



Implementation of Geo-visualization Web Dashboard for Monitoring Access to Improved Water using Geospatial Big Data

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Abstract. This study aims to develop an engaging, web-based visualization dashboard for improved water access in Indonesia. The dashboard map was made using three technologies: the Qgis2web Python plugin for producing two-dimensional (2D) dashboard maps, JavaScript leaflets for map visualization, and Hypertext Markup Language (HTML), Cascade Stylesheet (CSS), and JavaScript for the user interface. The built-in map dashboard has several features, including grid click, legend, zoom, search, and measure distance, which are meant to help users determine the location of the nearest water treatment facilities, identify geographical features, and keep track of areas that have poor access to improved water. Evaluation using the system usability scale (SUS) concludes the dashboard is acceptable with an excellent rating. Our results reiterate and enhance support for government institutions and relevant stakeholders in providing sustainable access to public water.

1. Introduction

One of the Sustainable Development Goals (SDGs) is access to improved water. The goal is essential for daily activities such as drinking, sanitization, washing, food preparation, and personal hygiene. According to the World Health Organization (WHO), a household is categorized as having access to improved water if the main source of drinking water comes from sources that can provide free water from contamination because of design and construction, including protected water (piped water, holes drill or well tube, well protected, protected springs) and rainwater catchment [1]. However, drinking from protected water and rainwater catchment is an unaccepted norm in Indonesia. They prefer to consume bottled water because it has more purity and safety [2]. The Ministry of Development Planning added a definition for households that use bottled drinking water can be categorized as having access to improved water if the source of water for bathing/washing/cooking uses protected water and rainwater [3].

Indonesia is a developing nation still facing significant challenges in accessing improved water. There are more than 24 million people who can't access improved water [4]. Instead, the government already planned that all populations would have access to improved water in 2024 with an intervention scenario [5]. Efforts to increase access to improved water require the involvement of various stakeholders from the central, regional, and village levels. However, stakeholder needs data with more granular and fast update frequency. For example, the central government through National Strategic Projects has planned to create piped water infrastructure for 10 million residential connections [6]. To



determine which families most urgently require access to improved water, actual data with a more granular level is needed [7]. Besides that, granular data is also needed to evaluate village funds related to access to improved water [8]. In the District government plan called Regional Action Plan Drinking Water and Environmental Health, actual data must be available to evaluate and track budget realization at least twice a year [9].

Indonesia's government uses the National Socio-Economic Survey (SUSENAS), to monitor access to improved water. SUSENAS only gathers information on access to improved water once a year with district-level presentations. Besides that, SUSENAS has a sizable sample of 320,000 households, leading to extraordinarily high costs. The collection and distribution of statistics by Statistics Indonesia also take a very lengthy period [10]. As a result, it could not examine the speedier (at least twice a year) regular monitoring at a granular level.

In Indonesia, research has been done on conveying data on access to improved water with more granular and quick updates. Our previous study established an estimated map of access to improved water using geospatial big data, Multi-Criteria Decision Analysis (MCDA), and machine learning (ML) that was first conducted in Indonesia with West Java Province as the case study. Cheaper prices, regular updates, and population representation with more granular are benefits of using geospatial big data [11]. The final output from that study is a 2.5 x 2.5 km grid map of access to improved water. We chose West Java Province as a case study because this province has the largest number of households without access to improved water in Indonesia [4].

Research results must be disseminated concisely and clearly, and have an impact on society. Building a dashboard is one way to support this. A dashboard is condensed and displayed on a single screen so that information may be viewed briefly as a visual representation of the most pertinent information needed [12]. A map dashboard is needed to support the various stakeholders involved in accessing mapping results easily. Using a map dashboard, stakeholders can plan, monitor, and evaluate policy faster and right on target [13], [14]. We suggest using website-based because can be accessible using any device that is connected to the internet (multi-platform) and has become a popular deployment environment for new systems [15], [16]. Besides that, if the government needs to collect data by name by address, a map dashboard also can reduce cost and effort at the data collection stage by focusing only on residential areas that lack access to improved water.

The goal of this project is to develop a website-based dashboard for granular access to improved water mapping, complete with a feature for tracking and locating pockets of the population that lack access to improved water. The structure of this study's research is displayed in Figure 1.

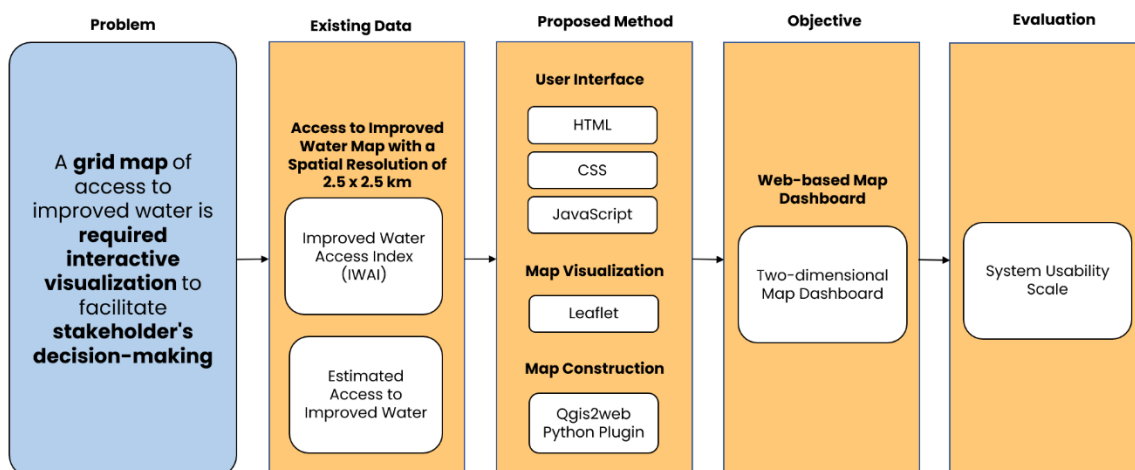


Figure 1. Research framework



2. Methods

2.1. Data Used

The granular map of access to improved water in West Java, Indonesia, is the data source shown by the website-based map dashboard developed for this study. Our previous research resulted in two mapping approaches: estimating models with machine learning and building composite indexes with multi-criteria decision analysis (MCDA). Figure 2 shows a simple explanation of the framework for estimating and mapping access to improved water in our previous research.

