Heliyon 9 (2023) e20298

Contents lists available at ScienceDirect

Heliyon

journal homepage: www.cell.com/heliyon

Assessment of surface water resource and allocation optimization for diverse demands in Ethiopia's upper Bilate Watershed

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ARTICLE INFO

Keywords:
HEC-HMS
Upper Bilate watershed
Optimization
Water-allocation
Water demand

ABSTRACT

Water planning and management is very crucial for all computing sectors for water uses to maximize the scarce and allocated water uses based on their demands sustainably in Ethiopia's upper Bilate watershed. The shortage of surface water, especially during dry months, has become a major point of contention between upstream and downstream water users in the upper Bilate River. Therefore, the key objectives of the study are to evaluate the surface water resources and determine the best distribution for a range of requirements in the watershed. The historical climatic and stream flow daily data for the period of 2010–2019 have been used for the analysis. Hydrologic Engineering Center Hydrologic Modeling System-Geospatial Hydrologic Modeling Extension with the Hydrologic Engineering Center Hydrologic Modeling System was used for rainfall-runoff analysis. The model output further represents that the yearly overall surface water of the watershed is 502 MC M. Estimated annual environmental requirement is 75.32MCM which is 15% of the average annual available flow in watershed. Current annual irrigation, livestock, and domestic water demand were estimated to be 19.34 MC M, 12.39 MC M, and 79.4 MC M, respectively. The net amount of water delivered was 19.25 MC M, 79.28 MC M, and 12.36 MC M for irrigation, domestic, and Livestock demands, respectively, in the reference scenario. In the currently available (reference) scenario, 99.8% of the water supply need had been fulfilled, yet only 0.2% of the requirements for water were unmet. Average annual water demand of 111.13 MC M in the current scenario growth to 176.08 MC M when the future growth scenario. In contrast, for the future irrigation development and population projections scenario, 69.8% of the supply-demand became acquainted, and 30.2% of the demand for water remained unfulfilled in 2035. Therefore, to realize good water availability for productive use and allocate water optimal manner constructing a hydraulic structure (dam) upstream of the watershed was recommended.

1. Introduction

Water is the most important natural resource for all life on the globe, but it is also finite, scarce, and not allocated in a way that meets population demands [1,2]. Population rise and along with the improved standards of living, urbanization, and industrial growth has led to raised demand, competition, and conflicts among different water use sectors [3,4]. In order to implement integrated water

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https://doi.org/10.1016/j.heliyon.2023.e20298
Received 15 June 2023; Received in revised form 15 September 2023; Accepted 18 September 2023
Available online 20 September 2023
2405-8440/

resource management and sustainable resource use, comprehending the water potential within watersheds is a significant advantage [5–7]. The supply and distribution of irrigation water are most often not adequate, equitable, and reliable. Without doing a thorough analysis of irrigation-water demand, the watershed distributes water to the fields based solely on water availability [8,9]. This leads to an uneven allocation of water among the system's water users [10]. The rise in the population often causes water shortages in many areas, leading to problems of allocation and conflicting rights over the limited supply of water [11]. Because of the growing scarcity of water resources for irrigation in some basins and the felt need for effective measures to resolve water shortages and improve water use, consideration of an alternative approach based on deficit irrigation principles has been advocated [12–14].

Unmet water demands may bring conflicts, and intensified demands and frequency of drought further exacerbate the conditions [3,15]. Water resource planners and engineers have created a wide range of tools and models to find solutions to balance demand and availability as well as to control shortages using different efficiency measures [16]. To prevent conflicts between water users, adopt sustainable management techniques for water resources, and raise the standard of living of the populace through effective and efficient water usage, water allocation among water users is crucial and necessary [17,18]. The efficient and ideal allocation of water resources plays a great role in balancing the demand and supply of water resources based on economic development [19]. When the demand for water exceeds the amount that is available, the distribution, however, cannot satisfy the gained demand. In the upper Bilate (UB) watershed, water is needed for livestock, agriculture, and the domestic water supply. The literature, such as the Master Plan (2009) and [17], [20], highlights a lack of focus in well water resource management and development in the Rift Valley Lakes Basin, which may result in disagreements over water use throughout future growth. Additionally, in the upper Bilate watershed (UBW), a populated area with expanding irrigation project there is a lack of reliable assessment of the potential for the surface water resources and its demands for multi-purposes. If an integrated strategy for planning and managing water resources fails to be developed, there is the potential that these conflicts over the uses of water resources, which typically occur between upstream and downstream portions of the watershed, could occur. The significance of the need for further thorough investigation in this area is highlighted by evidence indicating that action still has to be taken.

The HEC-HMS (Hydrologic Engineering Centre - Hydrologic Modelling System) is a popular hydrological tool for simulating streamflow and runoff in river basins [21,22]. This hydrological model is essential for predicting rainfall-runoff processes, forecasting floods, and managing water resources in Ethiopia's UBW, where managing water resources is essential for agriculture, energy, and water supply. It aids in decision-making for projects involving the development of infrastructure and the hydrological behavior of watersheds. The Food and Agriculture Organization (FAO) created the computer programmer CROPWAT to calculate crop water needs and schedule irrigation [23–25]. For farmers, agronomists, and water managers in the current research area, where agriculture is the foundation of the economy, CROPWAT 8.0 is a crucial tool. It aids in figuring out the different crops' water requirements, improving irrigation methods, and effectively managing water resources. Using CROPWAT 8.0, stakeholders can choose crops, choose irrigation techniques, and decide how much water to use, improving agricultural output and water management.

The WEAP model is a commonly used decision-support tool for the integrated management of water resources. The WEAP model aids in evaluating the effects of various water management scenarios in the present, where water scarcity and climatic variability provide important concerns [26,27]. It enables interested parties to evaluate how water supplies are distributed across competing

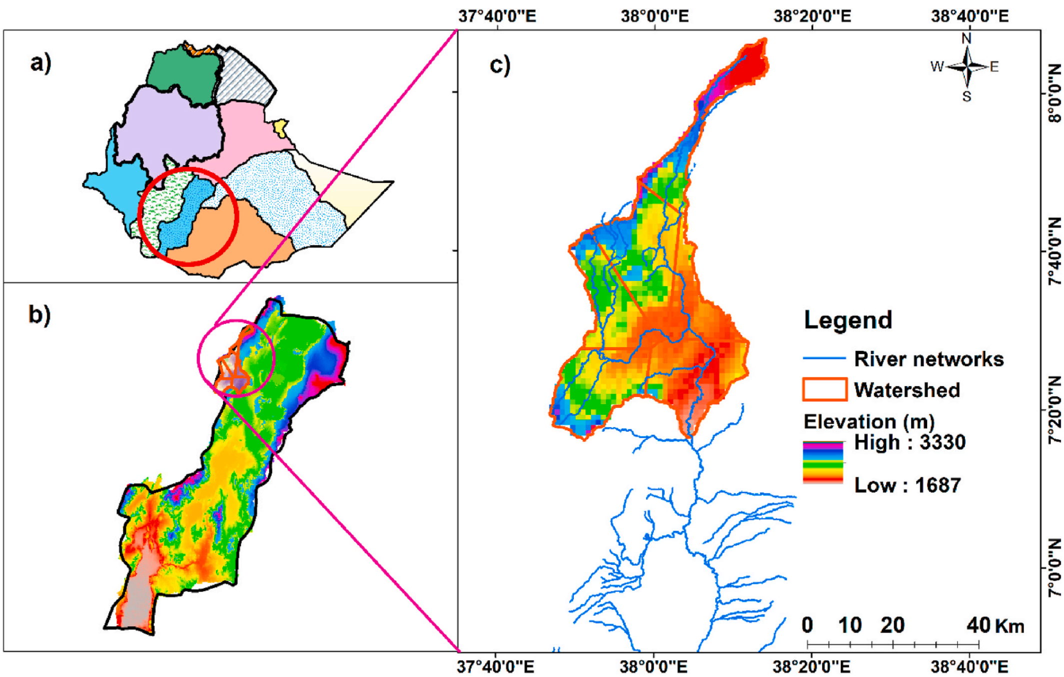

Fig. 1. The location of the study area Where; a) 12 Ethiopia major river basins, b) the Rift valley lakes-basin, c) the UBW.

industries, such as agriculture, manufacturing, and home consumption [3,17]. The WEAP model helps to build sustainable water management strategies and policies by taking into account many aspects such as climate change, population increase, and infrastructure development. Therefore, the following study objectives have been proposed in order to address the problems mentioned above. 1) to analyze the availability and utilization of surface water resources in Ethiopia's Upper Bilate sub-basin, 2) to identify and analyze the diverse demands placed on these surface water resources within the sub-basin, and 3) to develop optimization strategies to allocate water in a sustainable and equitable manner within the sub-basin. Finally, this study plans to contribute to sustainable water planning, management, and utilization by evaluating the potential, needs, and optimal allocations of surface water resources.

