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Exploring District-Wise Water Poverty in West Bengal through Geospatial Analysis: Aligning with SDG 6

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ABSTRACT

Water scarcity is a concern in West Bengal, with large variations in availability to safe drinking water between districts. This study uses geospatial analysis to investigate district-level water poverty in the state, in line with United Nations Sustainable Development Goal (SDG) 6, which seeks to provide universal access to clean water and sanitation. Data from the 2011 Census and the 2015-2016 National Family Health Survey (NFHS) were used to evaluate household access to drinking water, including distance to water sources and intake of untreated water. A composite Water Deprivation Index was created with standardized indicators and geographical inequality was assessed using Atkinson's index and Moran's I statistics. The study finds high regional variation in water availability, with minimal spatial autocorrelation indicating that water scarcity is driven less by geographical proximity and more by localized characteristics such as infrastructure, geography, and population density. The findings underline the importance of region-specific initiatives to promote water access, maintain sustainable water management, and alleviate water inequality.

Introduction

Although water makes up more than 70% of the earth's surface, just 3% of it is fresh water, and of that, two-thirds are buried deep underground or trapped as ice caps, glaciers, and permafrost (Oksana and Dmytro, 2021). Surface water sources, such as rivers, lakes, dams, and streams, also provide freshwater. As the population grows, there is a greater need for clean water for survival, making access and conservation a critical concern (Mishra, 2023).

Water is essential for survival, supporting health and daily activities (Mishra et al, 2021). However, access to clean and safe water is a persistent challenge, particularly in developing and underdeveloped nations. Many communities

face significant health risks and economic hardships due to the scarcity of this essential resource. Contaminated water sources lead to widespread diseases, while the lack of reliable water access disrupts livelihoods and hinders development. This makes water scarcity a pressing global issue that demands sustained attention, strategic investment, and collaborative efforts to ensure the well-being and prosperity of vulnerable populations (Obaideen et al, 2022). Human activities, particularly the rapid expansion of industries and the transformation of rural landscapes into urban areas, have profound and far-reaching impacts on water systems. Industrial development not only fosters technological innovation but also enhances the economic and social infrastructure of cities and towns. This process often leads

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to increased production and resource consumption, which places a significant strain on water resources (Zhu et al, 2019). Urbanization, on the other hand, involves the large-scale conversion of rural or undeveloped land into urban spaces equipped with residential neighbourhoods, commercial hubs, transportation systems, and various public and private infrastructure projects. While these changes support growing populations and economic progress, they also alter natural water cycles, increase water demand, and contribute to pollution through runoff from roads, industrial zones, and densely populated areas. Together, these developments highlight the complex relationship between human progress and the sustainability of water systems (Li et al, 2020, Yu et al, 2022).

The Sustainable Development Goals (SDGs) of the United Nations (UN) Agenda for 2030 include SDG 6, which aims to achieve sustainable water sanitation control for all by 2030. Water scarcity, whether caused by humans or nature, has severe repercussions on the health, dignity, and prosperity of billions of people globally. SDG 6, sometimes known as the 'water objective', aims to ensure water security and is essential for accomplishing all SDG targets. SDG 6, comprises eight different aims, targets affordable and secure drinkable water by 2030 (Target 6.1), health and sanitation services (Target 6.2), treating wastewater and reusing to improve quality of water (Target 6.3), better utilization of water and freshwater supplies (Target 6.4), integrated water resource management (Target 6.5), the preservation and rehabilitation of water-related ecosystems (Target 6.6), and global assistance and capacity (Target 6A), developed community engagement in water and sanitation management (Target 6B) (United Nations- Sustainable Development Goals, 2017).

Research on inequality has traditionally centered on identifying who benefits from resources and opportunities and understanding the factors driving this distribution. However, the spatial dimension, or the concept of "where," is equally important in analysing inequality, as it sheds light on how geographic location influences access to resources and opportunities Lombo et al. (2007). To evaluate inequality across different socioeconomic parameters and geographic regions, various statistical measures have been developed and widely used. The Gini index, for instance, is a common tool for measuring income inequality, while the Theil index and Atkinson index provide insights into the distribution of wealth and resources within and between groups. These indices, along with other analytical approaches, have been instrumental in highlighting patterns of inequality across diverse populations and areas, offering a deeper understanding of the interplay between social, economic, and spatial factors. (Ghosh et al, 2022). Traditional approaches for estimating spatial inequality do not account for spatial orientation or the link between inequality and geographical location. Spatial autocorrelation has a major impact on the geographical distribution of socioeconomic factors (Panzer

& Postiglione, 2020).

