, National University of Mongolia, Ulaanbaatar, Mongolia
[3]Department of Financial Management, University of Finance and Economy, Ulaanbaatar, Mongolia
Email: serod_b@must.edu.mn, KhurelbaatarB@gmail.com, tuul.s@ufe.edu.mn

How to cite this paper: Bayaraa, S.-O., Batjargal, K., & Ser-Od, T. (2024). The Estimating of Public Service Delivery Using Fuzzy Base. *Journal of Human Resource and Sustainability Studies, 12,* 803-810.
https://doi.org/10.4236/jhrss.2024.124042

Received: September 23, 2024
Accepted: December 6, 2024
Published: December 9, 2024

Abstract

The primary responsibility of any government is to enhance its citizens' quality of life and ensure their comfort. Government actions are closely linked to the country's social, economic, and political stability. Public servants play a crucial role in implementing government policies and delivering services. Consequently, the availability of these services is influenced not only by the number of government employees but also by factors such as citizens' lifestyles and settlement patterns. In developing countries, where agriculture, animal husbandry, and low-tech mining dominate the economy, land and natural resources are critical economic drivers. This reliance can lead to ecological issues like drought and desertification due to environmental imbalances. Additionally, inadequate government policies on land use, restoration, and conservation exacerbate these problems. Therefore, this research aims to examine how the availability of public services is affected by land area through fuzzy modeling methods.

Keywords

Fuzzy Logic Rule, Membership Function, Public Servant, Land Area, Quality of Life, Availability of Public Services, Cluster, Fuzzy Subset, Fuzzy Modeling, Fuzzy Weight

1. Introduction

Government services aim to address the fundamental social and economic needs of citizens. Anjula Gurtoo and Colin C. Williams (2015) investigated the state of public services in developing countries, focusing on health, infrastructure, labor, marginalized populations, the rural economy, and public administration. Gantulga Dashdelger, Ser-Od Bayaraa, & Battuvshin Gurbazar (2024) employed a model that relates the availability of public services to the number of civil servants, factoring in the country's population, land size, labor force, and GDP, using a cluster regression method. This research is valuable as it categorizes 108 countries by GDP and identifies the model that best fits each category. While the article supports the notion that the availability of government services is directly influenced by the number of public sector employees (PSE), relying solely on GDP as a determinant can produce skewed results, particularly for countries with small populations and land areas but high GDP. We utilized data from the 33 countries classified under Cluster II in the above article (see **Figure 1**).