2. Materials and methods

2.1. Description of study area

Upper Bilate River watershed is found in the southern nation, nationality and people's regional state. A section of the Hadiya, Gurage, Silte, Kembata-Tembaro, and Halaba zones are covered by the aforementioned river watershed [2,17,28] (Fig. 1c). The Rift Valley basin is one of Ethiopia's 12 major river basins, as seen in Fig. 1b, while Fig. 1a shows Ethiopia's 12 major river basins. In the Halaba zonal state, close to Alaba-Kulito town, the Bilate River begins flowing from the hill Gurage and the Hadiya highlands to the river's monitoring station. The mountainous regions of the Alicho Wiriro districts and, to a lesser extent, the Gumer area is the source of the periodic and permanent streams, Weira and Guder, respectively, which feed the major Bilate River [2]. Digital Elevation Model (DEM) in ArcGIS 10.3 version software was used to determine the boundaries of the watershed, which has a total area of about 1730

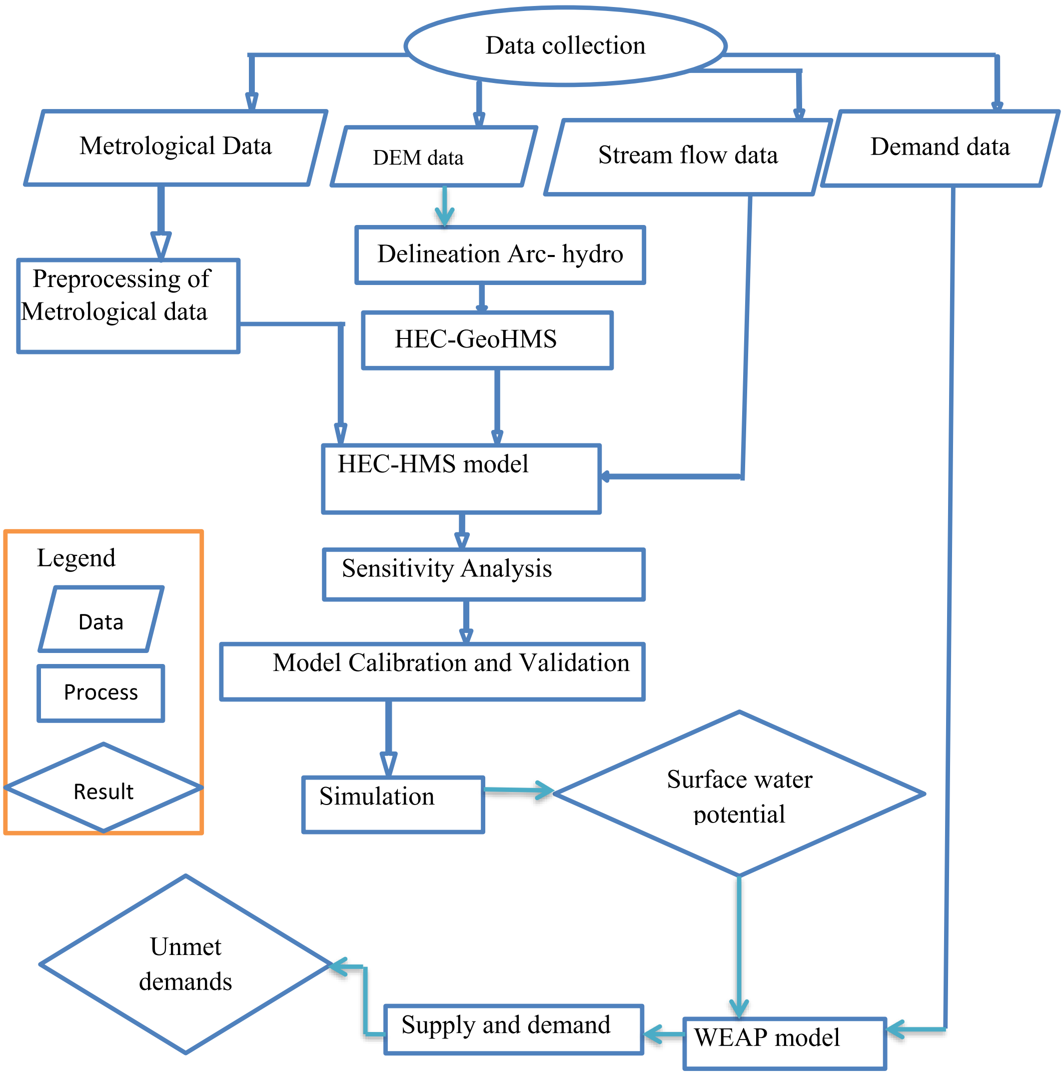

Fig. 2. Conceptual frameworks of the study.

km^2 and a boundary of 295 km. Elevation varies from 1687 to 3330 m above sea level.

2.2. Materials used

Microsoft Excel Spreadsheet was utilized for data processing in HEC-HMS, CROPWAT 8.0, and WEAP models. An ARCGIS 10.3 version and ARC HYDRO 10.3 version have been applied for stream delineation, which was an input for HEC-GeoHMS and terrain pre-processing. To process data in the watershed execution, create a Basin Models file, and import it into HEC-HMS, HEC-GeoHMS, and HEC-HMS have been utilized [21,22,29,30]. The assessed area's peak flow, peak time, and peak discharge volume were all determined using the HEC-HMS model. Utilizing monthly averages of environmental variables, CROPWAT 8.0 was used to determine the crop water requirements [24,31–33]. ETO was calculated using the Penman-Monteith method, and successful rainfall was predicted using the FAO calculation [25,32,34,35]. The program provided data on crops such as Kc, growing process, rooting depth, and soil moisture as defaults. In order to effectively allocate the readily accessible surface water supplies among multiple high-demand areas, a WEAP hydrological model was implemented [26,36–38]. The general processes and methodological design used for this investigation were determined by the conceptual flow chart depicted in Fig. 2.

2.2.1. Physiography

According to Refs. [39,40] volcano-tectonic, rift, erosion, and deposition processes are responsible for the study area's physiographic setting. In the UBW, there is a considerable topographic divide (Fig. 2), with the Bilate River gauging station having the lowest elevation. The HEC-GeoHMS model uses this information as its primary input to define watershed properties, including slope, catchment polygon, and drainage line processing.

2.2.2. Watershed's land-use/land-cover (LULC)

Land use is the practice in which land is used by people in a region through the intervention of labor, resources, and useable technology to generate what is required for use. Researchers assume the earth's surface to be physically covered by the ground cover [41–44]. To put it another way, a land cover is anything that can be seen visually on the ground as a natural or man-made object. In terms of an area covered, the UBW's significant land cover units include grassland, bushland, forest land, barren land, and a permanent open water body (Boyo-lake) [45,46] (Fig. 3).

Based on reclassification of the percentage of land-use area coverage is water body 8%, bushland (10.1%), grassland (6.2%), forest land (3.2%), agricultural land (60.2%), settlement/built up-area (10.2%) and barren land (2.1%), and shown in Fig. 3.

2.2.3. Soil types

The Ministry of Water, and Energy provided a soil map, which was used to establish the major soil texture in the UBW. The soil map was reclassified for study areas and depicted in Fig. 4. Sandy soil, loamy sand, and loam are three soil types found in the watershed.

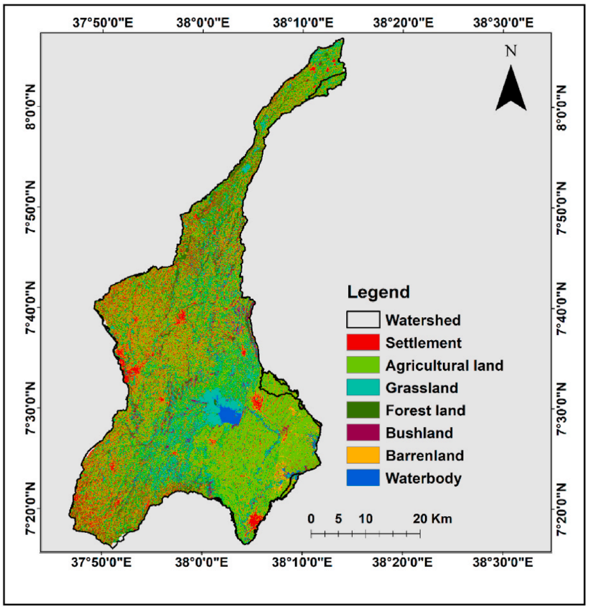

Fig. 3. The watershed's LULC.

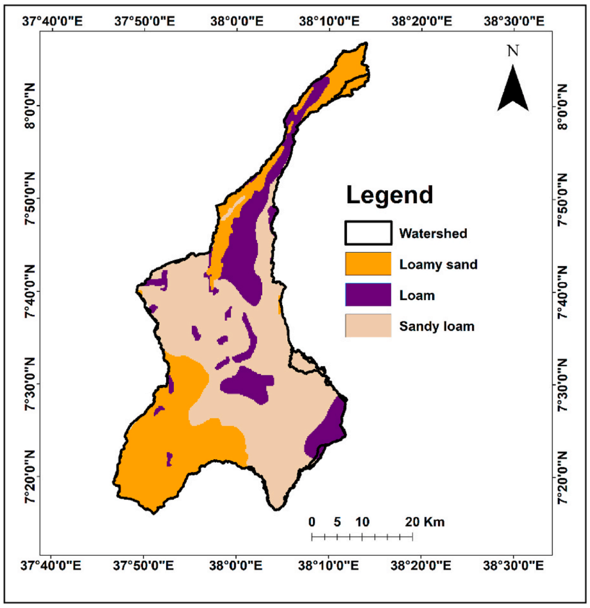

Fig. 4. Major soil types of the study watershed.