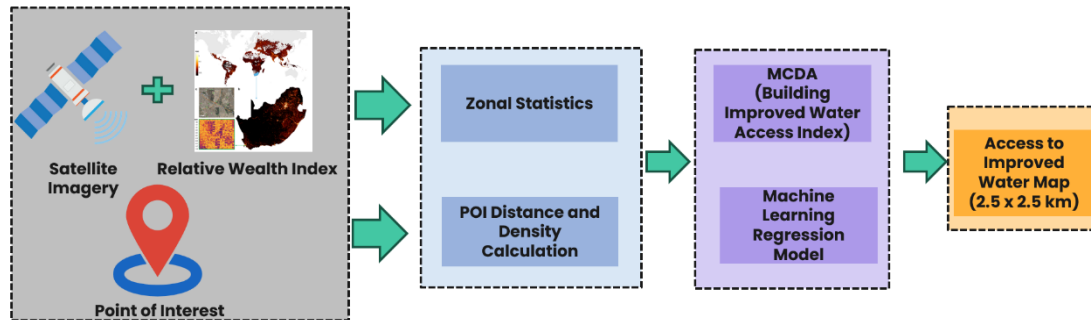


Figure 2. The framework of our previous research

The multi-source geospatial big data was used to create the maps that shown in Table 1. These variables are used as proxy indicators that are related to the concept of access to improved water. We use geospatial data such as point of interest (POI) from OpenStreet Map (OSM), slope and elevation data from the National Aeronautics and Space Administration of the Shuttle Radar Topography Mission (NASA-SRTM), Visible Infrared Imaging Radiometer Suite (VIIRS) sensor from Suomi-NPP (National Polar-Orbiting Partnership) satellite as well as multiple spectral bands from Sentinel-2 satellite including the near-infrared (NIR) and shortwave infrared (SWIR) bands. All explanations of the relationship between geospatial variables and the concept of access to improved water are shown in Figure 3. The green box and line show the relationship between the concept and geospatial big data variables, while the red box shows the components of the concept that are still excluded from our previous research.

Table 1. Detailed data used to create the granular maps of access to improved water

Data source	Spatial resolution	Updating period	Variable	Attribute used	References
NASA SRTM	30m	-	Elevation	elevation	[17]–[19]
			Slope	The local gradient is computed using the 4-connected neighbors of each pixel.	
Suomi-NPP (VIIRS)	463.83m	monthly	Night-time Light	avg_rad	[7], [19]–[22]
Sentinel-2	10m	Ten days	Normalized Difference Vegetation Index (NDVI)	B4 (Red) and B8 (NIR)	[7], [19], [23]–[25]
			Built-Up Index (BUI)	B4 (Red), B8 (NIR), and B11 (SWIR 1)	
Facebook/Meta	2.4km	-	Relative Wealth Index (RWI)	rwi	[17], [18], [26]



Data source	Spatial resolution	Updating period	Variable	Attribute used	References
Ministry of Public Works and Public Housing	Points	dynamically	POI Distance Water Treatment Plants	POI Distance: The distance from the center of the grid to the nearest point	[17]–[19]
OpenStreetMap and Sentinel-2	Points	dynamically (OSM) and Ten days (Sentinel-2)	POI Distance Proper Water bodies		
OpenStreetMap and Statistics Indonesia	Points	dynamically (OSM) and 10 years (Statistics Indonesia)	POI Distance Economic Facilities	POI Density: The sum of points in each grid	[2], [19]
Statistics Indonesia	District	yearly	Percentage of households with access to improved water		[27]

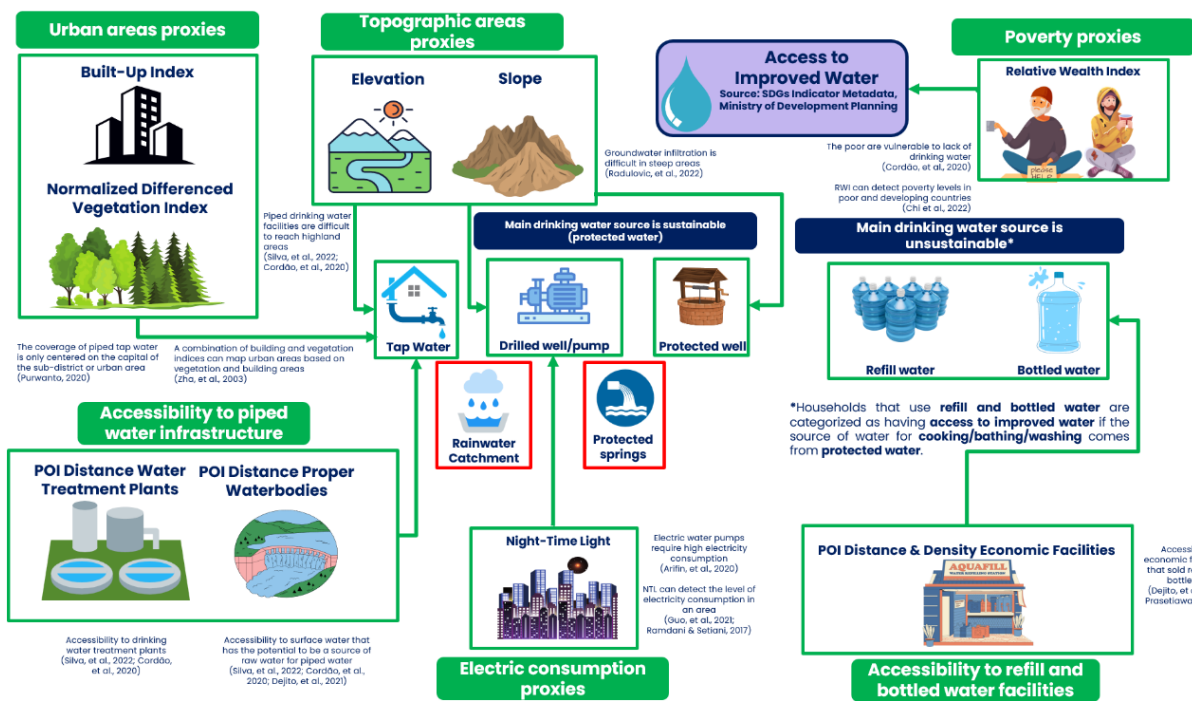


Figure 3. Relationship between geospatial variables and the concept of access to improved water