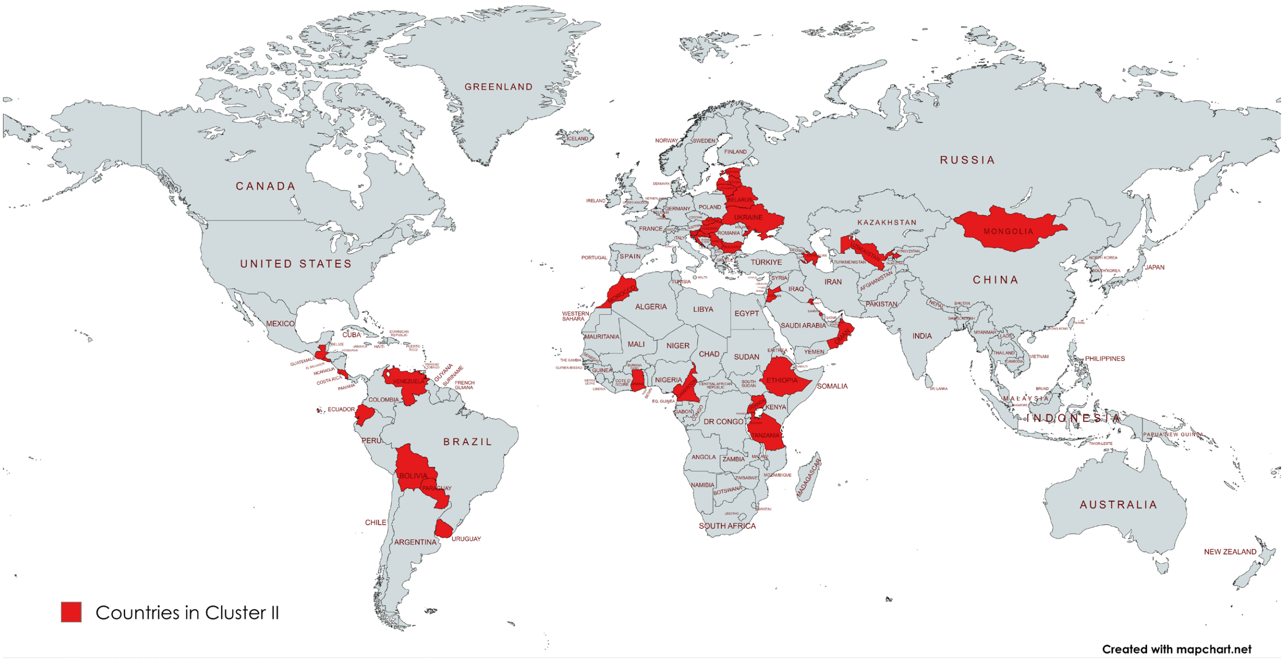

Figure 1. Description of the geographical location of the countries included in the study.

Among these countries, 36.4% are from Europe, 24.3% from the Americas, 21.2% from Asia, and 18.1% from Africa. Mongolia and Bolivia have the highest land area per civil servant, with 4 and 3 square kilometers respectively, while in the other 31 countries, this figure does not exceed 1 square kilometer. Bahrain, Luxembourg, and Kuwait, with land areas of just 760 square kilometers each, are the smallest in this group. Despite their small size, these countries have the highest GDP per capita in the cluster, which negatively affects our model's results. Consequently, our study will focus on evaluating public services in the remaining 30 countries, excluding Bahrain, Luxembourg, and Kuwait.

2. A Research Methodology

The sample research method, a cornerstone of research methodology, entails selecting a subset (sample) from a larger population to study and generalize findings about the entire population. Given the impracticality of studying the entire population, sampling enables researchers to draw valid inferences from a representative and manageable group. In the study, we used a cluster sampling method and employed a first-order linear regression model with four factors. When the system's structure is unknown, solving the modeling problem can be challenging. In such cases, using fuzzy logic relationships to construct the system model is advantageous. Initially, we estimate the number of public servants using fuzzy membership functions. Next, we develop a model to evaluate this number based on fuzzy logic rules. The following notation will be used for the variables and parameters. Here,

$X_1, \cdots, X_m$ —input fuzzy subsets, m—number of fuzzy divisions or fuzzy rules,

$x_1, \cdots, x_n$ —sample data, n—number of sample data,

$\mu_{X_1}, \cdots, \mu_{X_n}$ —membership functions of fuzzy subsets,

$R_i, i = 1, 2, \cdots, m$ —fuzzy logic rules, and

$\beta_j(\cdot), j = 1, \cdots, m$ —fuzzy weights.

Also, Y —the real sample values, $\hat{Y}$ —the values calculated using the fuzzy membership function, and $\tilde{Y}$ —the output values calculated using fuzzy logic rules. Algorithm for creating a fuzzy logic model is:

- Selecting the input variables based on available knowledge and experience; determining the maximum and minimum values for these variables; assessing their significance, and then constructing fuzzy subsets for each input variable.
- The predicted values $\hat{Y}$ are calculated by applying the membership functions to the input variables and using their membership degrees.
- The parameters of the fuzzy model are estimated using the least squares method by constructing fuzzy logic rules that relate input to output. Use them to find the $\tilde{Y}$ values.
- Comparing the output values as $Y = (Y_1, \cdots, Y_n)$, $\hat{Y} = (\hat{Y}_1, \cdots, \hat{Y}_n)$ and $\tilde{Y} = (\tilde{Y}_1, \cdots, \tilde{Y}_n)$.

3. The Modeling

We used data from the study of Gantulga Dashdelger, Ser-Od Bayaraa and Battuvshin Gurbazar for the number of public servants and the area size of the 33 cluster II countries (see **Table A1** in **Appendix**). From **Table 1**, input x is in the interval $X = [20000, 1600000]$.

Table 1. According to the area, countries are classified into fuzzy subsets.