2.3. Methods

To evaluate the data quality of parameters, there are several methods that can be employed by different scholars for stance RMSE methods [18,47,48], NSE approaches [28,47,49], coefficient of determination (R^2) [34,50,51] and Machine learning approaches (ML) [52,53]. To guarantee data quality and eliminate uncertainty, the collected data underwent a comprehensive process. With the help of HEC-GEOHMS and the ArcGIS tool 10.3, the UBW's parameters were precisely defined. The dependability and precision of the data used in these models are enhanced by this thorough process [50,54]. The HEC-HMS model was subsequently applied for simulating the surface water availability [55], and the WEAP model was implemented to estimate the needs of water.

For this study, various data collected from different sources as shown in Table 1.

2.3.1. Areal precipitation

The concept of areal rainfall is developed from the fact that the corresponding observations from uniformly distributed rainfall gauges in a given drainage basin divided into watersheds may not be implemented as a representative value for the designated watersheds. When using error propagation theory for areal rainfall estimations, there are several uncertainties that can arise. The following common sources of uncertainty should be taken into account when interpreting the results of calculations for areal rainfall: measurement errors, interpolation errors, model assumptions, data quality, parameter uncertainty, spatial variability, and temporal variability [56,57]. However, there are a number of techniques that can be used to measure and spread uncertainty in calculations of areal rainfall. Sensitivity analysis, Monte Carlo simulations, spatial interpolation, and ensemble forecasting are a few of these methods [58,59]. Sensitivity analysis was adopted in this investigation due to its complexity and widely used methodology [60,61]. We may provide more reliable interpretations of the data and gain a better understanding of the uncertainties related to areal rainfall estimations in Ethiopia's UBW with the use of this technique.

Therefore, it is calculated using Equation (1) to obtain a corresponding record of those stations' areal precipitation quantity in the designated watershed. The polygon's areal contribution of the stations has been reduced using the catchment's form, which contains

Table 1
Types and source of data collected.

No	Data type	Description	Period	Source
1	Meteorological	Daily data	2010–2019	ENMA
2	Streamflow	Daily data	2010–2019	MOWE
3	Spatial	DEM data	2019	MOWE
4	Irrigation demand	Command area(ha)	master plan period	RVLB (2009)
5	Livestock data	Number and demand	2017	CSA, (2017)
6	Water supply data	Water demand	Revised master plan	WMEO
7	Census	population number	2014–2017	CSA

Note: ENMA, refers to Ethiopian National Meteorological Agency, MOWE, refers to Ministry of Water and Energy, RVLB, refers to Rift valley lakes basin, CSA, refers to Central statistical Agency, and WMEO, and refers to water mine and energy offices.

the stations of the study's chosen ones. The mean rainfall depth across the entire area (A), given n stations and n polygons, is given by:

$$p = \sum_{i=1}^{n} \frac{Ai * pi}{At} \tag{1}$$

where, P = Areal average rainfall, P_i = Rainfall measured at station i, A_i = Area of subregion of i Station, and At = the total area of the watershed.

The Hossana Gauging Station has the smallest size of the watershed, as depicted in Fig. 5, whereas the Fonko Gauging Station has the largest area (Table 2), according to the Thiessen polygon (Fig. 5).

2.3.2. Stream flow data

Regarding the river flow assessment, model calibration, and model validation, the river flow gauging of the station close to the town of Alaba-Kulito existed as the watershed's outlet site. The thoroughness of the observed streamflow data, which is more complete than data obtained from most other streamflow gauging stations in the watershed, led to the selection of this particular measuring station. Using the flow data gathered at this station, the monthly averages for the period from January 2010 to December 2019 were derived. The analysis was based on information on the daily river flow collected from the nearby Alaba-Kulito Bilate stream gauge station. As shown in Fig. 6, the daily flows from the time period that was recorded were transformed into monthly mean flow data. The upper Bilate River reaches its maximum discharge during August of that year, as depicted in Fig. 6. From June to October, the average monthly flow is at its highest, and from December to February, it is at its lowest 40.6 m^3/s and 9.51 m^3/s, respectively, are the overall maximum and least mean streamflow values.

2.3.3. Data analysis

Hydrological and weather information were also included in this study's analysis in order to prepare input data for surface water resource simulation. Making sure that the data are adequate, whole, accurate, homogenous, and devoid of missing values is crucial. Because they induce bias in the results, errors brought on by improper data processing are serious [62–66]. Extreme values that greatly depart from the median range in a given data collection are known as outliers. For locating these extraordinary data points, the outlier formula is a helpful tool [67–70]. In order to analyses the quality of rainfall data in this study and detect outliers, we utilized outliers' mechanisms and calculated outliers using the method below: Calculate the interquartile range (IQR):

IQR = Q3 - Q1, where Q1 is the first quartile and Q3 is the third quartile. Quartiles divide the data into quarters, with Q1 representing the 25th percentile and Q3 representing the 75th percentile.

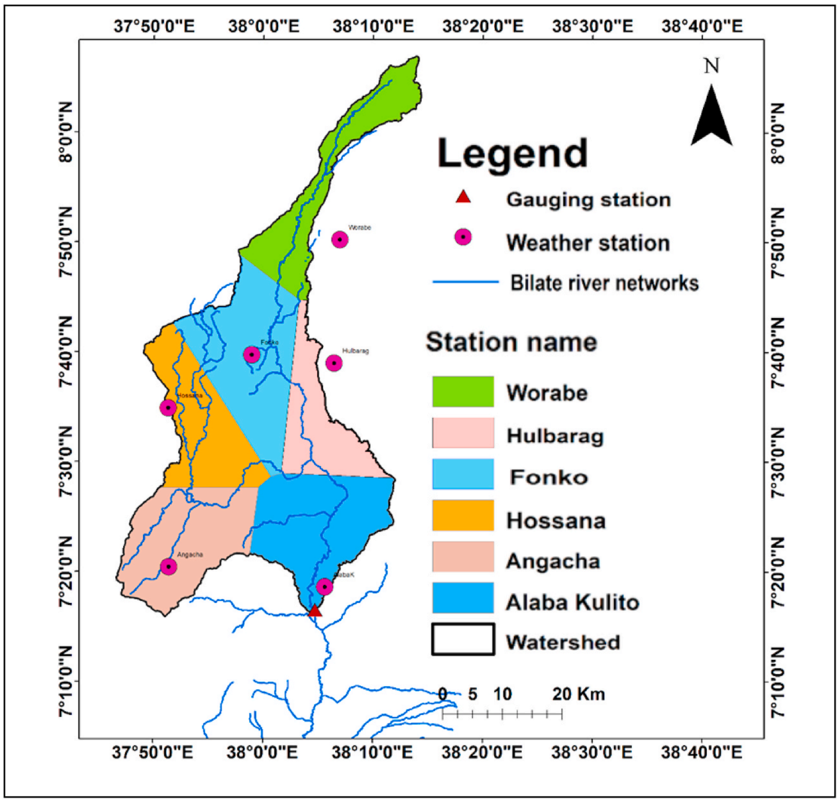

Fig. 5. The climatic gauge station and Thiessen polygons in the watershed.

Table 2
Areal coverage and an annual rainfall of the selected Stations.

Station	Fonko	Hossana	Angacha	Alaba-Kulito	Hulbarag	Total
Area (Km^2)	574	217	315	346	277	1730
Area ratio (%)	33.2	12.5	18.2	20	16.1	100
Rainfall(mm)	1097.4	1140	2334.9	1103.2	1000	

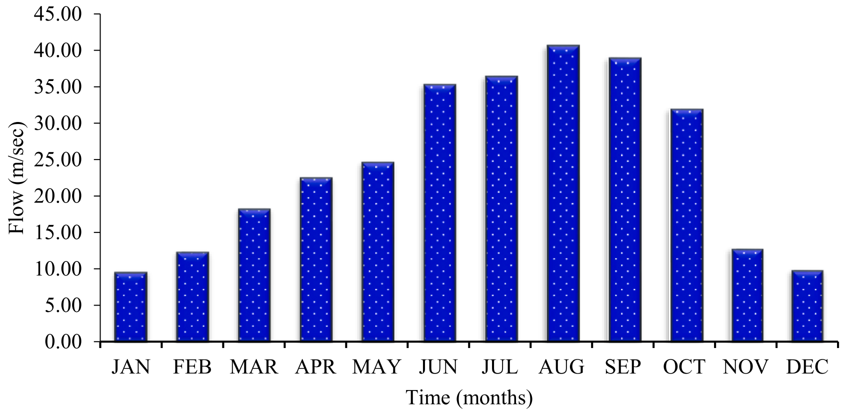

Fig. 6. Monthly average stream flow of the watershed (2010–2019).

Determine the lower and upper bounds for outliers: Lower Bound = Q1 - (1.5 * IQR), and the Upper Bound = Q3 + (1.5 * IQR).

2.3.4. Filling missing data

A number of technological issues could be to blame for missing information at weather stations. climatic circumstances, maintenance problems, communication problems, and sensor failure [71,72]. Due to the environmental conditions, maintenance problems, communication problems common in the Upper Bilate's watershed, it is vital to resolve these technological issues as soon as feasible in order to ensure the reliability and correctness of the meteorological data collected by the stations. When employing long-term time series data for hydro-meteorology research and modeling, the process of filling in missing data is of the utmost significance. A variety of techniques are used, including Station Average, Normal Ratio, Inverse Distance Weighting, Regression approaches and artificial intelligence techniques: such as ANN, equivalent imputation approaches [107], to estimate the missing variables. The method used to calculate mean precipitation is essentially similar to the Station Median method used to fill in missing data. The Normal Ratio technique is preferable in these circumstances [71]. In contrast to the Stations Median technique, this one derives weights using the mean yearly rainfall. We compare the alternative rain gauges in the network to the annual precipitation depths recorded by the broken rainfall sensors using the Normal Ratio approach. To estimate the lost values from stations adjacent to the failed-to-receive record station, the Normal Ratio approach was used in this study. This approach has been selected since it is both more sophisticated than the Station Median method and easier to apply. Due to their superior appropriateness for characterizing the UBW in comparison to the other stations (Equation (2)), five meteorological gauge stations were chosen for additional investigation.

