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Article

The Assessment of Climate Variables and Geographical Distribution on Residential Drinking Water Demand in Ethiopia

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Abstract: Water managers have increasingly shown that demand management solutions are more important than searching for alternative sources to resolve the challenges and shortages of water supply services. This study identifies the impact of climate variables on residential water demand in three geographically and spatially dispersed towns (Arba Minch, Ziway, and Debre Birhan) in Ethiopia. Monthly mean temperature, relative humidity, and precipitation are analyzed using multivariate regression models to identify and evaluate the impacts of the parameters on water consumption. Principal component analysis (PCA) is also used to determine the dominant independent variable affecting the rate of water consumption. Mean temperature is shown to be the dominant variable causing the changes in water consumption in Arba Minch. The water consumption at Debre Birhan is slightly affected by relative humidity. Analyzed climate variables do not affect the water consumption changes at Ziway. The main findings of this paper show that geographical distribution and other determinants are more important determinants of residential water demand. It is concluded that the analyzed climate variables are not the dominant determinants which impact drinking water consumption at the study sites. Thus, it is recommended to include relevant information about the climate variables alongside other determinants in order to enhance the water management system in evaluating and auditing water usage.

Keywords: water demand; climate variables; multivariate regression analysis; principal component analysis

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1. Introduction

Water used as a source for municipal water supply is worldwide likely experiencing stress from diminished water resources and greater demand [1]. Due to the demographic, socio-economic, and hydrological factors, the gap between the availability and demand of water resources is reaching a critical situation, even though the access to safe, affordable, and reliable drinking water is a fundamental human right [2]. Bio Intelligence Service [3] states that the existing changes to the Earth's climate will have far-reaching effects on the future availability of freshwater resources. This is an important challenge, because water availability is one of the major limiting factors of the economic growth for a town [4]. Thus, the implementation of successful water resource management plans necessitates in-depth knowledge of the hydrological parameters and their spatial distribution characteristics. Thus far the research into water management has had a limited scope of study.

Most researchers focus on residential water demand forecasting in order to manage the currently available water sources in use and plan for future needs. They classify water demand into two major categories: base water demand and seasonal water demand [5].

Accordingly, researchers classify household water use as base water consumption and outdoor water consumption as seasonal water consumption. Water used indoors is generally analyzed independent of the effects of climate variables, whereas seasonal use is influenced by weather conditions such as temperature, evaporation, and rainfall [6,7]. However, Gato et al. [7] caution that the conclusion that indoor water use is not impacted by climate variables overlooks certain climates where base water use may still be weather-dependent. According to Schleich and Hillenbrand [8], drinking water consumption factors are classified into categories such as economic, social, and environmental, and climate variables' impacts are grouped under the environmental category.

M Alshaikhli et al. [9] predicted factors affecting water consumption in Qatar by using a multi-regression model. Correlation analysis is also used to avoid multicollinearity between different independent variables. Population density and temperature is used as an independent variable to identify their impact on water consumption of Qatar. The result shows that the climate factor of temperature has a significant influence on the urban water demand.

Shibao Lu et al. [10] uses a daily water consumption per capita of 38 cities in China (2004–2014) dispersed spatially and temporally distributed to identify the major factor which increases the residential water consumption by using multiple regression models. From the nine independent variables that they used (annual average temperature, precipitation, amount of source water available, importance of the city, population density, per capita GDP, domestic water price, per capita housing area, and rate of using water-saving appliances), two of them (water price and the usage rate of water-saving appliances) were recognized as dominant influencing factors. Due to the lower price of the water, some towns do not have any awareness of water saving habits or water management methods. However, those parts of the country whose water prices are higher save water and use water management methods. Because of the humid-hot climate of southern cities, the residential water consumption is increasing tremendously.

Many related studies in Northern and Southern US and European cities show that water consumption is positively related with temperature and evapotranspiration and negatively related to precipitation [11,12]. Balling and Gobar [13] found significant correlation between climate variables and residential water consumption for Phoenix, Arizona between 1980 and 2004. Accordingly, they found that temperature and drought increase residential water consumption, while precipitation reduces it. Hoyos and Artabe [11] found that regions in Spain with lower average temperature and higher precipitation levels have lower water consumption, while regions with higher average temperatures and lower precipitation levels have higher water consumption. It may seem that the geographical distribution of the cities having different climate conditions may lead to different water consumption patterns, but all of the studies discussed above were performed in developed cities having well-organized water infrastructures and water supply management services. Thus, for the case of tropical sub-Saharan countries such as Ethiopia, which has spatially distributed weather conditions with no proper water supply infrastructures and management, the weather influences on water demands needed to be studied too. Some studies have focused on the estimation of price and income elasticities of water demand [14,15], while others have estimated the short-term and long-term demand management by suggesting that water demand is changing because of economic and weather conditions [16–18]. However, the study of the effects of climate variables on residential water consumption remains limited. The lack of literature regarding the influence of climate variables on residential water demand in developing countries such as Ethiopia is one challenge for such a study. Therefore, this paper fills the knowledge gap on water management issues in developing areas, both in terms of policy implication and sustainable water supply services at water-scarce cities.

The objectives of this study are (i) to evaluate the impact of hydrological factors on domestic water demand by using multiple regression models; (ii) to identify whether spatial variability and interannual climate difference within the country have a relation to residential water consumption; and (iii) to identify the dominant variable/s which cause/s water consumption changes.

Overview of Ethiopia

Ethiopia is characterized by high and ragged mountains, flat-topped plateaus, deep gorges, river valleys, and plains. There are 12 major river basins, with a capacity of annual surface water and ground water resources potential of about 122 billion m^3 and 36 billion m^3, respectively [19]. In spite of this immense resource potential, a considerable proportion of the country faces uneven water distribution and discrepancy of accessibility in terms of time and space [20]. Ethiopia has made enormous progress in extending access to safe water the last two decades (1990–2020), but sustaining systems and services remains a huge challenge. Non-governmental organizations (NGO) are also active in serving the remote areas of Ethiopia by providing clean water supplies. NGOs and other external agencies support about 56% of the required funds for water supply, while the government provides only 44% [21,22]. Still, almost half of the Ethiopian population has no access to clean water supplies nearby. In addition, weather predictions made by WHO/DFID [23] indicate (Vision 2030) that average temperature and rainfall are likely to increase in East African countries (including the Ethiopian highlands), and, consequently, there might be increased frequency of extreme weather events which would pose negative impacts on residential water supplies. As a result, uneven temporal and spatial distributions of water resources and climate variability within Ethiopia is causing a stress on a residential water supply service. Ethiopia is currently facing a problem of unreliable and insufficient water demand across the country because of socioeconomic, demographic, and hydrological changes. Residents of urban and rural towns of Ethiopia are receiving 15–20 L of water per capita and day on average [24]. The dearth of access to clean water in the face of tremendous potential resources adds a level of urgency to the Ethiopian case.