Size of area (square kilometers)	Fuzzy subsets (square kilometers)			
	Up to 150,000	[100,000, 500,000]	[400,000, 1,000,000]	More than 800,000
Fuzzy logic variables	Very small	Small	Medium	Large
Countries	Slovenia, El Salvador, Estonia, Slovakia, Costa Rica, Croatia, Latvia, Lithuania, Azerbaijan, Serbia, Jordan, Hungary, Guatemala, Bulgaria	Bulgaria, Uruguay, Uganda, Belarus, Ghana, Ecuador, Oman, Paraguay, Uzbekistan, Morocco, Cameroon	Uzbekistan, Morocco, Cameroon, Ukraine, Venezuela, Tanzania	Venezuela, Tanzania, Ethiopia, Bolivia Mongolia

For each fuzzy subsets, the membership functions $\mu_{VS}(\cdot), \mu_S(\cdot), \mu_M(\cdot)$ and $\mu_L(\cdot)$ are selected accordingly. Then,

$$\mu_{VS}(x) = \begin{cases} 1, & x \le 20000 \\ \dfrac{150000 - x}{130000}, & 20000 < x \le 150000 \\ 0, & \text{others} \end{cases} \tag{1}$$

$$\mu_S(x) = \begin{cases} 0, & x \le 100000 \\ \dfrac{x - 100000}{200000}, & 100000 < x \le 300000 \\ \dfrac{500000 - x}{200000}, & 300000 < x \le 500000 \\ 0, & 500000 < x \end{cases} \tag{2}$$

$$\mu_M(x) = \begin{cases} 0, & x \le 400000 \\ \dfrac{x - 400000}{200000}, & 400000 < x \le 600000 \\ \dfrac{1000000 - x}{400000}, & 600000 < x \le 1000000 \\ 0, & 1000000 < x \end{cases} \tag{3}$$

$$\mu_L(x) = \begin{cases} 0, & x \le 800000 \\ \dfrac{x - 800000}{600000}, & 800000 < x \le 1400000 \\ 1, & 1400000 < x \end{cases} \tag{4}$$

Therefore, the variable x in the formulas (1) - (4) replaced by the sample values $x_1, x_2, \cdots, x_{30}$ and we estimated the values of membership degrees on each sample values (see Table A1 in **Appendix**). Using those fuzzy membership functions, the fuzzy weights are found by formula (5).

$$\beta_j(x_i) = \frac{\mu_j(x_i)}{\mu_{VS}(x_i) + \mu_S(x_i) + \mu_M(x_i) + \mu_L(x_i)}, \quad i = 1, \cdots, 30;\ j = VS, S, M, L. \tag{5}$$

Now, using the weights of formula (5), the values calculated using the fuzzy membership function $\hat{Y} = (\hat{Y}_1, \cdots, \hat{Y}_n)$ are calculated by following formula (6) (see Table A1 in **Appendix**).

$$\hat{Y}_i = (\beta_{VS}(x_i) + \beta_S(x_i) + \beta_M(x_i) + \beta_L(x_i)) \cdot Y_i, \quad i = 1, \cdots, 30. \tag{6}$$

The fuzzy model we will build is one input and one output, defined by the system of equations $\Delta\theta = Y$. Here Δ is the fuzzy transformation matrix, $\theta = (\theta_1, \theta_2, \cdots, \theta_8)$ are the model parameters and $n = 30$, $m = 4$. Let's create a fuzzy logic rule.

R_{VS} : IF x is "very small" THEN $\tilde{Y}_{VS}(x) = \theta_1 + \theta_5 x$.

R_S : IF x is "small" THEN $\tilde{Y}_S(x) = \theta_2 + \theta_6 x$.

R_M : IF x is "medium" THEN $\tilde{Y}_M(x) = \theta_3 + \theta_7 x$.

R_L : IF x is "large" THEN $\tilde{Y}_L(x) = \theta_4 + \theta_8 x$.

Our goal is to estimate the parameter θ of the fuzzy logic model using the least squares method. And the fuzzy transformation matrix has the following form.

$$\Delta = \begin{bmatrix} \beta_{VS}(x_1) & \beta_S(x_1) & \beta_M(x_1) & \beta_L(x_1) & x_1 \cdot \beta_S(x_1) & x_1 \cdot \beta_M(x_1) & x_1 \cdot \beta_L(x_1) \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ \beta_{VS}(x_{30}) & \beta_S(x_{30}) & \beta_M(x_{30}) & \beta_L(x_{30}) & x_{30} \cdot \beta_S(x_{30}) & x_{30} \cdot \beta_M(x_{30}) & x_{30} \cdot \beta_L(x_{30}) \end{bmatrix}$$