The general formula to estimate Px is

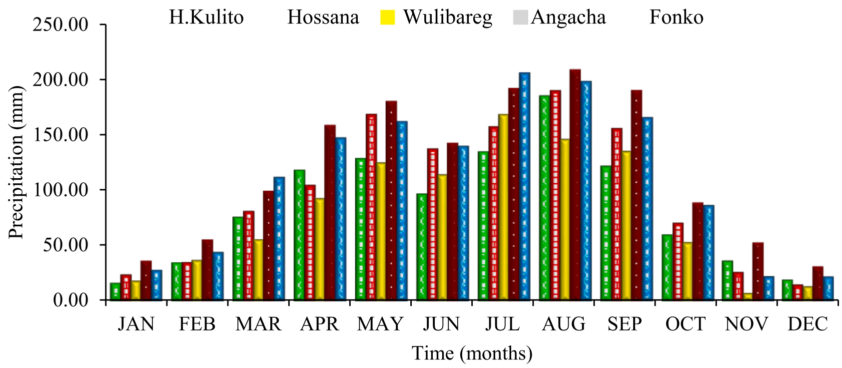

Fig. 7. Mean monthly rainfall between 2010 and 2019.

$$Px = \left(\frac{Nx}{N}\right) * \left(\frac{p1}{N1} + \frac{p2}{N2} + \frac{pn}{Nn}\right) \tag{2}$$

Note: P_x is the missing-value of the precipitation to be computed. The methodology makes the assumption that the proportion of actual precipitation to average precipitation stays largely constant across time. The Normal Ratio Method is typically regarded as being computationally efficient because it only requires simple arithmetic calculations. However, the dataset size and the available computer resources might also affect efficiency.

Nx is the average value of rainfall for the station in question for the recording period.

N1, N2 … Nn is an average value of rainfall for the neighboring station.

P1, P2 … Pn is the rainfall of neighboring stations during a missing period and N is the number of stations used in the computation.

Filled daily rainfall data of all selected stations were changed into long mean monthly rainfall data. These long mean monthly data of selected stations were produced graphically to assist in cross stations comparison to assist understanding on both the seasonal variability and inter-year variability of recorded rainfall as follows in Fig. 7.

For the majority of part, it has rarely been possible to acquire statistics over time for water-related study, and a hydrology data report is often brief and occasionally contains records-breaking anomalies. The association between an entire datasets upstream or downstream gauging station and monitoring discrepancy station is determined using a regression approach [2,18,73–81]. The relationship between a whole dataset and either an upstream or a downstream gauging station as well as the observation gap station is determined using regression analysis [82]. The technique might be connected to the closest stations by using numerous R-program regression to fill in the gaps left by the directly measured streamflow gauging stations. However, the upstream and downstream gauge stations fully lack the necessary time length for this study in the flow line to fill the missing value, and a sizable number of observation values were missing. This results in missing values in the hydrological time series data for the Bilate River [2]. If there is a proper record length of estimated data available [83], then such data may be used for the required purpose. In order to overcome the issue, the average method in the gauge station results was utilized in this study. In order to fill in the missing value at the Bilate gauge station in Halaba Kulito, an average observation on a comparable day from the year prior to and the year after the missed value was used.

However, in order to fill in the missing value of the hydrological time series data for the Bilate River, neither the upstream nor the downstream gauge stations have the necessary amount of time in the flow line. The UBW's HEC-HMS model has been implemented, taking into account and segmenting the watershed into five sub-watersheds (Table 3). The Specified Hyetograph approach had been selected for this study [50,84–87]. There was a total of five climatic gauge stations used to represent the catchment. The stations are selected depending on their relative position to each sub basin and they have a good location to characterize the watershed compared within the remain stations.

2.4. Model validations

Based on their relevance to the research aims their possible impact on the study results, and their availability and trustworthiness of data, the parameters for sensitivity analysis in this study were chosen [13,88–91]. The significance of the factors impacting the system under inquiry as well as their potential for policy interventions or decision-making were also taken into consideration while choosing the parameters. The objective was to select parameters that provide insightful information about the model's sensitivity and could aid in identifying important change agents in the Ethiopian's UBW setting.

In the context of Ethiopia and UBW, the sensitivity analysis of the event model was conducted with a focus on three parameters: initial loss (mm), the constant rate of (mm/HR), and imperviousness (%). According to Refs. [13,88–91], the initial and constant technique was applied to manage infiltration loss in Watersheds. Thus, the parameters associated with this method, namely initial loss, constant rate, and imperviousness, were calibrated. To model the transformation of precipitation excess into direct surface runoff, the Clark Unit Hydrograph method was utilized.

Over the course of six years, daily flow data were calibrated and validated as part of the HEC-HMS model's validation procedure. The calibration specifically included the years 2010–2015, whereas the validation covered the years 2016–2019. The model's parameters were adjusted during the calibration phase to make sure that the simulated flow data and the observed flow data for the chosen period (2010–2015) were in agreement. The goal of this approach was to provide results that were nearly in line with the predictions made by the model and the actual recorded flow measurements [54,87,92]. After the calibration, the model's effectiveness was evaluated during the validation stage. The validation process is crucial as it helps to assess the model's ability to simulate real-world flow patterns and predict future flows accurately. It provides confidence in the model's performance and ensures that it can be relied upon for decision-making regarding water resource management, flood forecasting, or other related applications.

To evaluate model performance, simulated and observed runoff graphs were compared, and Nash and Sutcliffe efficiency criteria (NSE) were calculated. A measure of efficiency that links the model's goodness-of-fit to the variance of the estimated results is the coefficient of Nash and Sutcliffe. NSE can range from - to 1, and an efficiency of 1 denotes a full agreement between observed and simulated discharges as well as a successful model run [21,84].

Table 3
UBWs and the contributing rainfall stations.

Watershed	w650	w700	W1100	w850	w630
Contributing Stations	Fonko	Hossana	Alaba-Kulito	Angacha	Hulbarag

According to the commonly used NSE criteria, a coefficient of 1 indicates a perfect match between observed and simulated discharges (Table 4). The model's performance in this study was good, as indicated by the calculated NSE [54]. In summary, the sensitivity analysis of the event model in Ethiopia involved three parameters, and the initial and constant method was used to handle infiltration loss in watersheds. The Clark Unit Hydrograph method was used to model the transformation of precipitation excess into direct surface runoff. The HEC-HMS model had been calibrated, verified, and evaluated by computation NSE as well as comparing the generated and measured discharge diagrams. It was determined that the model functioned satisfactorily.

R^2 and NSE evaluate how well the simulation findings over a particular time frame and for a certain time phase match the patterns of the data being monitored (Equation (3)). These measurements were calculated for a daily time period in this research.

R^2 is computed as:

$$R^2 = 1 - \frac{\sum_{\mathbf{i=0}}^{\mathbf{n}}\left[(\mathbf{Qsim,i} - \bar{\mathbf{Q}}\mathbf{sim}\right)(\mathbf{Qobs,i} - \bar{\mathbf{Q}}\mathbf{obs})\mathbf{2}\Big]}{\sum_{i=1}^{n}((\mathbf{Qsim,i} - \bar{\mathbf{Q}}\mathbf{sim})\mathbf{2}(\mathbf{Qobs,i} - \bar{\mathbf{Q}}\mathbf{obs})\mathbf{2})} \quad 3$$

$R^2 > 0.6$, is a satisfactory fit.Where, Qsim,i is the simulated value of the quantity in each model time step, Qobs,i is the measured values of the quantity in each model time step, Qsim,i is the average simulated value of the quantity in each model time step, and Qobs, is the average measured value of the quantity in each model time step (Equation (4)). While, NSE is computed as follows:

$$\text{NSE} = 1 - \frac{\sum_{i=1}^{n}(Qobs,i - Qsim)2}{\sum_{i=1}^{n}(Qobs,i - \overline{Q}obs)2} \quad (4)$$

NSE >0.5, is good of fit.

Whereas, Q_{sim}, i, is the quantity's replicated values, Q_{obs}, i, is the quantity's measured value in each model time step, and Q_{obs}, is each model time step, it is the quantity's average calculated value.

2.5. Water allocation

2.5.1. Input data and schematic of the WEAP model

The WEAP input data refers to the examination of the data used in the model, which depended on water demands, irrigation schemes, and residential, animal, and environmental needs. The reference scenario started in 2021, with 2035 serving as the analysis's final year. For every demand site, several levels of disaggregation were made. A schematic diagram is a visual representation of a system's components that omits realistic pictures in favor of symbolic representations. As stated by Refs. [15,26,36,37], the Schematic View serves as the foundation for all WEAP operations (Fig. 8).