Explorative Spatial Data Analysis (ESDA) approach (Haining, 2003) has been used to estimate local water quality features in West Bengal districts. Spatial dependency and heterogeneity (Anselin, 1988, 2010) of various components of water condition are required to implement new policies to improve the many dimensions of water health in specified places. The use of spatial statistics is crucial since it has assisted in identifying district clumps with certain traits while taking geographical impacts into consideration. The objectives of this research are to demonstrate the extent of water deprivation in rural areas, to quantify the regional disparities in water accessibility, and to examine the spatial autocorrelation pattern in water deprivation among the districts of West Bengal.

Data and Methods

The research used data from India's 2011 Population Census for housing tables, including household amenities and assets. Data from the Census of India, 2011 house listing tables were used to determine the accessibility and availability of drinkable water and use of untreated water for households at the district level.

Data on treated and untreated water were collected from the 2019-2021 National Family Health Survey (NFHS). This descriptive household survey, conducted countrywide, investigated 601,509 homes. The International Institute for Population Sciences in Mumbai serves as the lead institution for conducting these household surveys. The NFHS-5 used two-stage stratified sampling, with main units determined using proportional probability to size (PPS) the sampling.

In the Drinking Water Deprivation context, indicators are used in order to resolve the issue. The percentage of homes acquiring water from a distant source was calculated by analysing data on the availability of drinking water 500 meters away from the dwelling. The data on untreated water availability was used to compute the total percentage household having untreated drinking water since there was no other alternative.

The composite measure of Water Deprivation was determined through multiple steps. First, the district-level values of chosen indicators were standardized using the following formula:

$$Index_{id} = \frac{i_d - i_{min}}{i_{max} - i_{min}} \dots \dots (i)$$

In this equation, i_d represents the actual value of the districts' selected indicators, while i_{max} and i_{min} represent the maximum and lowest values for each indicator. The numbers range from '0' to '1', representing the best and poorest

performing areas in terms of water consumption and related problem in the rural Bengal.

To calculate inequality-adjusted Water Deprivation, Atkinson's index was used for inequality to evaluate the extent of geographical disparity among West Bengal districts for each indicator. Geospatial inequality may be estimated using many methods, including the Gini and Theil indices employed the Gini index to assess geographic inequality in India, including housing and health (Cowell, 1998, Ghosh (2018) and Ghosh et al. (2021). Atkinson's index of inequality is appropriate because of the way it reacts towards disparity at the bottom of the distribution and its simplicity in approaches (Atkinson, 1970). It was used by Ghosh et al, 2023 for the Indian districts for the WASH Poverty measurement.

$$I_x = \frac{n}{\sum_i \sum_j w_{ij}} \frac{\sum_i \sum_j w_{ij} (x_j - \bar{x})(x_i - \bar{x})}{\sum_i (x_i - \bar{x})^2} \dots\dots\dots(iii)$$

In this equation, n represents the number of districts studied, xi represents the variable's value in district i, x represents the mean value of the determined variables and wij represents the weights of a W contiguity matrix representing spatial closeness between I and j. Moran's I value ranges from 1 to +1, with +1 indicating high positive spatial autocorrelation (clustering) and 1 indicating significant negative spatial autocorrelation. The value '0' implies no geographic autocorrelation in the distribution. Various weighting methods, including contiguity-based (Queen) and distance-based (K-nearest neighbor weightage), are used to determine spatial weightage for distinct locations.