2. Study Area

This study was conducted in three urban towns of Ethiopia, each located at different altitudes: Arba Minch, Ziway (1600 m), and Debre Birhan (2800 m). Traditionally there are three climate classifications in Ethiopia. The "Kola", which is characterized by a semi-desert climate, is below 1500 m above sea level. The next class is called a "Weina Dega", ranging from 1500 to 2400 m above sea level and similar to a tropical climate. The highest class is the "Dega", which includes areas higher than 2400 m and commonly features a temperate climate. Each of the case study sites is at different elevation point and characterized under the different climatic zones stated above. Arba Minch (1300 m) is classified as a Kola; Ziway (1600 m) is in a Weina Dega area; and Debra Birhan (2800) is a Dega site, one of the few towns of its size at such an elevation.

Arba Minch is a city found 500 km south from the capital city Addis Abeba, located at geographical coordinates of 6°2′0″ N 37°33′0″ E. Even though the city is categorized as one of the hotter climate areas, it is surrounded by two big natural lakes (Abaya and Chamo) and considered as one of the areas with a good groundwater potential zone in the country. The total area of the city was estimated at 1095 hectares, with a total population of 200,373. The town is located at an altitude of 1300 m above sea level with an average annual temperature of 29 °C and average annual rainfall of 900 mm.

Ziway is located 163 km southeast of Addis Abeba. The town has a latitude and longitude of 7°56′ N 38°43′ E with an elevation of 1643 m above sea level. Ziway's annual rainfall is 700–800 mm, and the mean annual temperature is 20 °C. The town has a total population of 72,350. Ziway Lake (Hora-Dambal) has a major role in the economic activity of the town and surrounding county, as it supplies water for the traditional irrigation system of the community as well as the huge rose farms surrounding the lake.

Debre Birhan is one of the coldest towns in Ethiopia, located 120 km northeast of Addis Abeba. The town has a latitude and longitude 9°41′ N 39°31′ E, with an elevation of 2840 m above sea level and a mean annual temperature of 15 °C. Having a mean annual rainfall of 1219.2 mm makes the groundwater potential of the area a potential water supply source for all residents of the town. The town is home to about 180,000 residents. Details of the study area's locations are presented in Figure 1.

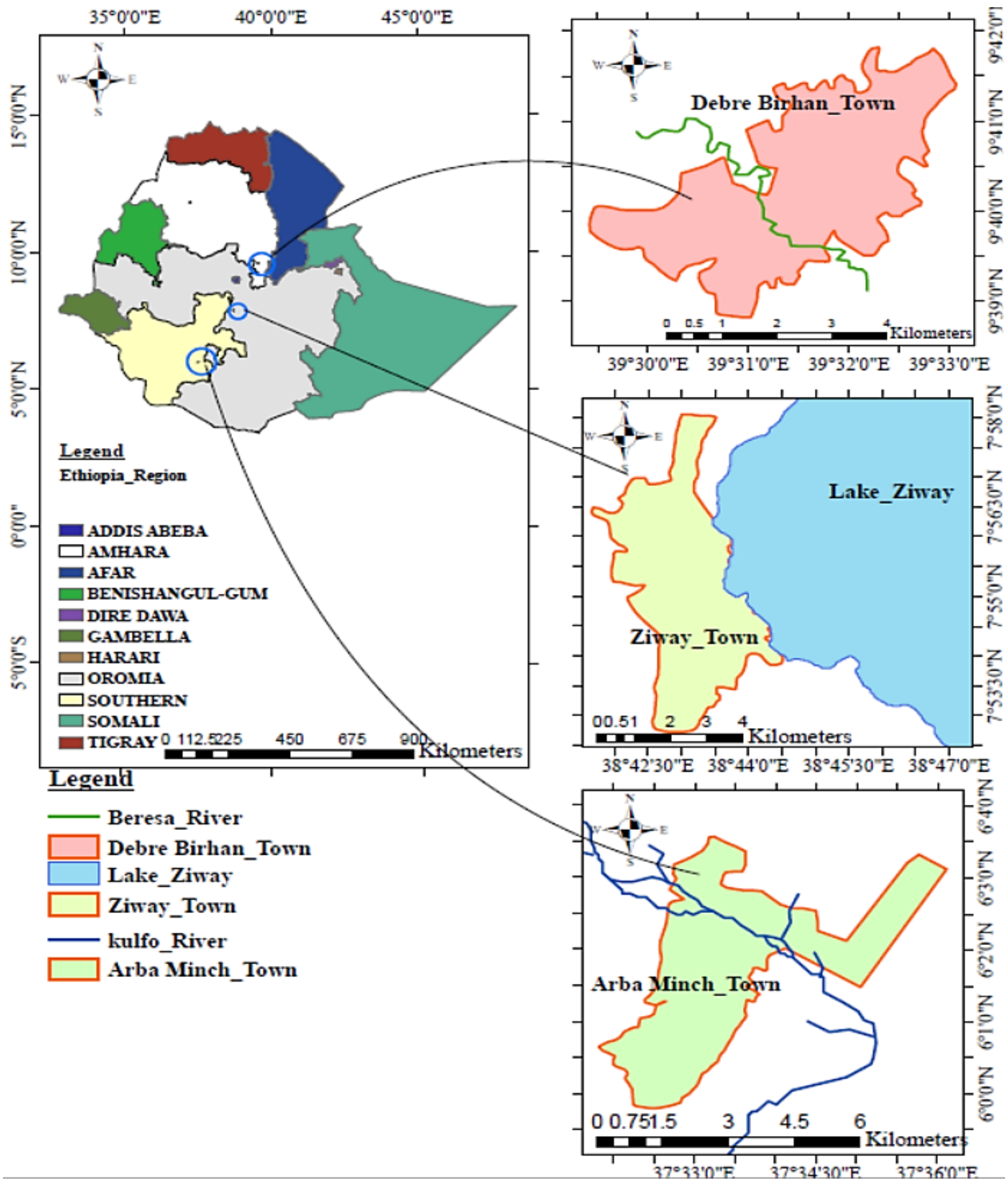

Figure 1. Study area locations in Ethiopian map.