2.5.2. Scenario development

The water demands are influenced by different demand and supply factors such as changes in population growth, changes in land-use policy, industrialization, etc. Supply is affected by variation in natural climate temperature, rainfall, stream flow [93]. To address a broad range of "what if" questions, the scenario was created and their possible impacts on the water resource. Therefore, irrigation and population growth future scenario were developed to enhance future products and water demand consideration. The increased population growth and irrigation will be the main water demand than other consumptives because of its economic potential in the area. The following scenarios were used to achieve the demand. Baseline water demand: The baseline water demand was done using currently available current demand data of livestock, domestic water supply, and Irrigation demand based on the current condition of the study watershed Reference scenario: This was performed by extending the trend of the baseline water demand in the future. Scenario-1: In this scenario, was tried to see, what will happen, when the proposed irrigation area expansion projects and traditional irrigation practice will be changed to increase productivity and efficiency. Scenario-2: This is a situation with increasing water demand; as a result of projected population expansion, per capita water consumption is projected to increase. What will the availability be in this scenario? In order to estimate the population during the study period, the average population growth rates of the watershed were found to be 2.9% and 3.2% for rural and urban centres, respectively [94]. The current population for each location was calculated based on the current population and growth rate to 2020, and the current population number in 2020 was used to calculate the 2035 population using the arithmetic increase method. This allowed us to estimate the population of the watershed to be in a future scenario. The predicting of the population was employed in this calculation (Equation (5)).

Table 4
General performance for recommendation satisfaction.

Performance	NSE
Very Good	$0.75 < \text{NSE} \leq 1.0$
Good	$0.65 < \text{NSE} \leq 0.75$
Satisfactory	$0.50 < \text{NSE} \leq 0.65$
Unsatisfactory	$\text{NSE} \leq 0.50$

Source: From HEC-HMS user guide manual

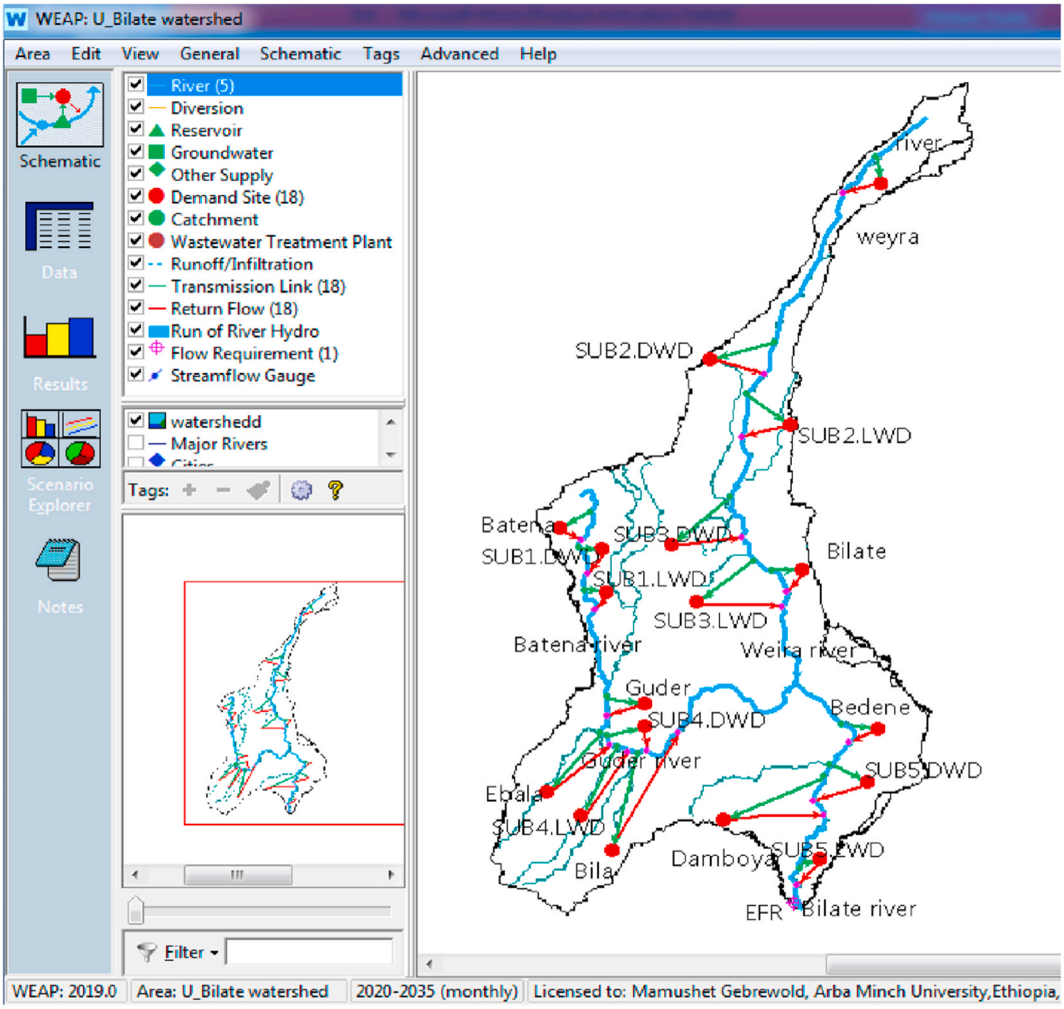

Fig. 8. WEAP schematic view of the watershed with demand site.

$$P_n = Po + nK \qquad 5$$

where; n is the number of decades between now and the future, and Pn is the population at that time. K is the average (arithmetic mean) of population growth over the known decades.

Therefore, this study used the estimated total current population in 2020 and, the future projection in 2035 for the WEAP model as input data based on UBW.

3. Results and discussions

3.1. HEC-HMS model performance

The HEC-HMS model was used to calibrate and validate daily flow data for a period of six years, from 2010 to 2015 and 2016 to 2019, respectively. The findings of the ultimate verification and calibration procedures are shown in Table 5, which shows that the watersheds observed until generated flows coincide fairly well. This is supported by the correlation coefficient and Nash-Sutcliffe

Table 5
Summary of the HEC-HMS model Performance.

Performance	Nash Sutcliffe (NSE)	Coefficient of Determination (R^2)	Remark
Calibration	0.76	0.80	ok
Validation	0.72	0.765	ok
Recommended	>0.5	>0.6	Based on the HEC-HMS user guide manual

efficiency values, which show that the maximum and minimum discharges of both the observed and simulated results align well. Overall, there is a good match between the observed and model-simulated results.

3.1.1. Calibration and validation

Model calibration is the process of changing the model's parameters to closely match the observed data. Adjustment can be carried out manually or automatically utilizing computer-based techniques. As a result, manual calibration was utilized in this study to align model parameters with collected data. The calibration findings demonstrate an adequate agreement between simulated and observed stream flow. Fig. 9 shows the calibration findings for the model, which include a Nash Sutcliffe (NSE) value of 0.76 and a Coefficient of Determination (R^2) value of 0.8. For the validation of the calibrated model, observed flow data from January 1, 2016 to December 31, 2019 was used. It is important to run the model out of the data used for the calibrated time range (Fig. 9).

The HEC-HMC model simulation results for streamflow in Ethiopia's UBW are generally good based on the data presented in Table 5. The model's ability to faithfully replicate extreme flow occurrences is demonstrated by its ability to capture the streamflow. The model's predictions and the data from the measurements do not always agree. Nevertheless, given that the overall simulation results are deemed to be "well captured," it can be assumed that the model has both overstated and underestimated the flow in relation to the measured data. The model, in particular, exaggerated wet seasons while underestimating dry ones (Fig. 9). This shows that the model might be constrained in its ability to precisely estimate the precise quantity of flow due to environmental factors, maintenance issues, and communication issues. The NSE value of 0.72 and the R2 value of 0.76 demonstrate a reasonable performance in capturing the observed stream flow during the validation phase, where the model's performance is tested using independent data. According to the suggestions in Table 5 in the HEC-HMS user guide manual [95], an NSE value above 0.5 and an R2 value above 0.6 are regarded as acceptable results. Overall, the HEC-HMC model performs well at capturing stream flow, however there are some differences between it and the actual data. However, based on the specified performance measures and guidelines, the model's performance is within the acceptable range.

The overall HEC-HMC model simulation results show the peak flow is well captured. However, there is an underestimated and overestimated result compared with the measured data.

3.2. Surface water potential

3.2.1. Modeling result of the surface water potential

The modeling results of the surface water potential were obtained through the use of the HEC-HMS model, which calculated the runoff produced from rainfall in the study area using the rainfall-runoff process. The total annual surface runoff in the Watershed was found to be 502MCM (million cubic meters). This estimated runoff was then used as the river flow, as suggested by Ref. [96]. The Rainfall-Runoff model was used to represent the available surface water resources of the UBW. This available water was then allocated to the water users in order to understand the potential of water relations with the water demands within the watershed. Fig. 10 shows the long-term average monthly replicated streamflow in the Watershed from 2010 to 2019. This figure provides valuable insights into the water flow patterns and trends in the Watershed, which can be useful for water resource management and planning.