All geospatial big data variables must be integrated at the same spatial resolution. A 2.5 x 2.5 km grid map was used considering the smallest spatial resolution which is Relative Wealth Index with 2.4 x 2.4 km spatial resolution. After all variables have been integrated, we applied Multi-Criteria Decision Analysis (MCDA) and Machine Learning (ML). The MCDA method produces an index that can describe access to improved water, called the improved water access index (IWAI). IWAI is an updated version of Water Shortages Risk (WSR) [18] and Risk of Water Shortages (RWS) [17]. WSR and RWS only measure the risk of water shortages to provide tap water for urban water supply systems (UWSS), meanwhile, IWAI can measure the vulnerability of access to improved water. The MCDA methods that are used are a weighted sum model with two weights (Pearson correlation and equal weight) and the first component of PCA.



A machine learning method has also been applied to geospatial big data to estimate access to improved water. Machine learning is part of the artificial intelligence approach that learns meaningful relationships and patterns from available training data [28]. There are many machine learning models implemented in making estimates because it has advantages, namely focusing on achieving the best accuracy [29]. Previous research only uses a Random Forest Regressor (RFR) [19]. To get better results, we add eight machine learning models, Decision Tree Regressor (DTR), Support Vector Regressor (SVR), Gradient Boosting Regression Tree (GBRT), Support Vector Regressor (SVR), AdaBoost Regressor (ABR), Extreme Gradient Boosting Regressor (XGBR), and Multi-Layer Perceptron (MLP).

To get the best mapping of both MCDA and ML approach, we use Pearson Correlation, Coefficient of Determination (R^2), Root Mean Square Error ($RMSE$), Mean Absolute Error (MAE), and Mean Absolute Percentage Error ($MAPE$) by compare with official data from Statistics Indonesia at district-level. The range values of the two approaches are different. The machine learning approach resulted in the same range value as official data, but the IWAI range value is different (between 0-1). To overcome this, we performed simple linear regression to predict official data using IWAI as the independent variable and official data as the dependent variable. Before mapping, we overlaid with a grid map population from Worldpop to exclude unpopulated areas [30]. Figures 4 and 5 show static maps of the best-estimated access to improved water by MCDA and ML approach that will be used in dashboard development.

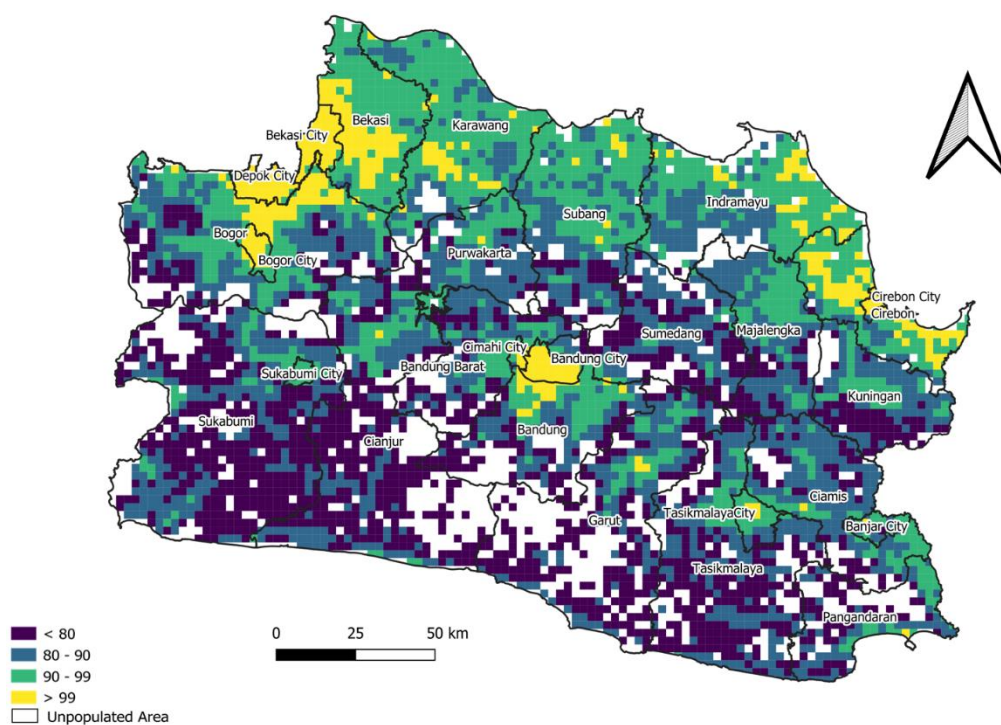


Figure 4. Static map of estimated access to improved water using the best MCDA approach