3. Data and Methodology

3.1. Climate Data

Climate data for all the study sites were collected from the National Meteorological Agency Office of Ethiopia. Daily and monthly data of meteorological variables of the past 30 years, from 1990 to 2020, were used in order to see the trend analysis of the selected climate variables data of the past years. Nine years of climate data (2012–2020) were used to assess the impacts of the variables on water demand. Three climate variables were selected to assess the relationship with drinking water consumption within the three case studies: rainfall, mean temperature, and relative humidity. These parameters are among the most known factors which illuminate the possible relationship between environmental resource degradation. Table 1 summarizes all the climate data for the study areas. Most of the research papers produced in this area use similar variables such as temperature and rainfall [25]. In a similar model, Sarah Praskievicz and Heejun Chang [26] used relative humidity, sunshine hour, cloud cover, maximum and minimum temperature, precipitation, and wind speed to correlate their significance with residential water consumption. Renwick and Green [27] used maximum temperature and monthly cumulative rainfall in their research model to estimate the water demand management policies in California. With slight alterations, a focus on rain, temperature, and humidity has generally been shown to be a key element to assessing water demand. The terminology "water demand" and "water consumption" were used interchangeably in this study with the same meaning.

Table 1. Average monthly climate data of year 2012–2020.

Months	Arba Minch			Debre Birhan			Ziway		
	Max Temp. (°C)	Precipitation (mm)	R. Humidity	Max Temp. (°C)	Precipitation (mm)	R. Humidity	Max Temp. (°C)	Precipitation (mm)	R. Humidity
January	31.34	12.66	0.66	16.75	3.07	0.54	20.41	3.54	0.40
February	33.23	22.01	0.63	18.51	13.57	0.54	21.76	26.43	0.35
March	32.89	66.00	0.70	19.95	44.09	0.57	22.96	38.63	0.37
April	30.14	176.34	0.85	19.81	52.10	0.65	23.29	59.13	0.49
May	28.70	156.05	0.91	19.49	47.36	0.69	23.15	88.29	0.51
June	27.79	86.11	0.89	19.79	55.30	0.67	22.57	85.86	0.58
July	27.62	31.34	0.88	18.68	318.65	0.79	20.78	220.60	0.67
August	28.17	42.40	0.89	17.63	279.18	0.86	20.75	111.51	0.67
September	29.00	109.61	0.88	17.15	97.72	0.83	21.03	90.39	0.63
October	29.95	132.64	0.88	16.81	28.10	0.66	21.05	22.36	0.50
November	29.54	113.07	0.82	16.75	13.46	0.59	20.48	4.50	0.47
December	30.67	35.98	0.72	15.97	1.17	0.54	19.34	1.61	0.41

The climatic data (rainfall, average temperature, and relative humidity) of the meteorological stations in each of the cities (Arba Minch, Ziway, and Debre Birhan) had a total of 6% missing data as estimated by using grid data from the Climate Data Tool (CDT). The quality of the data was checked to identify any outliers and eliminate data contamination. The outliers were detected for each station for each month by using a standardization of the mean square method. The reason for standardizing the infit and outfit mean square statistics is to allow their statistical significance (or p-values). A familiar method to use for this purpose is the Z-score or the standard scores [28]. Homogeneity testing was performed using XLSTAT software in which the standard normal homogeneity test (SNHT) of rainfall, mean temperature, and relative humidity for each required meteorological station were plotted against time in order to detect the change in series of the variables.

3.2. Water Consumption Data

Nine years (2012–2020) of monthly water consumption data are collected from the water supply and sewerage offices of the three study sites. The data collected are comprised of the monthly consumed or billed water used by customers, as it is impossible to obtain daily data for water consumption in Ethiopia. The data collected are limited to indoor residential water used and do not include the outdoor water consumption such as that used for gardening, swimming pools, or backyard fountains.

3.3. Methods

3.3.1. Multiple Linear Regression Model

A multiple linear regression is an extension of a simple linear regression, and it is a statistical tool that evaluates the relationship between a dependent variable and one or more independent variables. Two or more independent variables are used to predict or explain the variance in one dependent variable. It examines whether there is a statistical relationship between the independent variables and, if there is a relationship, how good it is. A general multiple regression model equation is given as [29]:

$$\hat{y} = b_0 + b_1\, x_1 + b_2\, x_2 + b_3\, x_3 + \cdots + b_n\, X_n \quad (1)$$

where $\hat{y}$ is the predicted value of the dependent variable, and x is the independent variable of the nth observation. The independent x value input or predictor will fluctuate with y value output or response in its unique way. The regression coefficients (bn) of independent variables are respective changes in y per unit change of x_n. The regression constant (b_0) is the y intercept when all predictors or x values are zero. The following regression model was developed to analyze the factors which influence water demand in the study sites while taking into consideration the three climate parameters (temperature, precipitation, humidity). Where $\hat{y}$ is water demand of the town depending on the variables (m^3/year), x_1 is an average monthly temperature of the town (°C); x_2 describes an average monthly precipitation (mm); x_3 is an average monthly relative humidity of the town; b_0 is the regression constant; and b_1 to b_3 are regression coefficients for x_1 to x_3, respectively. The regression analysis was conducted for the period of 2012–2020, which coincided with the water consumption data availability of the case study towns.

We reported significant findings by formatting the results as F (Regression df, Residual df) = F-Ratio, *p* = Sig. In this case, the 95% confidence interval for the coefficients shown by many regression packages gives the same information. We have 95% confidence that the real, underlying value of the coefficient that we are estimating falls somewhere in that 95% confidence interval. So, if the interval does not contain 0, the *p*-value will be 0.05 or less. The regression analysis of the model was determined with the SPSS statistical package. Origin 2018 version was used to draw a better resolution graph. SPSS statistical package version 26 was used for the principal component analysis (PCA).