3.3. Water demands

3.3.1. Illustration of a water consumer demand scenario

The anticipated combined water usage for all three of these users was 111.13 MC M, and an additional 75.32 MC M was needed to

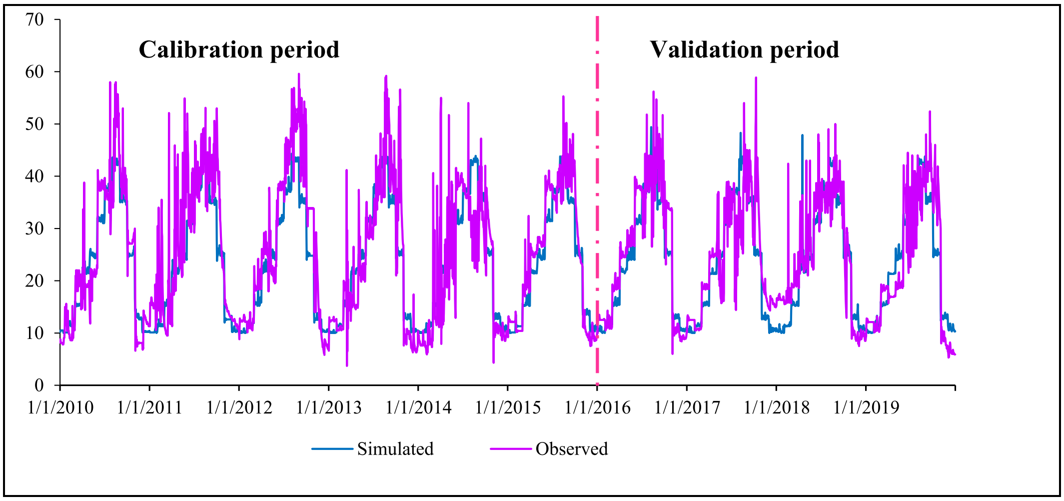

Fig. 9. Replicated versus measured daily stream flows in model calibration and validation.

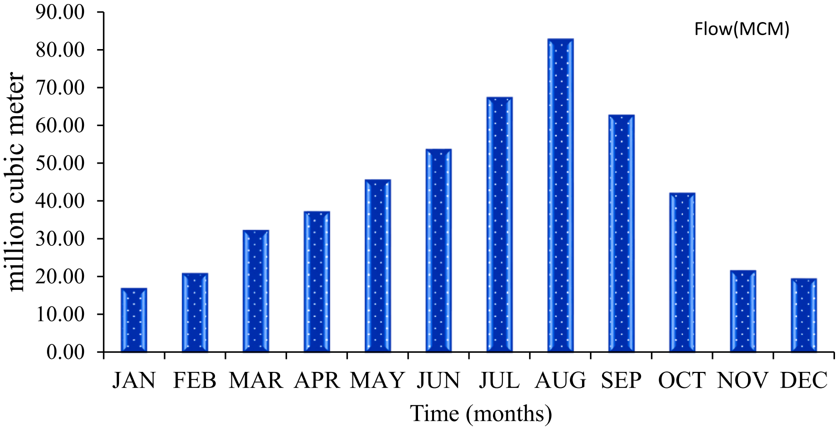

Fig. 10. Long-term average monthly simulated streamflow in the Watershed (2010–2019).

meet environmental flow requirements. This brings the Watershed's overall water consumption to 186.45 MC M, or 22.14% of the 502 MC M/yr of surface water that is readily available. Table 6 shows the water consumer demand for each demand category for the illustrative case scenario accounting year in the UBW.

In addition, this research estimate that domestic water use at demand sites, coupled with irrigation demand estimates of 17.4% and 11%, will account for 71% of the simulation's overall water usage. The overall average demand for water for the reference scenario results in contrast shown in Fig. 11, and Fig. 12. Figs. 11 and 12 illustrate that the months of January, February, March, April, October, November, and December had the highest demand requirements relative to the maximum, while May, June, July, August, and September had the lowest demand requirements due to the rainy season compared to the other months.

Fig. 13 Show that the total annual volume of water supplied for irrigation systems was 19.25 MC M, with the SUB1. LWD, SUB2. LWD, SUB3. LWD, SUB4. LWD, and SUB5. LWD receiving 3.15, 1.71, 3.88, 1.53, and 2.11 MC M for livestock, respectively, and 79.28 MC M for domestic use in the reference scenario. Therefore, the total annual availability of water was 110.91 MC M for domestic, irrigation, and livestock water demands. However, according to the WEAP outcome, the mean monthly water requirement for all demand sites was not entirely met in the current scenario. The gap between the annual quantity of water demand (111.13 MC M) and the annual quantity of water supply (110.91 MC M) indicates that there is unmet in the watershed.

3.3.2. *Unmet demand for reference account*

The total amount of water that is needed but not being delivered from the source is the subject of the unfulfilled needs for the references account. The magnitude of water shortage is important to understand, as highlighted in studies by Refs. [6,97–100]. In this regard, the number of site conditions that are not met under the current scenario is addressed. Agriculture is the primary source of livelihood for the people in the UBW, and the purpose of WEAP modeling is to optimize social benefits by ensuring efficient water delivery for different uses in the watershed. Consequently, a result, it is important to consider the effects of insufficient demand while creating strategies for the sub basin's effective use of water (Fig. 14).

For irrigation, animals for consumption, and water for domestic use, respectively, there was a gross annual unmet of 0.09 MC M, 0.01 MC M, and 0.12 MC M based on the outcomes of the reference scenario. This indicates that the watershed has a water shortage of 0.22 MC M compared to the total amount of water needed. As a result, it can be assumed that the watershed's need for water for agriculture, livestock, and residential use is not adequately met, which causes disputes over water use between ecosystems upstream and downstream. Without supplementary supplies of water to meet the demand, the situation might get worse and increase river depletion.

3.3.3. *Environmental flow requirement*

Environmental flow is a vital component of water resource planning, management, and distribution, aimed at ensuring the natural protection and restoration of marine ecosystems through sustainable flow. Previous studies have found that the environmental flow requirement should be between 10% (lower limit) and 35% (fair/good habitat conditions) of flow [101]. In the UBW, previous studies have assigned 15% of the overall average annual available flow to the environmental discharge requirement, resulting in an estimated annual environmental requirement of 75.32 MC M.

Table 6
Reference scenario Water requirement.

Demand	Water requirement (MCM)
Irrigation	19.34
Domestic water demand (DWD)	79.4
Livestock water demand (LWD)	12.9

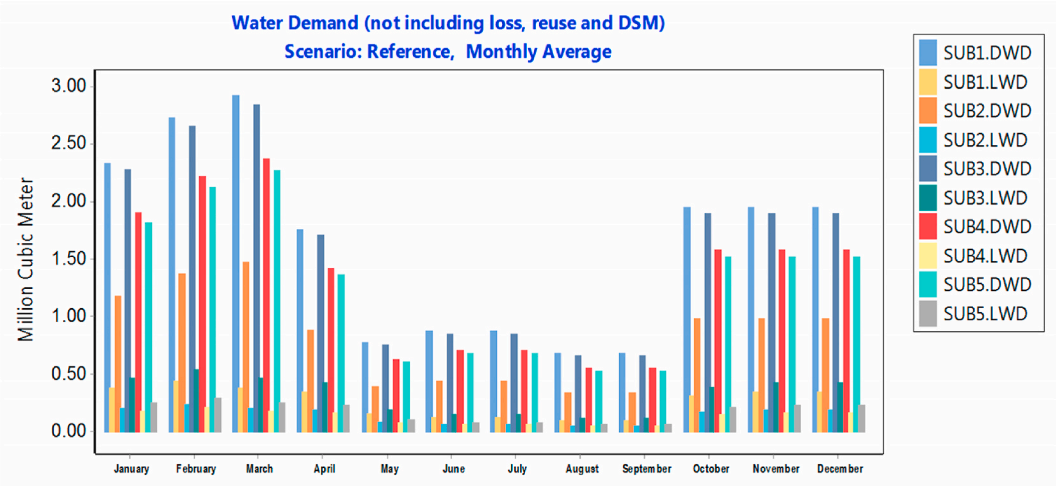

Fig. 11. Mean monthly water for the domestic and livestock demands. Note: SUB, refers to subbasin, DWD, refers to domestic water demand, LWD, refers to livestock's water demand.

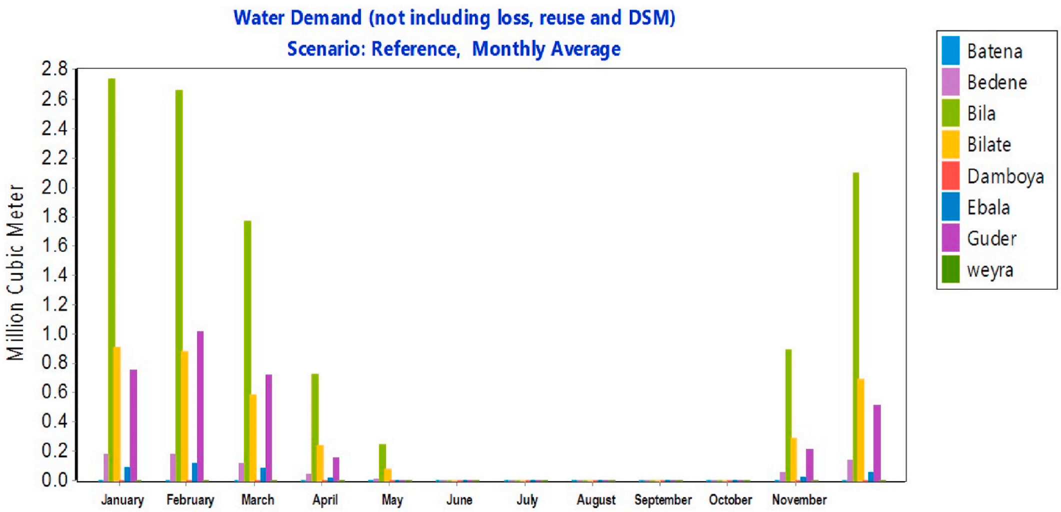

Fig. 12. Mean monthly water for the Irrigation demands.