Then, the estimated value of the parameter θ of the fuzzy model by the method of least squares, the parameter $\tilde{\theta}$ is found by formula (7).

$$\tilde{\theta} = \left[\Delta^{\mathrm{T}}\Delta\right]^{-1}\Delta^{\mathrm{T}}Y \tag{7}$$

Here $(\cdot)^{\mathrm{T}}$ is the matrix transposition, $(\cdot)^{-1}$ is the inverse of the matrix and Y is the sample data of the number of civil servants. We used MATLAB for the calculation of formula (7). The results:

$$\tilde{\theta} = [167171.274\ \ 1886354.619\ \ 4676899.151\ \ 5340754.068\ \ 5.01\ \ -3.266\ \ -2.396\ \ -3.189]$$

Thus, we were able to create a following fuzzy logic model,

R_{VS} : IF x is "very small" THEN $\tilde{Y}_{VS}(x) = 167171.274 + 5.01x$.

R_S : IF x is "small" THEN $\tilde{Y}_S(x) = 1886354.619 - 3.266x$.

R_M : IF x is "medium" THEN $\tilde{Y}_M(x) = 4676899.151 - 2.396x$.

R_L : IF x is "large" THEN $\tilde{Y}_L(x) = 5340754.068 - 3.189x$.

The total output of the fuzzy model is calculated by formula (8) using the values of the fuzzy membership (1) - (4).

$$\tilde{Y}(x) = \mu_{VS}(x)\cdot\tilde{Y}_{VS}(x) + \mu_S(x)\cdot\tilde{Y}_S(x) + \mu_M(x)\cdot\tilde{Y}_M(x) + \mu_L(x)\cdot\tilde{Y}_L(x). \tag{8}$$

For each sample value, (8) estimates of the number of public servants estimated by the fuzzy logic model are shown in the table (see Table A1 in **Appendix**).

4. Discussion

We compared the $\tilde{Y}$ values of the fuzzy logic model established by the formula (8) with the original real Y value and the fuzzy values $\hat{Y}$ established by the formula (6) (see Table 2). And Table 2 shows the statistics of these values. It can be seen that the results of the fuzzy logic model (see the last column in Table 2) show a lower mean deviation and a more regularity of the normal distribution compared to the other two values.

Table 2. Statistical outputs of calculation results.

Statistic outputs	Actual and estimated values for number of civil servants (by person)		
	Real values: Y	Fuzzy values with membership functions: $\hat{Y}$	Fuzzy values with logic rules: $\tilde{Y}$
Mean	1,091,589	647,246	629,793
Median	609,310	365,370	355,093
Maximum	4,803,330	4,306,665	2,948,781
Minimum	164,910	99,505	267,783
Standard deviation	1,250,078	852,350	536,924

Continued

Skewness	1.739134	2.974040	2.845722
Kurtosis	4.673734	12.5292	12.64936

For each series, the coefficient of Skewness is positive, indicating a rightward skew in their distributions relative to the normal distribution. This explains why the mean of the fuzzy model results is higher than that of the normal distribution. Furthermore, the Kurtosis value for each series exceeds three, suggesting that the distributions are leptokurtic (peaked). This implies that the results are more concentrated around the mean, indicating less stability (see **Table 2**).

5. Conclusion

The surveyed countries have an average land area of 333,909 sq. km and an average of 1,091,589 civil servants, with a standard deviation of 1,250,078. In countries like Mongolia and Bolivia, the vast land area per civil servant negatively affects the availability of public services. To address this issue, implementing electronic government services is crucial. Conversely, countries such as Bahrain (760 square kilometers), Luxembourg (2590 square kilometers), and Kuwait (17,820 square kilometers) have the smallest land areas in the cluster (Dashdelger, Bayaraa, & Gurbazar, 2024). Due to their high population density, concentrated settlements, and strong economic capabilities, the availability of public services in these countries was not considered in our model. The fuzzy logic rule offers the advantage of calculating the degree of membership for each factor across different fuzzy values (Zadeh, 1965). For instance, in the fuzzy partition shown in **Table 1**, some countries belong to multiple categories simultaneously. Tanzania, for example, has a membership value of 0.286 in the "medium" category and 0.143 in the "large" category, meaning that the country is 28.6% closer to the smaller end of the spectrum and 14.3% closer to the larger end. The standard deviation of actual civil servant values across these countries was 1,250,078, indicating significant variability. However, using a fuzzy logic rule-based model reduced this standard deviation to 536,924, reflecting lower variability. The fuzzy logic model we developed proved to be effective in estimating the number of civil servants for countries classified in Cluster II. Fuzzy models are well-suited for approximating uncertain and imprecise situations, making them ideal for forming preliminary judgments in decision-making. However, since the model used area size as an irrelevant factor in the fuzzy analysis, it may not be suitable for long-term predictions of civil servant numbers. In the future, we plan to develop a more advanced model incorporating multiple fuzzy variables and logic rules, including dynamic factors such as GDP per capita.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