3.3.2. Predictor Variable

Principal Component Analysis

Principal component analysis (PCA) is one of the variable selection methods most frequently used in multivariate analysis. PCA is a technique used to examine the interrelations among a set of variables in order to identify the underlying structure of those variables. PCA assumes the dataset to be linear combinations of the variables, and regression determines a line of best fit to a dataset, while factor analysis determines several orthogonal lines of best fit to the dataset. Locations along each component (or eigenvector) are then associated with values across all variables. This association between the components and the original variables is called the component's eigenvalue. PCA reduces the dimension of the multivariate data via replacement of a number of variables by a smaller number of derived variables. Thus, it is a dimension reduction technique by combining features. The number of principal components to be used is always less than the number of features or predictors. Those components having an eigenvalue above 1 will be selected, and their percentage of the variance in the matrix will be identified [30].

$$\mathrm{PC1} = b_{11}X_1 + b_{12}X_2 + \cdots + b_{1k}X_k = \sum_{j=1}^{k} b_{1j}X_j \quad (2)$$

$$\mathrm{PC1} = b_{21}X_1 + b_{22}X_2 + \cdots + b_{2k}X_k = \sum_{j=1}^{k} b_{2j}X_j \quad (3)$$

where X_1, X_2 ... X_k represents the original variables in the data matrix, and b_{ij} represents the eigenvectors. The component loading values which are greater than 0.75 (>0.75) are considered as "strong"; the values ranging from 0.50 to 0.75 (0.50 ≥ component loading ≥ 0.75) are considered "moderate"; and the values ranging from 0.30 to 0.49 (0.30 ≥ component loading ≥ 0.49) are considered "weak" component loadings [31,32].

A recent research study (Mohammed Gedefaw et al. [33]) focusing on optimal predictor variable selection used a multiple regression model for the water demand forecasting performed on Gonder Town, Ethiopia. The study summarizes that PCA (principal component analysis) is a more appropriate method for predicting water demand of urban towns and, thus, can be used for other towns in Ethiopia. Therefore, following the recommendation of Mohammed Gedefaw et al., we also adopt the PCA method in our study as a variable predictor model to identify the variable.

4. Results and Discussion

4.1. Water Demand/Consumption

Drinking water scarcity is one of the pressing issues in developing countries such as Ethiopia. Researchers state that climate variability and uneven spatial and temporal distributions of hydrological parameters have an impact on drinking water demand [34,35]. Since drinking water source availability is one of the major limiting factors of economic growth [4], focusing on the demand management programs is one of the best solutions to reduce upcoming problems. The three selected case study areas are representative locations of the varying climate characteristics across all Ethiopian towns. Consequently, the residents of the three study areas have similar living standards.

According to the Ethiopian federal guidelines, in order to estimate a town's actual water the base water demand is multiplied by the mean annual precipitation and altitude difference of the town. For example, if the mean annual precipitation of the town is less than 600 mm, multiplied by 1.1; if between 601–900 mm, by 1.0; and multiplied by 0.9 if the precipitation is above 901 mm [36]. However, using the same climatic factor for two different towns located at the same altitude or having equivalent annual mean precipitation amount does not seem right, as they might have different climatic situations and socio-economic conditions. Water demand forecasting should be performed using a suitable mathematical formula that incorporates compatible water demand models with different climatic variables and has an affiliation with water consumption [37]. An Ethiopian Ministry of Water Resources report states that population size, economic, social, and climatic factors as well as the town's mode of service should be considered while evaluating urban water demand [36].

Multiple regression models were used to assess and calculate the residential water demand by calculating average temperature, precipitation, and relative humidity of nine consecutive years in relation to dependent monthly billed water consumption data. Results of this study are expected to provide important information which will help in developing an effective water demand management system in urban Ethiopian towns. Additionally, this research study will produce guidelines to more accurately calculate water demand by incorporating the impacts of climate variables on residential water demand. The results of the impacts of the selected climate variables on the water demand in each study area town will be discussed. The results of demand analysis and impact prediction output for each study area will be illustrated in detail.

4.2. Seasonal Water Consumption

The evolution of water consumption for Arba Minch shows an increasing trend throughout the study period (2012–2020). To verify the seasonal impact, the seasonal component of the residential water consumption was investigated. The plot shows the total water consumption in m^3 (y-axis) with corresponding years (x-axis). The analysis resulted in several important observations. The highest consumption occurs during the Belg season (Feb–May), which is the short rainy season of the country, with an average value of 34.5% of total annual consumption. The lowest water consumption (32.2% of the total) occurs during the Kiremt (October–January), while water demand in the Bega season (June–September) represents 33.3% of the total annual consumption. The residential water consumption shows an increasing trend throughout the study period, as shown in

Figure 2. The maximum water consumption, seasonal based component occurs in March and a minimum in August.