3.4. *Future scenario analysis*

3.4.1. *Future scenario (Scenario-1and Scenario-2)*

This section combines Scenario-1 and Scenario-2 as future growing scenarios to avoid repeated subheadings. A key scenario has been defined to describe possible future irrigation and population situations in the UBW. In Scenario-1 (Irrigation Expansion), the impact of proposed irrigation area expansion projects and changes to irrigation methods on productivity and efficiency are analyzed (Fig. 15). Scenario 2 (Population Growth), it is investigated if surface water can supply additional household water in response to anticipated expansion in population. The premise for both of these scenarios is the fact that the expansion of irrigated areas and increases in population are given priority in accordance with the recently adopted water resources handling policy. Model simulation results show that the watershed has an average annual water demand of 111.13 MC M in the reference scenario.

Figs. 15 and 16 illustrate the average monthly irrigation and domestic water demands for the future duration under the irrigation expansion and population growth scenario. The combined scenario results in an overall average annual demand for water of 176.08 MC M in 2035. This indicates an increase in the average annual irrigation and population growth demand for water from 111.13 MC M to 176.08 MC M when the growth scenario was modeled.

Figs. 17 and 18 show the mean monthly irrigation and domestic water supply delivered of the future time growth scenario. In 2035, the total average annual water supply supplied under irrigation area is rising and population growth estimates are 158.91 MC M with an increase in average daily water consumption demand. This illustrates that when the hypothetical scenario was modeled, the total

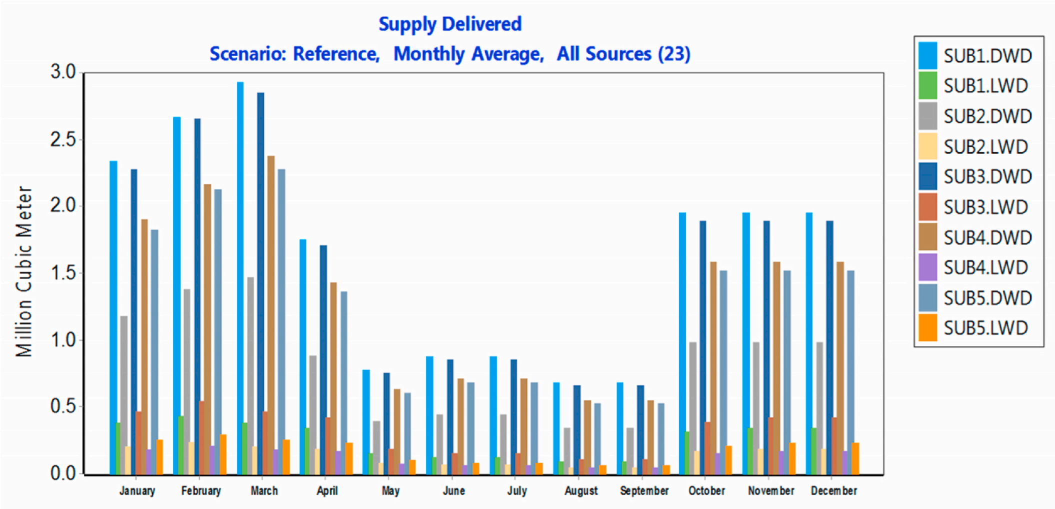

Fig. 13. Monthly average supplies delivered for domestic and livestock demands.

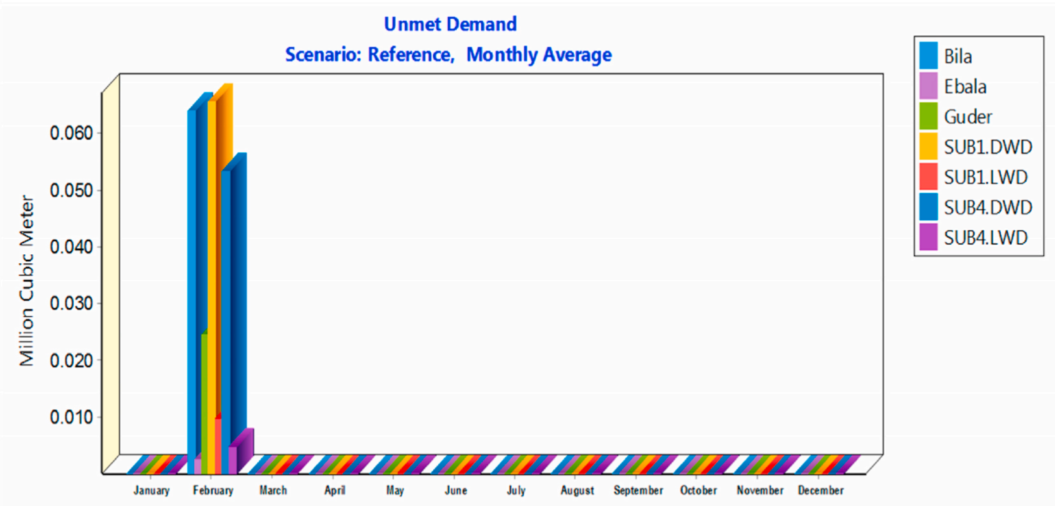

Fig. 14. Mean monthly unmet demand of the reference scenario the results.

annual supply of water provided in the watershed increased from 110.91 MC M to 158.91 MC M in 2035.

3.4.2. Unmet demand in future scenarios

Fig. 19 depicts the unmet water demand in a rising scenario that spans from 2021 to 2035. Plans for long-term water conservation in the watershed are then developed using the potential findings of unmet criteria. The scenarios for future growth are intended to provide answers to issues such as "What would happen if the irrigation area increased to meet the demand for irrigation water?" and "What if the population grows in numbers?" The future scenario predicted that the watershed's water consumption will rise from 111.13 MC M to 176.08 MC M. According to this, water demand in the UBW would rise from 0.22 to 17.16 MC M between 2021 and 2035 as a result of an increase in both population and irrigation requirements. Meanwhile, the scenario of the future would make the shortage of water worse. In both the historical and prospective scenarios, the WEAP model forecasts that from 2021 to 2035, the watershed in question would experience increasing water shortages (unmet).

According to various studies [25,44,102–106], changes in land use, such as an increase in the area under irrigation, would increase water demand, leading to an increase in unmet demand. This finding aligns with Mutiga's practical work on water demand. In the future scenario, the demand for water would increase due to the expansion of irrigation areas and changes in population numbers in the watershed. Therefore, it is necessary to implement more efficient management strategies for the available water in the watershed to address the unmet water demand caused by the development of irrigation areas and population growth. The strategies should focus on mitigating water scarcity by enhancing the supply of the watershed and allocating water fairly. This research concludes that solving the

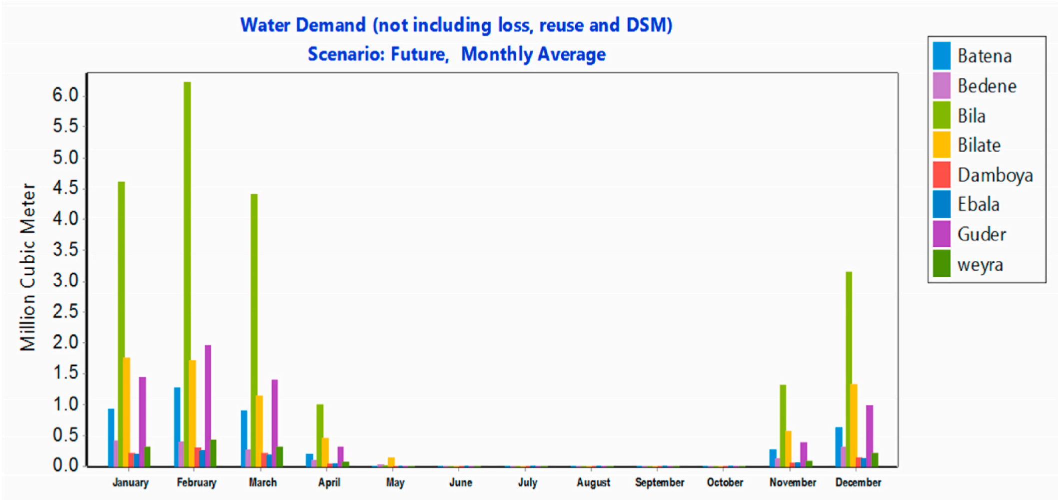

Fig. 15. Mean monthly Irrigation demand for future (2020–2035).