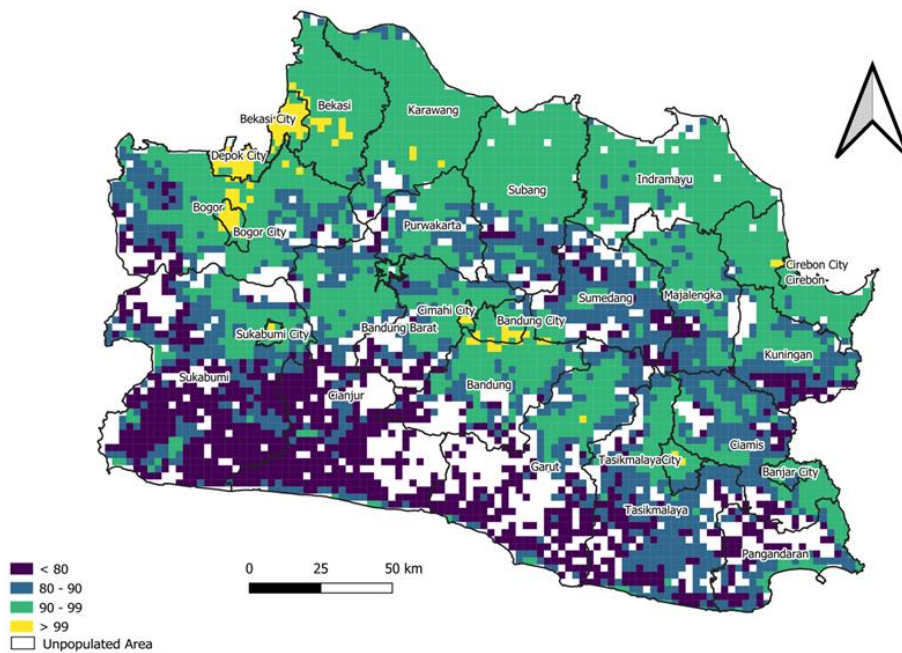


Figure 5. Static map of estimated access to improved water using the best ML approach

2.2. Dashboard Development

The homepage of the map dashboard presents information that provides background, data source, framework, and link to the dashboard. Raw data from a 2.5 km grid map is integrated according to spatial attributes and stored in geojson format for visualization. The map visualization is created using the Leaflet JavaScript package, while the user interface is built using HTML, CSS, and JavaScript. The 2D map features are designed to monitor areas of low access to improved water, identify geographical characteristics, conduct searches, and measure distance.

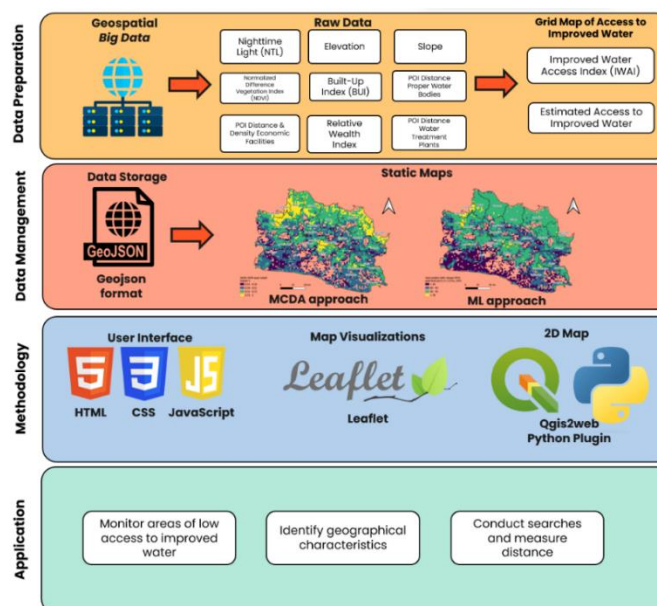


Figure 6. Website-based map dashboard framework



2.3. Evaluations

Many visualizations lack consideration of the purpose and context for which the visualization has been created. It happens because some visualizations have been inappropriately designed and evaluated. Usability issues are crucial for information visualization [31]. We used the System Usability Scale (SUS) to evaluate our map dashboard. The advantage of SUS can be used on small sample sizes with valid and reliable results, so it can differentiate usable and unusable systems. SUS is a simple evaluation, using only ten-item questions to give a global view of subjective assessments of usability [32]. This evaluation used a Likert scale that ranged from Strongly Disagree (1) to Strongly Agree (5). Table 2 shows the questionnaire of SUS. We built the online questionnaire using Google Forms and published the evaluation link through the homepage of the map dashboard, so users can evaluate easily. SUS's final score will be in the range 0-100. This score can be divided into six adjective ratings as explained in Table 3 [33]. Dashboard usability can be accepted if it has a final SUS score above 51.

Table 2. Questionnaire of System Usability Scale

Questions	1	2	3	4	5
Q1: I think that I would like to use this system frequently					
Q2: I found the system unnecessarily complex.					
Q3: I thought the system was easy to use					
Q4: I think that I would need the support of a technical person to be able to use this system					
Q5: I found the various functions in this system were well integrated.					
Q6: I thought there was too much inconsistency in this system.					
Q7: I would imagine that most people would learn to use this system very quickly					
Q8: I found the system very cumbersome to use					
Q9: I felt very confident using the system.					
Q10: I needed to learn a lot of things before I could get going with this system.					

Table 3. Adjective ratings and acceptability scores, with the average SUS score [33]

SUS Score	Adjective ratings	Acceptability scores
0 - 25	Worst Imaginable	
26 - 39	Poor	Not Acceptable
40 - 51	Ok	
52 - 74	Good	
75 - 85	Excellent	Acceptable
86 - 100	Best Imaginable	

3. Results

3.1. Technical Details

Any device with an internet connection can access the dashboard by visiting <https://bigdata.stis.ac.id/pemetaan-akses-air-minum-layak/>. After clicking the link, users can navigate to the home page and scroll down to the map dashboard.



3.1.1. Homepage User Interface. The homepage presents information about what, why, and how mapping access to improved water with more granular is implemented, such as background, data source, framework, and link to the dashboard. Figure 7 shows the homepage that we built.