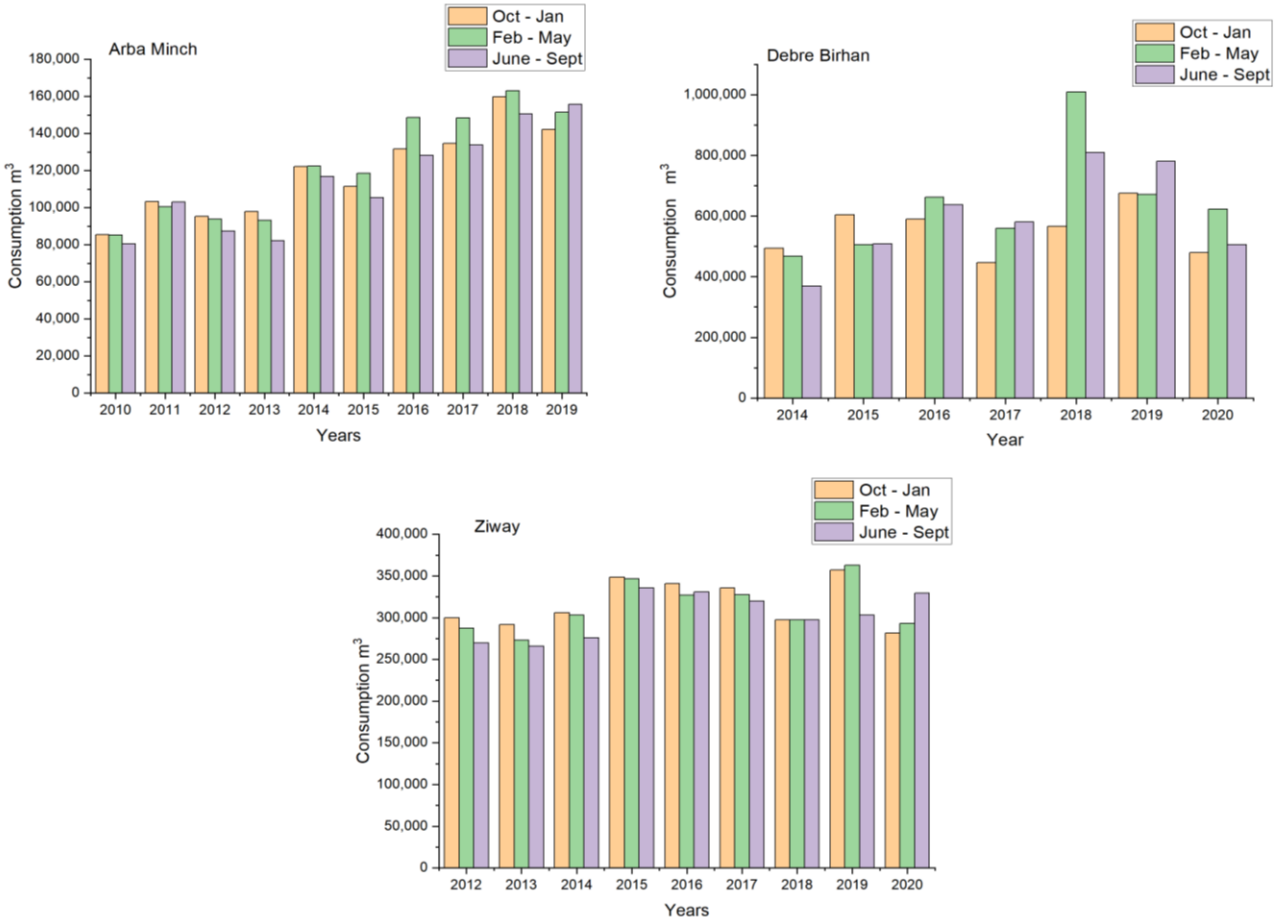

Figure 2. Seasonal water consumption distribution.

Seasonal average water consumption of Debre Birhan showed a rising trend in average water consumption ranging between 0.4 Mm^3 and 0.7 Mm^3 during the study period. The highest levels of water consumption came in the year 2018 during the Belg season. This change can be attributed to water demands from newly emerged brewery industries and factories relying on municipal water supply sources (information confirmed from the town water supply office) and temperature increases during the same period. Interannual monthly water consumption of the town showed that less water consumption occurred during the months of October to January, which is the peak rainy season. Overall, the highest consumption occurred during the Belg season (February–May), with an average value of 35.8% of total annual consumption. The lowest water consumption (30.7% of the total) occurred during the Kiremt season (October–January), while water demand in the Bega season (June–September) represented 33.4% of the annual consumption.

Ziway town is a moderate climate area that can be classified by its temperate climate conditions. The seasonal water consumption throughout the study period for the town was almost flat, as shown in Figure 2. The highest water consumption occurred during the Kiremt season (October–January), with an average value of 34.0% of total annual consumption. The lowest water consumption (32.5% of the total) occurred during the Bega (June–September), while water consumption in the Belg season (February–May) represented 33.5% of the annual consumption.

According to the analysis, the percentage of seasonal water consumption in Arba Minch and Debre Birhan are correlative, and the highest and lowest seasonal water consumption occurs during the months with maximum temperature and minimum precipitation, respectively. This result looks similar to other studies which found a significant relationship between annual total water consumption, temperature, and precipitation. Bailing and Gober [13] found a negative relation with precipitation and positive relation with temperature. Furthermore, it is obvious that people consume more water during hot weather and less water during high precipitation weather. This finding is similar to the results of Kumudu Rathnayaka et al. [38], who found that weather is shown to be a significant determinant of shower water use. We may infer that weather differences are one of the determinants that cause high water demand in Arba Minch: the frequency of taking showers in hotter climates such as that of Arba Minch is not the same as areas with cold weather such as Debre Birhan.

4.3. Per Capita Water Consumption

According to a 2019 WHO/UNICEF JMP report, only 41% of the Ethiopian population has access to safely managed drinking water. For urban populations, 51% of the total supply is accessed by city pipes and water infrastructure. However, unaddressed socioeconomic, demographic, and hydrological changes have created unreliable and insufficient water demand across the country. The water supply service level varies from place to place depending on economic status and other factors. While developed countries use up to 500 L per capita per day of water, in less developed countries such as Ethiopia this figure is out of reach, and they are challenged to achieve even 15 L per capita per day [39]. As such, Ethiopia has set a target towards achieving middle income status by 2025 with 40 to 100 L per capita per day (LCD) in urban areas and 25 LCD at maximum distance of 1 km access of supply point in rural areas [36]. The monthly average distribution of per capita water consumption for the three case studies was shown in Figure 3. This consumption rate shows only the households which have access to the town's water supply services. Accordingly, Arba Minch consumed an average of around 70 L per day, Ziway 50 L, and Debre Birhan uses 40 L on average.