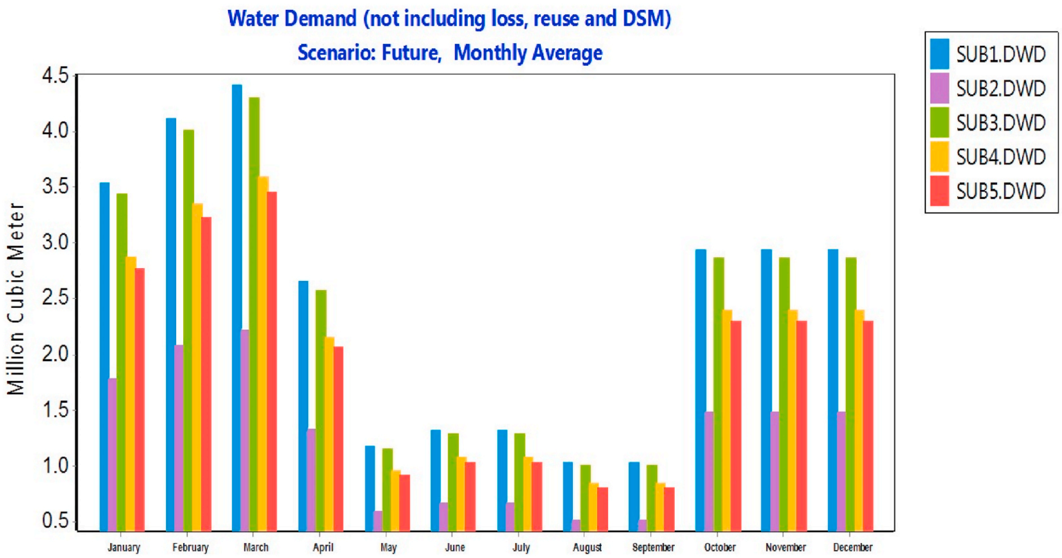

Fig. 16. Mean monthly irrigation and domestic water demand for future (2020–2035).

water shortage in the watershed requires the development of effective strategies to manage available water resources.

4. Conclusions

In this analysis, the HEC-HMS model was utilized to simulate the potential of surface water resources, and the model's efficiency was measured by the Nash Sutcliffe efficiency (NSE) and coefficient of determination (R^2). The NSE and R^2 values for calibration were 0.76 and 0.80, respectively, while for validation, they were 0.72 and 0.76, respectively, at the outlet of the watershed. These values indicated that the model's performance was good, and it could simulate watershed flow. The mean annual flow of the watershed was simulated to be 502 MC M. The monthly simulation of the daily flow from 2010 to 2019 showed that January and February had the lowest potential for surface water resources in the watershed, indicating seasonal variability. The WEAP model was developed to distribute water resources based on developing demand and supply scenarios in order to achieve sustainable growth, which requires allocating limited water resources for varied uses. In the reference scenario, the annual demands for irrigation, domestic, and livestock water were 19.34, 79.4, and 12.39 MC M, respectively, while the net supply of water was 19.25, 79.28, and 11.69 MC M, respectively. The result showed that the watershed could not satisfy demand sites in the dry months, while the remaining months could meet the water demands. The water demand analysis indicated that 99.8% of the supply requirement was met, while only 0.2% was unmet demand in the reference scenario. However, in the future growing scenarios (scenario-1) and (scenario-2), only 69.8% of the supply

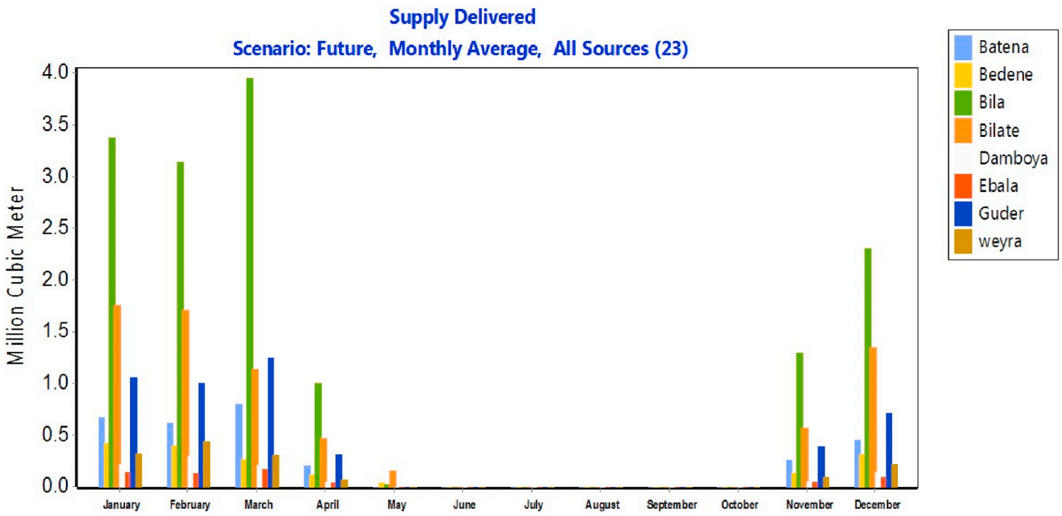

Fig. 17. Mean monthly supply delivered for Irrigation growth (2020–2035).

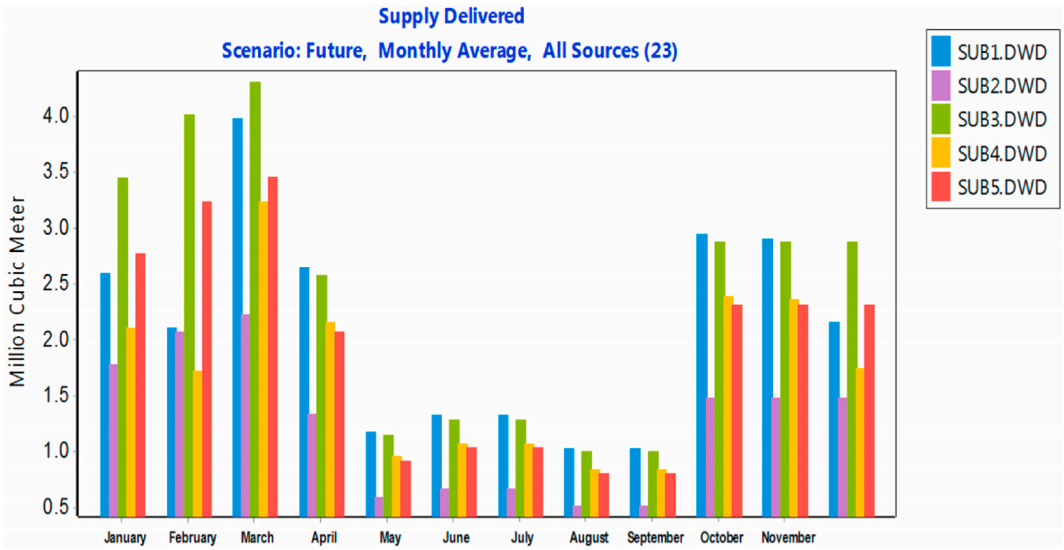

Fig. 18. Mean monthly supply delivered for population growth (2020–2035).

requirement was satisfied, and 30.2% was unmet demand occurred in 2035. The surface water potential of the UBW was unable to satisfy demands in the dry season in both reference and future scenarios, and unmet demand occurred in dry months. When water demand exceeds the available water potential, the allocation fails to fulfill the developing demand. The research's general conclusions have substantial implications for Ethiopia's UBW's water planning and management. There has been an increase in hostility between upstream and downstream water users in the area as a result of the lack of surface water, particularly in the dry months. Furthermore, policymakers and stakeholders can manage water resources sustainably and prevent disputes among water users by recognizing the present and future water demands as well as any potential gaps in achieving those demands. These findings also advance scientific knowledge by providing insightful information on the management of water resources across the watersheds of the world. It is necessary to use Life Cycle Assessment (LCA) to its full potential in order to advance sustainability, water efficiency, and the attainment of development goals. This requires raising awareness and building capacity, integrating LCA into policies and regulations, cooperating and sharing data, working with international experts, and conducting monitoring and evaluation. Adopting LCA studies will improve the general prosperity and well-being of Ethiopians while protecting the environment and water for the coming generations.

Author contribution statement

Mamushet Gebrewold Genjebo: Conceived and designed the experiments; Performed the experiments; Analyzed and interpreted

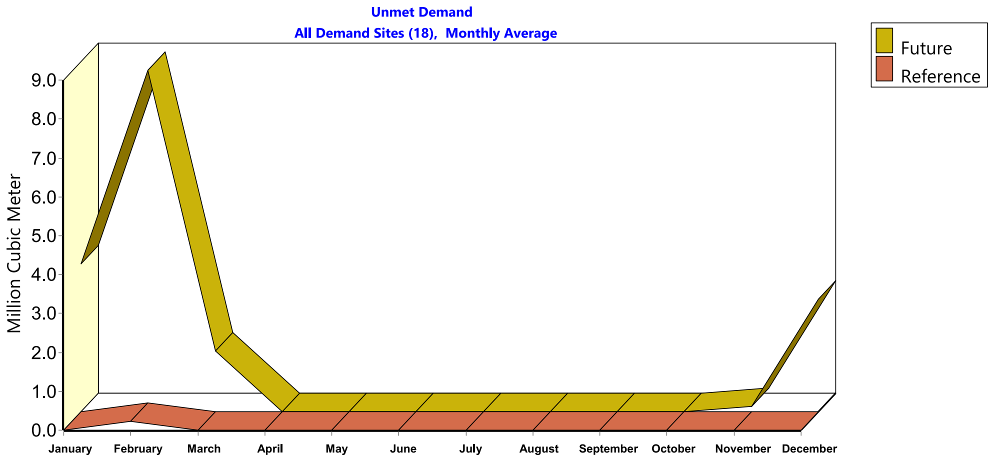

Fig. 19. Mean monthly unmet demands for future scenario.

the data; materials, analysis tools or data; Wrote the paper. Abdella Kemal: Conceived and designed the experiments; Analyzed and interpreted the data; materials, analysis tools or data; Wrote the paper. Abera Shigute Nannawo: Conceived and designed the experiments; Analyzed and interpreted the data; materials, analysis tools or data; Wrote the paper.

Funding

There is no funding from any source to conduct this research.

Data availability statement

The data that has been used is confidential.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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