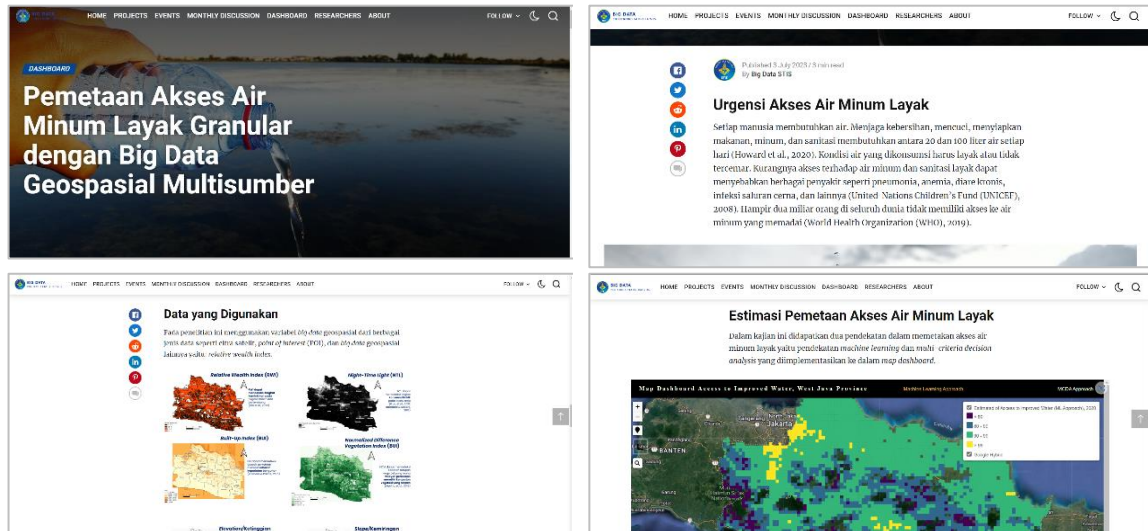


Figure 7. Homepage of map dashboard

3.1.2. Map Dashboard User Interface. A web-based map dashboard presents both the MCDA and the machine learning approach. The map dashboard view is shown in Figure 8.

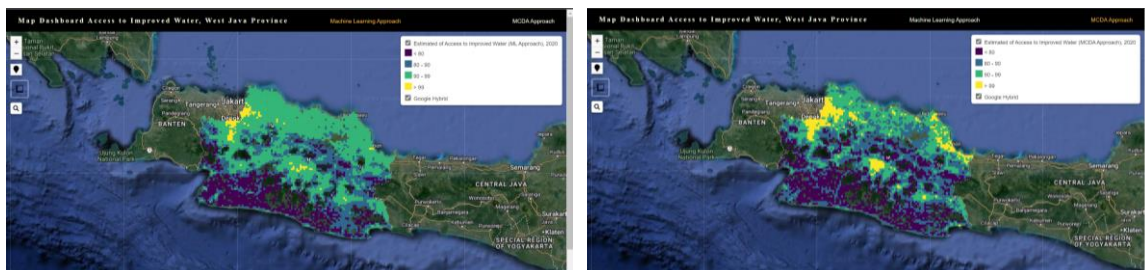


Figure 8. Map dashboard of multi-criteria decision analysis (left) and machine learning approach (right)

Figure 9 demonstrates the map dashboard's user interface preview. Both maps have similar dashboard features. Each of the user interface preview details is explained in the paragraphs that follow.

- 1) Canvas; is the map display area
- 2) Legend; shows the currently displayed layer
- 3) Zoom; is a tool to zoom in or zoom out
- 4) “Show me where I am!”; positioning the display according to the user's location point
- 5) Measure distance; is an analytical tool to calculate the distance between two defined points
- 6) Search; is a tool to search for a certain area on the map

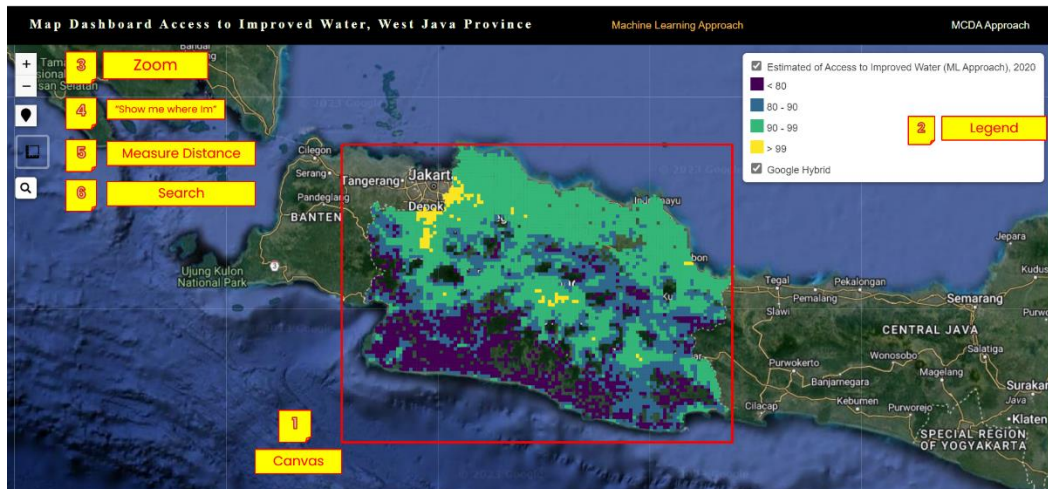


Figure 9. Map dashboard user interface

3.1.3. *Functional Features.* The usage of the map dashboard has the benefit of making it simpler for users to locate specific geographic areas on each 2.5 km grid using a high-resolution Google Hybrid. The map dashboard created for this study has several auxiliary elements that could help stakeholders determine access to improved water more precisely. Grid click, legend, zoom, search, and measure distance are the available features.

a. Grid Click

In addition to supporting data used in model development, such as poverty proxies (RWI), urban area proxies (BUI and NDVI), electric consumption proxies (NTL), topographic area (elevation and slope), accessibility to piped water infrastructure (POI distance proper water bodies and water treatment plants), and accessibility to bottled water facilities (POI distance and density economic facilities) are all made easier for users to view using the grid click feature. An illustration of the grid click feature implementation on the map dashboard is shown in Figure 10.