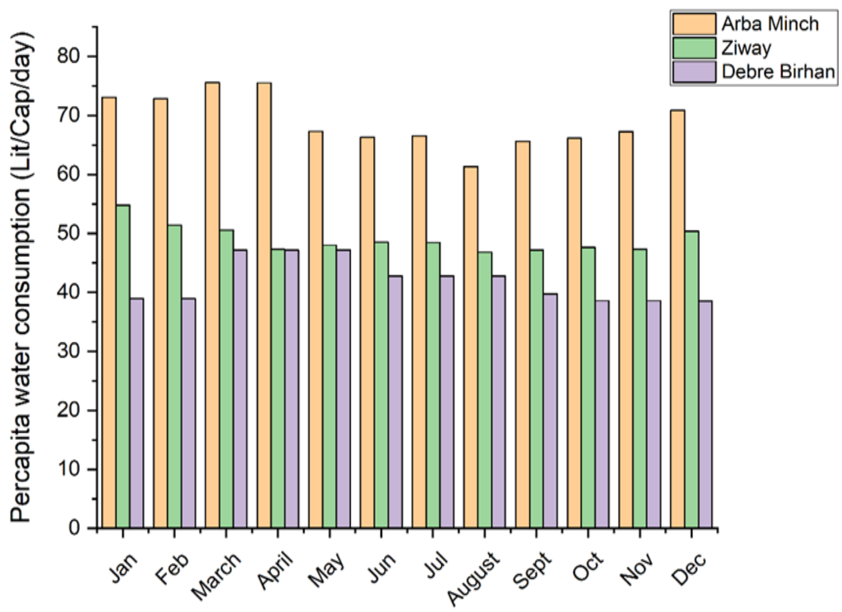

Figure 3. Average per capita water consumption distribution of 2012 to 2020 study period.

4.4. Annual Mean Temperature

Debre Birhan is the coldest place in Ethiopia, with an average mean temperature of 18 °C throughout the study period (2012–2020). According to Figure 4, the water consumption trend is compatible with the mean annual temperature (with the exception of an abrupt change in 2017 which might be due to a data recording mistake). The graph shows that when the temperature increases, the water consumption also increases. Average monthly water consumption of Debre Birhan during the months of February to May increased with a rise in mean temperature during the same months. The implication of this finding confirms that outside temperature plays a very strong role in increasing or reducing seasonal water demand [40]. Figure 4 shows that the minimum monthly mean temperature value for Arba Minch (around 20.75 °C) area is greater than the highest mean monthly temperature for Debre Birhan. Arba Minch and Debre Birhan have a trend of increasing mean annual temperature, while Ziway does not follow this upward trend. This may be due to the study area's location at mid-latitude, where there are more variabilities of temperature across years and within the same year. However, the total water consumption variation is compatible with the mean annual temperature fluctuations.

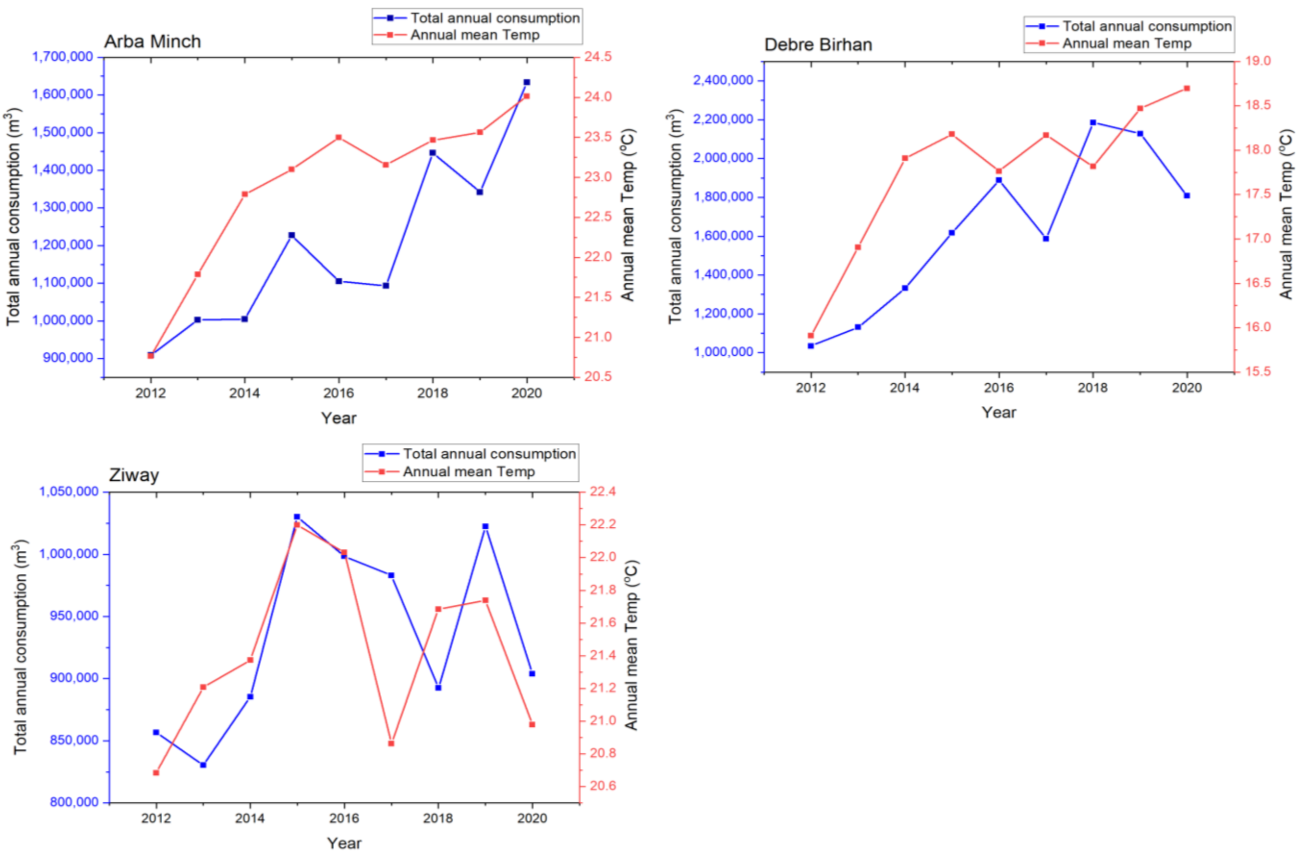

Figure 4. Total annual water consumption vs. annual mean temperature of the study area.