For this, software like ArcGis 10.8, Microsoft office 2019 and Geoda 23 has been used. Here the whole study was done on Districts of West Bengal as this district has the variety of physical and cultural set up and that create a various approach towards water accessibility. Here the whole study was done on Districts of West Bengal as this district has the variety of physical and cultural set up and that create a various approach towards water accessibility.

$$A(\epsilon) = 1 - \left(\frac{1}{y} \left(\frac{\sum_{i=1}^n y_i^{1-\epsilon}}{n} \right)^{\frac{1}{1-\epsilon}} \right) \dots\dots\dots(ii)$$

Moran's I statistics (1948) was used to analyze the geographical dependency and disparity of drinking water facilities in West Bengal. The global Moran's I index (Moran, 1948) and Moran's I scatter plot have been used to depict spatial dependence. The Moran's I index can be expressed as follows:

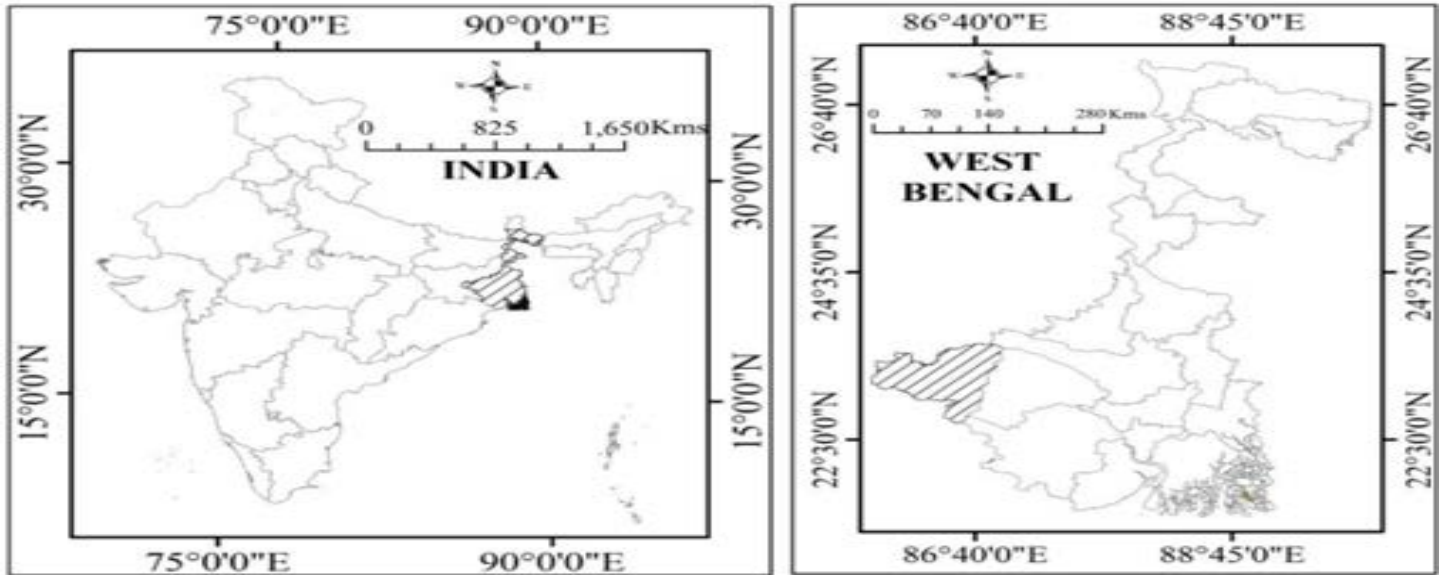


Figure:1 Study area (Prepared by authors)