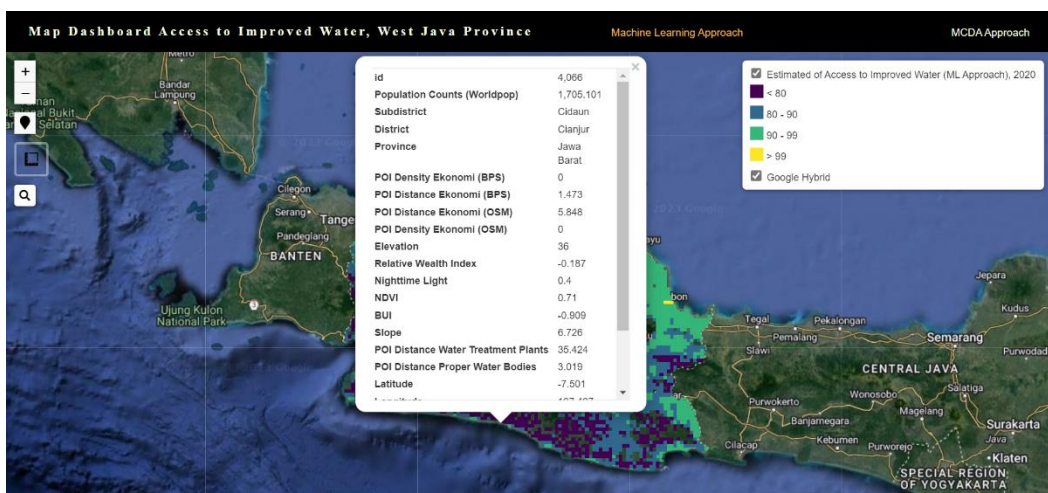


Figure 10. Visualization of grid click feature

b. Zoom

More flexibility might be provided by the Zoom tool when focusing on the region they wish to watch. The mouse scroll wheel may be used to zoom in and out. An illustration of the zoom-in application may be seen in Figure 11.



Figure 11. Visualization of the zoom feature

c. “Show me where I am” (Global Positioning System)

Global positioning system (GPS) can display the user's location point on the map dashboard. In determining the households that most need access to improved water, the government needs by name-by-address or georeferenced data. Using GPS will help enumerators to get by-name-by-address data with more cheaper, easier, and fast in data collection process because only focusing on low area based on the map dashboard.

d. Legend

Based on the map's colors, the legend feature is important for showing how to attain increased access to improved water by levels. Users may choose which layers to display on the dashboard using the checkboxes included in this feature. With Google Hybrid, this function might be utilized for visual geographical identification.

e. Search and Measure Distance

To find a certain focus area on the map users can utilize the search option. Besides that, using the measure distance tool, a user may determine the distance between two points on a map, such as a water treatment plant and a populated region with limited access to improved water.

3.2. Evaluation Results

We got 17 respondents that fulfilled the questionnaire. The data that has been collected is transformed and weighted to obtain the final SUS value. The transformation process is carried out with the item value minus one for odd questions and five minus the item value for even questions. The final SUS value is obtained by weighting it by multiplying the sum of all the transformation scores by 2.5. The results of the transformation and weighting process are shown in Table 4. The final SUS score of 77.5 implies the usability of the map dashboard has been accepted with an excellent rating (see Table 3).

Table 4. Results of Evaluation Map Dashboard using SUS

Respondent	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9	Q10	Sum	Sum x 2.5
1	3	3	3	3	3	3	3	3	3	3	30	75
2	2	3	3	3	3	3	3	3	3	1	27	67.5
3	3	4	4	4	3	4	4	4	4	3	37	92.5
4	3	4	4	4	3	4	4	4	3	4	37	92.5
5	3	4	3	4	3	3	4	4	3	3	34	85
6	2	2	2	2	1	2	2	2	2	1	18	45
7	3	4	4	4	4	4	4	4	4	3	38	95



Respondent	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9	Q10	Sum	Sum x 2.5
8	2	2	2	2	1	2	3	3	2	1	20	50
9	3	4	3	3	4	4	4	4	4	4	37	92.5
10	4	3	4	3	4	4	3	3	3	3	34	85
11	3	3	4	4	2	4	4	3	3	3	33	82.5
12	3	4	4	4	4	4	3	4	4	3	37	92.5
13	3	3	3	4	2	4	3	3	4	2	31	77.5
14	4	4	4	4	4	4	4	4	4	4	40	100
15	1	2	2	3	2	3	3	4	2	2	24	60
16	2	2	3	2	2	2	3	3	3	3	25	62.5
17	2	3	3	4	1	3	3	3	2	1	25	62.5
Final Score (Average)												77.5

4. Discussion

4.1. Application Simulation and Insights

With the recent advancements in satellite imaging analytics and Earth observation technology, there are many chances to accurately and efficiently monitor geographical elements on the surface of the Earth [36-38]. For a variety of advantageous machine learning use cases, several readily available sensors, including optic, radar, thermal, and Light Detection and Ranging (LIDAR) [39,40]. They serve as important sources of low-cost, regularly updated, and granular characterization of land uses, land coverings, and sea surfaces [41,42].

This research's development of a website-based map dashboard is anticipated to facilitate and enhance stakeholders' decision-making, particularly through mapping regions for building drinking water facilities. The simulation of using the dashboard map for each application target and the insights discovered are covered in this part. Our four key discussion points are using dashboard maps to monitor areas of low access to improved water, identify geographical characteristics, conduct searches, and measure distance.

4.1.1. Monitor areas of low access to improved water. The capacity to track up to 2.5 km more thoroughly up to 2.5 km is made possible by employing a website-based map dashboard to monitor regions with limited access to improved water. This dashboard map presents estimates of access to improved water along with data on variables that can indicate improved water, such as topographic area (elevation and slope), poverty proxies (RWI), urban area proxies (BUI and NDVI), electric consumption proxies (NTL), accessibility to piped water infrastructure (POI distance proper water bodies and water treatment plants), and accessibility to bottled water.

Two low places are selected for the experiment using the map dashboard, as illustrated in Figure 12. The first is a 2.5 km² region in Nanggung, Bogor Regency, with an estimated 67.802% access to improved water. This area has a low built-up index (BUI), a high normalized difference vegetation index (NDVI), which indicates rural areas, and a comparatively low relative wealth index (RWI) value, which means a relatively high level of poverty. It also has a high slope value, which indicates steep terrain. These places, on the other hand, are close to appropriate water sources and water treatment facilities. However, the second location, a 2.5 km grid area in Naringgul, Cianjur Regency, is predicted to have just 62.95% access to improved water. This area also has a low BUI value, a high NDVI, and a low RWI value, suggesting a comparatively high level of poverty, rural areas, and steep areas. These places are far from proper water bodies and water treatment facilities compared to the first areas with more access to improved water. The same thing happens in mapping access to improved drinking water in Nigeria, where urban areas have higher access than rural areas [7].