4.5. *Average Relative Humidity*

Relative humidity plotted with annual average consumption (Figure 5) shows a trend of compatibility for all three study. The Arba Minch plot shows a compatible relationship between average relative humidity and water consumption, while in Debre Birhan and Ziway it varies and fluctuates from year to year. This also proves that average relative humidity and average annual water consumption have perfect compatibility with each other such that when relative humidity increases, water consumption also increases. The relative humidity plot of Ziway was increasing starting from 2015 until the peak in 2016. This may be because the drought season occurred around this area at the end 2015 until 2016. Arba Minch and Debre Birhan plots of the water consumption and relative humidity have a good compatibility trend. Generally, relative humidity has a significant relationship with air temperature and rainfall. Therefore, relative humidity plays a crucial role in spatial patterns of urban water consumption.

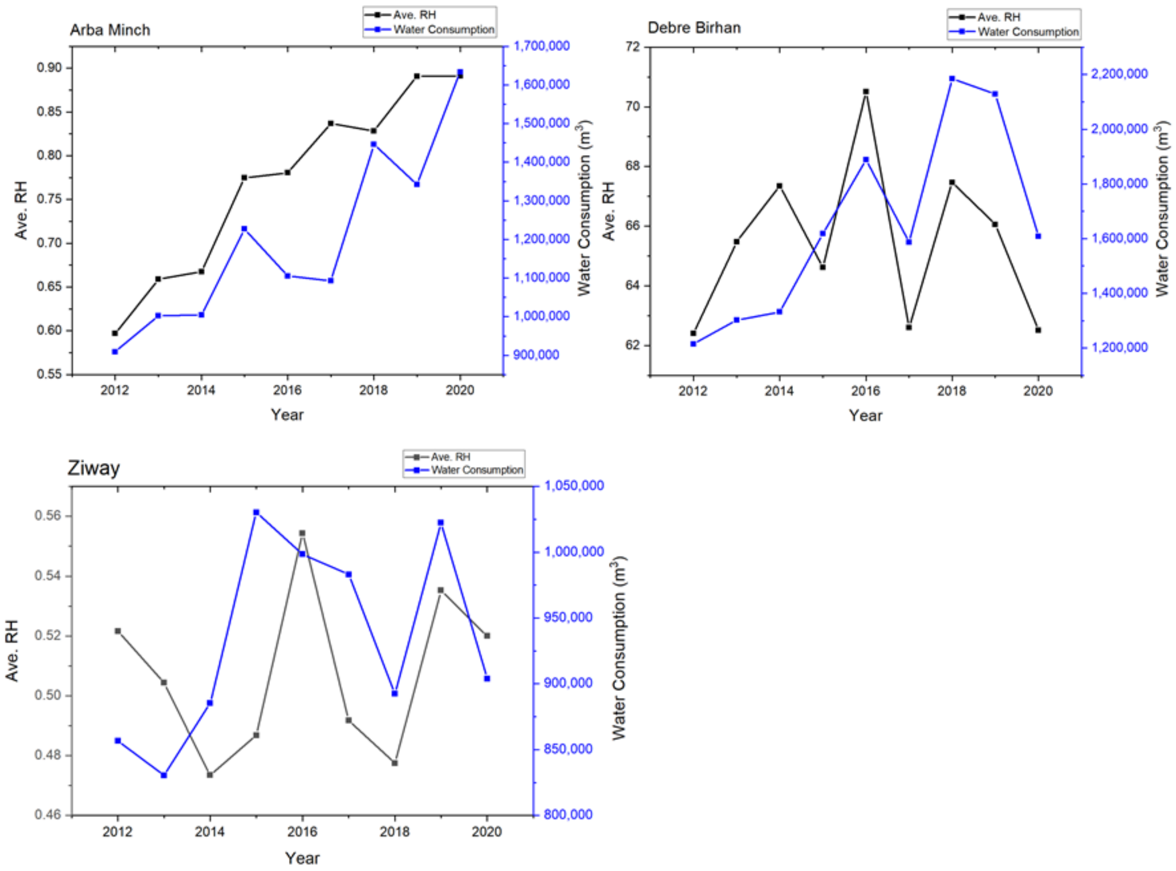

Figure 5. Average relative humidity vs. water consumption for the study areas.

4.6. Average Annual Precipitation

Rainfall plots throughout the study period (2012–2020) show huge fluctuation in all case study areas. The absence of rainfall around the year 2015 is indicative of a major drought which impacted large areas of the Horn of Africa. The 2015 drought was the worst to occur in decades, affecting around 10 million people living across 30% of the country [41]. It confirms that the drop in rainfall for Ziway area in 2015 is the cause of the drought. Other urban towns also confirm that there was less rainfall recorded around the years 2015 and 2016. It is clear from Figure 6 that Debre Birhan has more rainfall compared to the other study areas. Arba Minch's rainfall amount ranged between 700 and 900 mm, with less fluctuation throughout the study period, while for Ziway and Debre Birhan the amount of fluctuation in precipitation was relatively large year to year. As identified in Figure 6, the general compatibility of water consumption with annual precipitation for all study areas was fairly low. Thus, they also have a negative correlation with each other. This means that when precipitation increases, annual water consumption decreases and vice versa.

Ziway and Debre Birhan have similar trends in precipitation, with a single modal where the highest peak rainfall occurs in the months from July to October for both study areas (Figure 7). Annual rainfall of Debre Birhan ranges from 814 to 1080 mm with about 70% rain falling between June and September [42], while Arba Minch has a different precipitation trend with bimodal rainfall type. Arba Minch receives the highest peak rainfall at two times during the year, April and October, though other areas receive less rainfall during these months. Even though there is plenty of rainfall in the months of March and April, the water consumption was high due to the temperature and humid air.