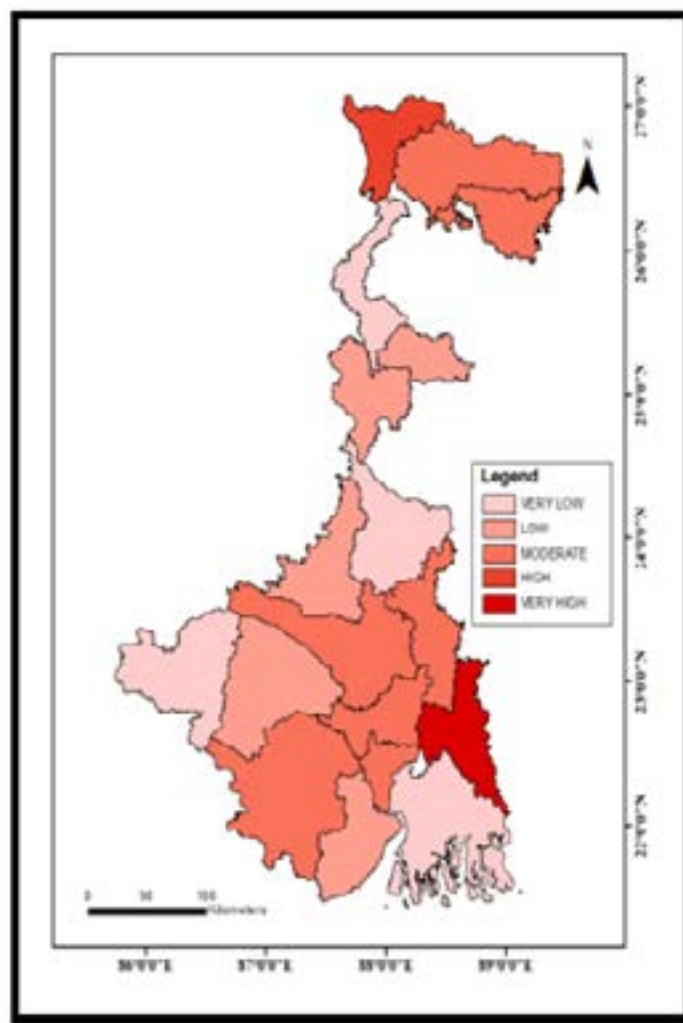
Results and Discussion

Water Deprivation Component	Mean	Median	SD	Atkinson's Index	Moran's I Value
Source of Water away From the House	31.76	34.15	12.19	0.18	0.04
Untreated Water Consumption	11.80	7.4	14.43	0.42	-0.10

Table 1: Water Deprivation Components and their Statistical Values (prepared by authors)

Here are some of the findings about the proportion of individuals who lack access to safe water. Across districts, 32% of families had water sources that were far away from their homes. This shows that water sources are, on average, not that far from houses in these areas. The minor skew (median > mean) may indicate that some areas have very few households that travel long distances for drinking water. According to Atkinson's Index 0.18, there is a considerable imbalance in water collection among West Bengal districts. It shows that not all districts had the same circumstance in rural locations. However, there is still need for improvement in the households' water supplies. There are several districts with mountainous topography in the northern Himalayas, harshly climatic regions, extensive forest areas in the northern, southern and western parts, some low places with immature water level like in deltaic region, drought-prone plateau regions in the west and sparse settlements that may have water sources further away from their homes. The plateau region often lacks of river and face the difficulties of digging so people rely on far away well or handpump. Similarly, in deltaic region intrusion of saline water in the time of storm surge or flood effects the groundwater so the drinking water. Spatial autocorrelation was measured by Moran's I, which showed whether or not equivalent distances cluster according to location. Weak positive spatial autocorrelation is indicated by a score of 0.04; this means that districts with comparable distances do not cluster very much. Simply stated, there was only a faint geographical connection between the districts and its household which were deprived from the near primary source of drinking water. There aren't many regional trends in the distribution, which seems almost random. The confined autocorrelation suggests that water access difficulties in one district are not significantly impacted by nearby districts. Inequality in water availability does not follow clear regional patterns, presumably due to specific variables like infrastructure development. Natural water availability (rivers and groundwater), Socioeconomic circumstances. Indicates random spatial patterns, where no relationship exists between values in neighbouring districts. For the section of percentage of population get the untreated water as drinking water shows from the mean that consumption of untreated water is significantly higher than the median, indicating a right-skewed distribution which implies smaller number of districts with very high untreated water consumption likely pulls the mean upwards. The Atkinson Index measures inequality, with a value of 0.42 indicating moderate to high inequality in untreated water consumption. A few districts likely account for disproportionately high untreated water consumption, while many rural households in other districts consume untreated water relatively little. Here in the untreated water consumption map showing that in North 24 Parganas and in Darjeeling face the main problem. The reason behind North 24 pargana is that this is the most populous district,