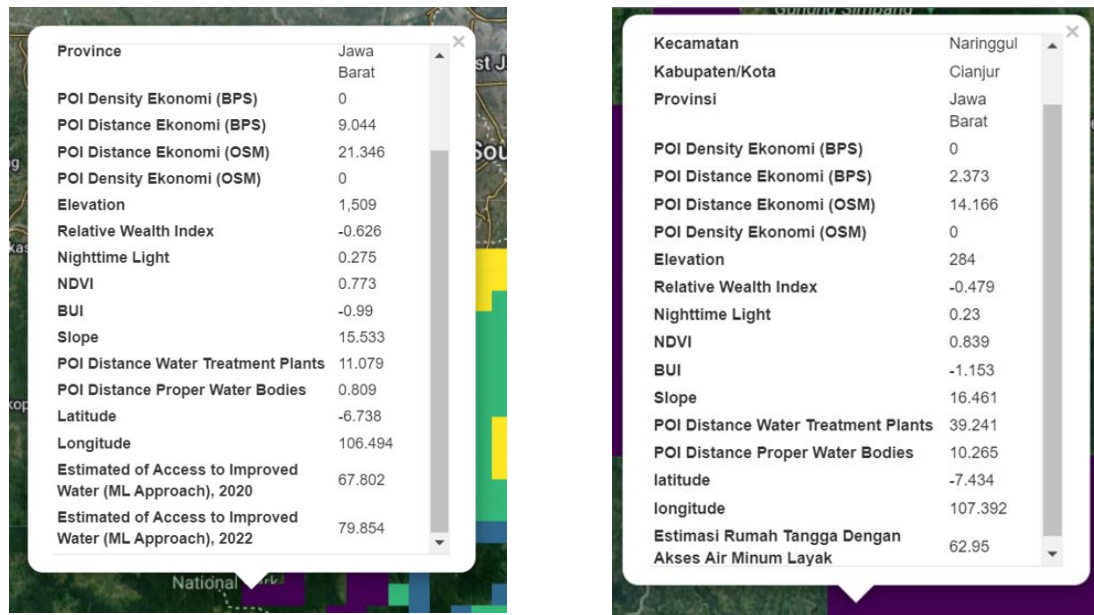


Figure 12. Monitoring simulation of 2.5 km low access to improved water area of Bogor Regency (left) and Cianjur Regency (right)

4.1.2. *Identify geographical characteristics.* Ground truth verification is essential for access to improved water monitoring, especially to pinpoint the geographic conditions of the intended place. However, because of the requirement for a substantial sum of money, time, and effort, this ground truth verification is quite constrained. On the other hand, a ground-truth checking technique feature employing a high-resolution Google Hybrid is offered by the website-based map dashboard developed in this work. As a result, one way to do a ground-truth check is by learning about the local geography.

In this simulation, the Cianjur Regency's locations with a lack of access to improved water are identified geographically (62.95%) (Figure 13). Users may examine images of the Earth's surface from Google Satellite and points of interest from Google Maps by zooming in on the location and turning on the Google Hybrid layer, as demonstrated in Figure 14. Due to its rural and mountainous terrain, which is far from any infrastructure for piping in water, it is obvious that the area has limited access to improved water. Pipeline water distribution to highlands, especially in areas far from water treatment facilities, is very difficult because it requires a lot of money and effort [17], [18].

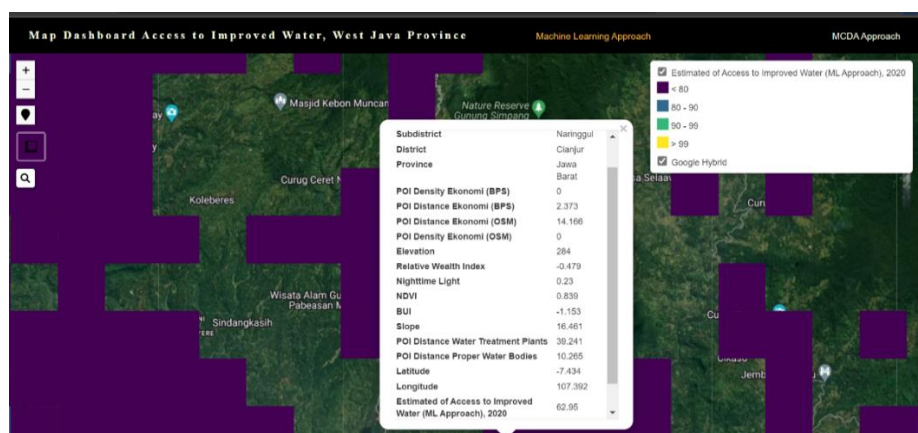


Figure 13. Cianjur Regency's low access to improved water identification (grid)

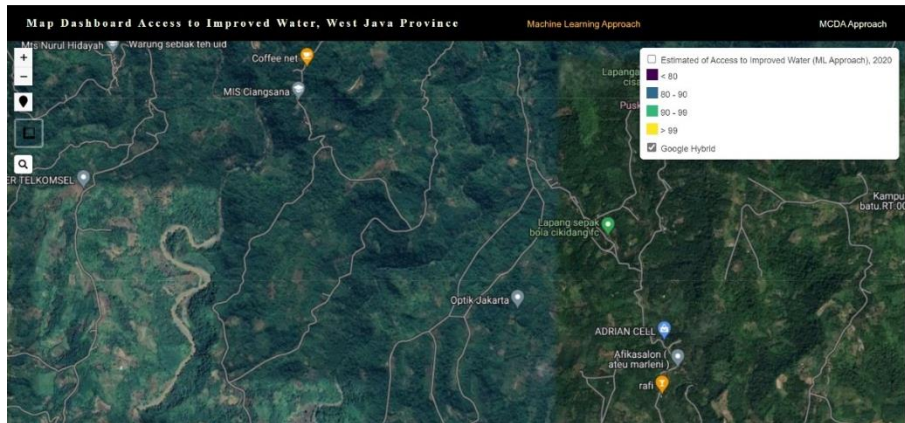


Figure 14. Cianjur Regency has low access to improved water identification (Google Hybrid)

4.1.3. Conduct searches.

Users may be interested in monitoring particular locations when monitoring. Users may search for specific locations using the 'search' tool on the website-based granular map dashboard developed in this study. For instance, the Regional Disaster Management Agency identified Ciwaru's Village in Kuningan Regency and Cidaun, Cianjur Regency as vulnerable to water scarcity [34], [35]. We double-check using the map dashboard's search function, which indicates that this community has poor access to improved water (83.505% and 68.354%) in Figures 15 and 16.