References

Dashdelger, G., Bayaraa, S.-O., & Gurbazar, B. (2024). Modeling the Efficiency of Public Service Delivery Using GDP Indicators. *Journal of Human Resource and Sustainability Studies, 12,* 439-455. https://doi.org/10.4236/jhrss.2024.123025

Gurtoo, A., & Williams, C. C. (2015). *Developing Country Perspectives on Public Service Delivery*. Springer (India) Pvt. Ltd. https://doi.org/10.1007/978-81-322-2160-9

Zadeh, L. A. (1965). Fuzzy Sets. *Information and Control, 8,* 338-353.

Appendix

Table A1. The calculation of fuzzy logic modeling.

	Countries	Territory	The number of PSE	mu_VS	mu_S	mu_M	mu_L	Estimated number of PSE: $\hat{Y}$	Estimated number of PSE: $\tilde{Y}$
1	Bahrain	760	68,784	-	-	-	-	-	-
2	Luxembourg	2590	24,430	-	-	-	-	-	-
3	Kuwait	17,820	442,680	-	--	-	-	-	-
4	Slovenia	20,140	190,901	0.999	0	0	0	190,695	267,783
5	El Salvador	20,720	221,778	0.994	0	0	0	220,549	269,477
6	Estonia	42,390	164,910	0.828	0	0	0	136,507	314,175
7	Slovakia	48,088	763,560	0.784	0	0	0	598,584	319,919
8	Costa Rica	51,060	275,528	0.761	0	0	0	209,698	321,921
9	Croatia	55,960	511,070	0.723	0	0	0	369,700	323,736
10	Latvia	62,200	296,380	0.675	0	0	0	200,170	323,369
11	Lithuania	62,674	390,588	0.672	0	0	0	262,372	323,219
12	Azerbaijan	82,658	1,024,920	0.518	0	0	0	530,924	301,115
13	Serbia	87,460	680,360	0.481	0	0	0	327,305	291,217
14	Jordan	88,780	461,214	0.471	0	0	0	217,196	288,185
15	Hungary	90,530	1,295,952	0.457	0	0	0	592,848	283,958
16	Guatemala	107,160	272,365	0.330	0.036	0	0	99,505	287,010
17	Bulgaria	108,560	538,261	0.319	0.043	0	0	194,618	292,223
18	Uruguay	175,020	266,900	0	0.375	0	0	100,114	493,158
19	Uganda	199,810	713,400	0	0.499	0	0	356,022	615,715
20	Belarus	202,910	3,600,000	0	0.515	0	0	1,852,380	629,629
21	Ghana	227,540	772,480	0	0.638	0	0	492,610	729,024
22	Ecuador	248,360	486,710	0	0.742	0	0	361,041	797,591
23	Oman	309,500	762,446	0	0.953	0	0	726,229	833,940
24	Paraguay	397,300	334,950	0	0.514	0	0	171,996	302,334
25	Uzbekistan	425,400	3,297,840	0	0.373	0.127	0	1,648,920	649,900
26	Morocco	446,300	985,320	0	0.269	0.232	0	492,660	950,267
27	Cameroon	472,710	825,748	0	0.136	0.364	0	412,874	1,335,257
28	Ukraine	579,320	4,803,330	0	0	0.897	0	4,306,665	2,948,781
29	Venezuela	882,050	3,404,430	0	0	0.295	0.137	1,469,437	1,101,604
30	Tanzania	885,800	1,144,940	0	0	0.286	0.143	490,606	1,089,095
31	Bolivia	1,083,300	384,384	0	0	0	0.472	181,493	890,558
32	Ethiopia	1,112,000	3,486,120	0	0	0	0.52	1,812,782	933,184
33	Mongolia	1,553,560	390,888	0	0	0	1	390,888	386,451