and large population requires large amount of drinking and water treatment facilities might be insufficient leading people to rely on untreated sources, the natural sources of water like rivers groundwater are already overused, high density leads to increased industrial, agriculture and domestic waste which pollute the source of water. In mountainous region natural springs and streams are mostly used, which are mostly untreated. the Moran's I value is **-0.01** for untreated water consumption, it suggests that there is **almost no spatial autocorrelation** in the distribution of untreated water consumption across districts in West Bengal. A value of -0.01 is near zero, indicating that untreated water consumption shows almost no clear spatial pattern in West Bengal. Districts with high percentages of untreated water consumption are not consistently surrounded by districts with similar percentages, and vice versa. Districts where a high percentage of people consume untreated water are scattered randomly across the state. West Bengal has diverse topographies: the Himalayan region in the north, plateaus in the west, and deltaic plains in the south. These geographical variations could lead to inconsistent water access and consumption patterns.



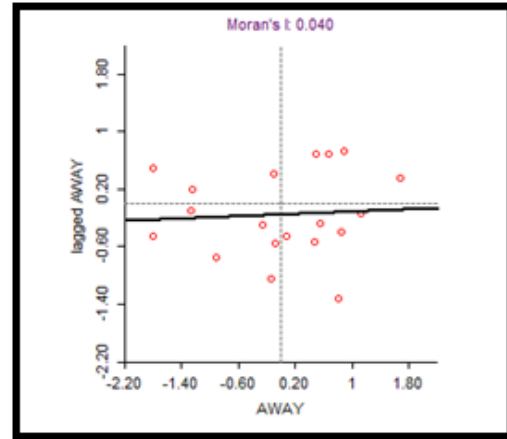
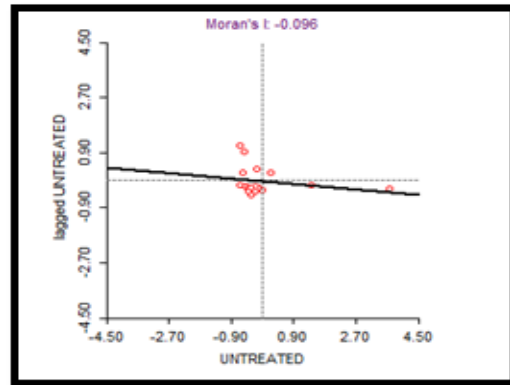
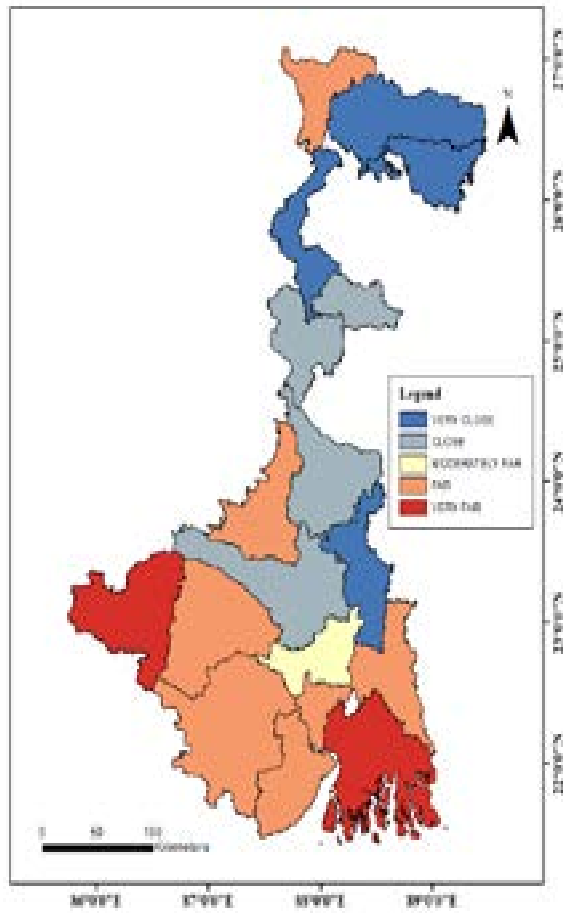


Figure 2, 3, 4, 5: A- Consumption of Untreated Water by the Number of Household
 B- Number of Household who Have Primary Drinking Water Source Away from Their Home
 C & D- Moran's I for Untreated water and Far away Source of Water
 (All figures prepared by the Authors)