Figure 15. Search feature to Ciwaru's Village, Kuningan Regency

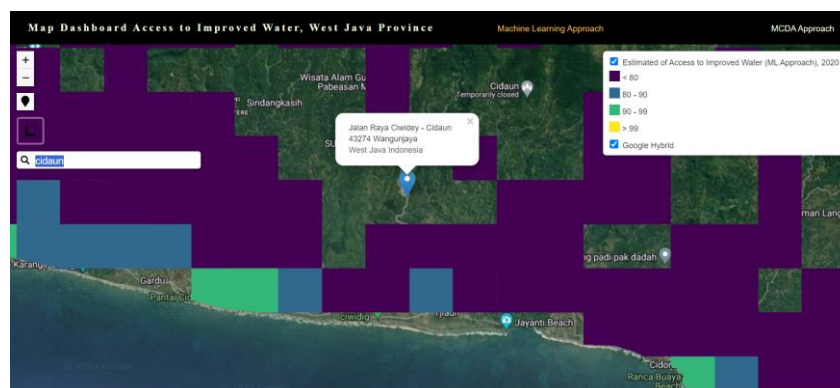


Figure 16. Search feature to Cidaun, Cianjur Regency



4.1.4. Measure distance.

To support decision-making, stakeholders must consider the availability nearest water facilities infrastructure from populated areas. To overcome this, stakeholders may use the 'measure distance' tool on the website-based map dashboard in this study. Figures 17 and 18 show areas that have high access to improved water near water treatment plants (IPA Dekeng Tirta Pakuan Bogor (616 meters)).

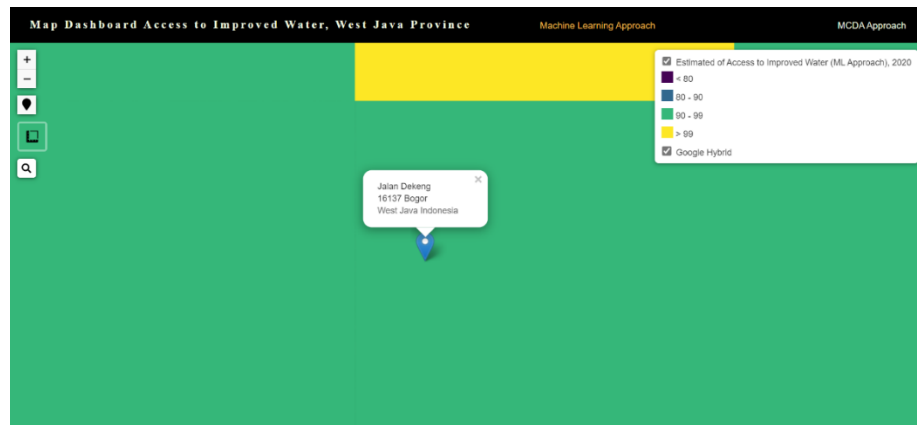


Figure 17. Focus area to measure distance

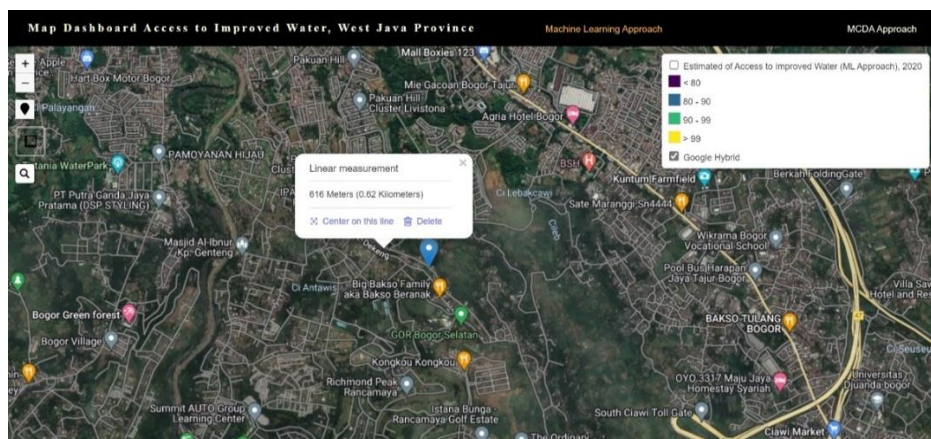


Figure 18. Nearest distance to water treatment plants

4.2. Limits and Opportunities for Advancement

The dashboard map is still restricted to the West Java region and the 2020 reference year. Expanding the coverage area and routinely updating the data can convert these restrictions into possibilities for research development. The map was developed based on multi-source geospatial big data accessible for every province in Indonesia and had an update time of no longer than one month (except for POI economic facilities from Statistics Indonesia (BPS)), making this notion feasible.

This dashboard only provides data at the 2.5 km grid level. In determining the households that most need access to improved water, the government needs by name-by-address or georeferenced data. To support this, complete field data collection is needed, which requires a large amount of money, energy, and time. However, this can be overcome by integrating the field data collection application with this dashboard. This can be done because it will only focus data collection on areas shown by the dashboard as having a grid with low access to improved water.

5. Conclusion

This project was effective in developing a website-based map dashboard of access to improved water with more granular. The dashboard map was made using three technologies: the Qgis2web Python



plugin for producing 2D dashboard maps, JavaScript leaflets for map visualization, and Hypertext Markup Language (HTML), Cascade Stylesheet (CSS), and JavaScript for the user interface. It is designed to measure the distance to the closest water treatment facilities, determine geographical features, and monitor regions with poor access to improved water. Evaluation using the system usability scale (SUS) concludes the dashboard is acceptable with an excellent rating. Our findings confirm and strengthen support for relevant government agencies and stakeholders in ensuring long-term public water access.

References

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