Conclusion

This study highlights the considerable water scarcity difficulties encountered by several districts in West Bengal, highlighting the importance of targeted actions to provide equal access to clean drinking water. The investigation finds that about 32% of families rely on remote water sources, while 11.8% drink untreated water, showing significant regional differences in water supply. The Atkinson Index results indicate moderate to high disparity in water availability, notably between districts with varying topographies, population densities, and socioeconomic situations. Despite advances in water infrastructure, modest positive spatial autocorrelation, as demonstrated by Moran's I, suggests that geographical proximity has little effect on water scarcity concerns. Instead, these difficulties are influenced by a variety of local circumstances, including infrastructural availability, natural resource depletion, and environmental challenges unique

to certain areas. North 24 Parganas, for example, suffers from overexploitation of natural water sources because to its high population density, whilst Darjeeling's steep geography limits water availability and increasing reliance on untreated natural springs. These findings illustrate the complexities of water scarcity, where a one-size-fits-all approach is ineffective. The report recommends a more sophisticated strategy to addressing water shortages and ensuring water security, which is consistent with SDG 6's aims.

References

Anselin, L. (1988). Lagrange multiplier test diagnostics for spatial dependence and spatial heterogeneity. *Geographical analysis*, 20(1), 1-17.

Anselin, L. (2022). Spatial econometrics. *Handbook of spatial analysis in the social sciences*, 101-122.

Ghosh, P., Hossain, M., & Alam, A. (2022). Water, sanitation, and hygiene (WASH) poverty in India: a district-level geospatial assessment. *Regional Science Policy & Practice*, 14(2), 396-417.

Haining, R. P. (2003). *Spatial data analysis: theory and practice*. Cambridge university press.

Li, W., Hai, X., Han, L., Mao, J., & Tian, M. (2020). Does urbanization intensify regional water scarcity? Evidence and implica-

- tions from a megaregion of China. *Journal of Cleaner Production*, 244, 118592.
- Lombo, L. M., Hooks, G., & Tickamyer, A. R. (2007). Introduction: Advancing the sociology of spatial inequality. In L. M. Lombo, G. Hooks, & A. R. Tickamyer (Eds.), *The Sociology of Spatial Inequality* (pp. 1–25). New York-USA: State university, of New York press.
- Mishra, B. K., Kumar, P., Saraswat, C., Chakraborty, S., & Gautam, A. (2021). Water security in a changing environment: Concept, challenges and solutions. *Water*, 13(4), 490.
- Mishra, R. K. (2023). Fresh water availability and its global challenge. *British Journal of Multidisciplinary and Advanced Studies*, 4(3), 1-78.
- Moran, P. (1948). The interpolation of statistical maps. *Journal of the Royal Statistical Society B*, 10, 243–251.
- Obaideen, K., Shehata, N., Sayed, E. T., Abdelkareem, M. A., Mahmoud, M. S., & Olabi, A. G. (2022). The role of wastewater treatment in achieving sustainable development goals (SDGs) and sustainability guideline. *Energy Nexus*, 7, 100112.
- Oksana, T., & Dmytro, G. (2021). Earth's Water Distribution. In *Clean Water and Sanitation* (pp. 1-14). Cham: Springer International Publishing.
- Panzer, D., & Postiglione, P. (2020). Measuring the Spatial Dimension of Regional Inequality: An Approach Based on the Gini Correlation Measure. *Social Indicators Research*, 148, 379–394.
- Sustainable Development Goals. (2016). <https://www.un.org/sustainabledevelopment/water-and-sanitation/>.
- United Nations. (2016). The 17 goals | sustainable development. United Nations. <https://sdgs.un.org/goals>
- Yu, M., Chen, Z., Long, Y., & Mansury, Y. (2022). Urbanization, land conversion, and arable land in Chinese cities: The ripple effects of high-speed rail. *Applied Geography*, 146, 102756.
- Zhu, J., Zhu, M., & Xiao, Y. (2019). Urbanization for rural development: Spatial paradigm shifts toward inclusive urban-rural integrated development in China. *Journal of Rural Studies*, 71, 94-103.