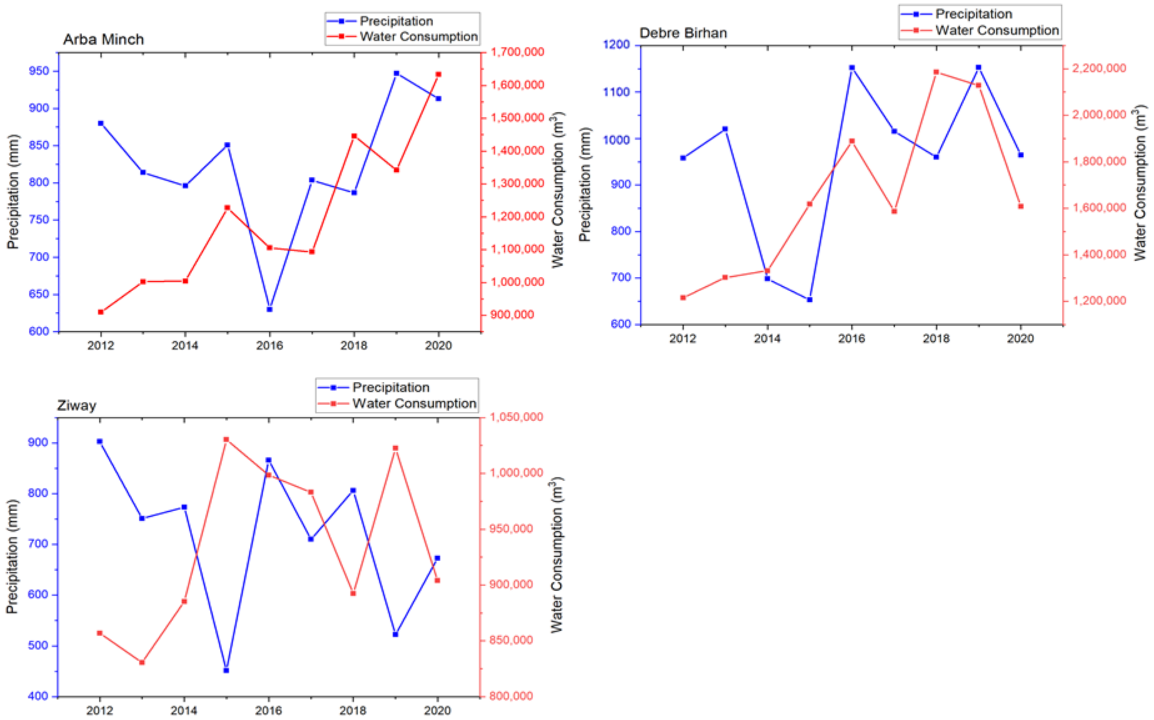

Figure 6. Annual average precipitation vs. average water consumption.

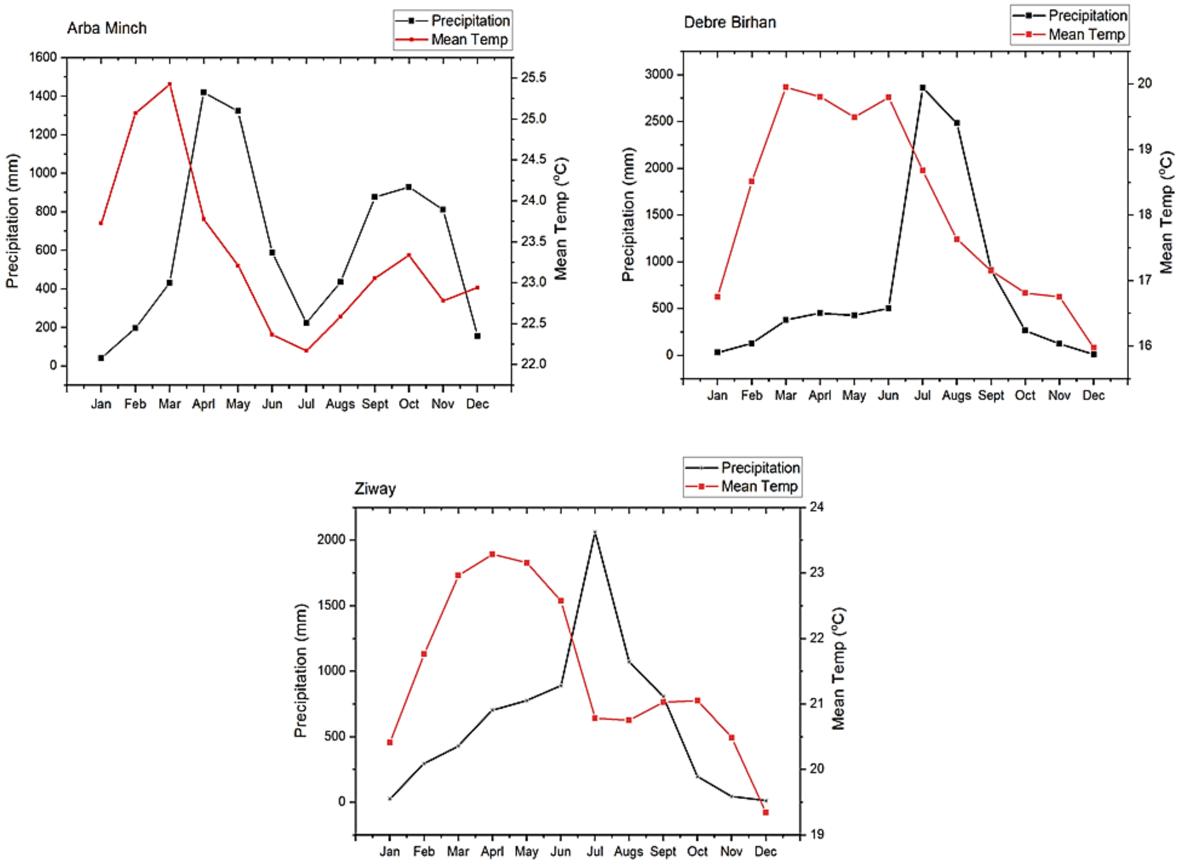

Figure 7. Total precipitation vs. mean temperature of the study areas (2012–2020).

4.7. Correlation between Climate Variables and Monthly Water Consumption

The correlation between the total water consumption in Arba Minch and recorded mean temperature shows weak correlation. Relative humidity and precipitation do not have any correlation with average monthly water consumption. The percent variation in the consumption rates for each 1 °C increase in average temperature is computed based on the trend line in Figure 8. Accordingly, the slope shows that a mean temperature increase of 1 °C causes an average increase in the rate of water consumption by 5.28%. The trendline slope shows that a 1% increase in humidity caused a 0.16% decrease in water consumption, and a 1 mm increase of precipitation caused a 0.02% decrease of water consumption. The R-square value for relative humidity and precipitation parameters shows that the predictor explains less than 1% of the variability in the dependent variable, whereas 13% of the variance in water consumption is explained by the variability of mean temperature. Therefore, mean temperature has a relatively positive correlation with water consumption when compared with the other analyzed parameters.

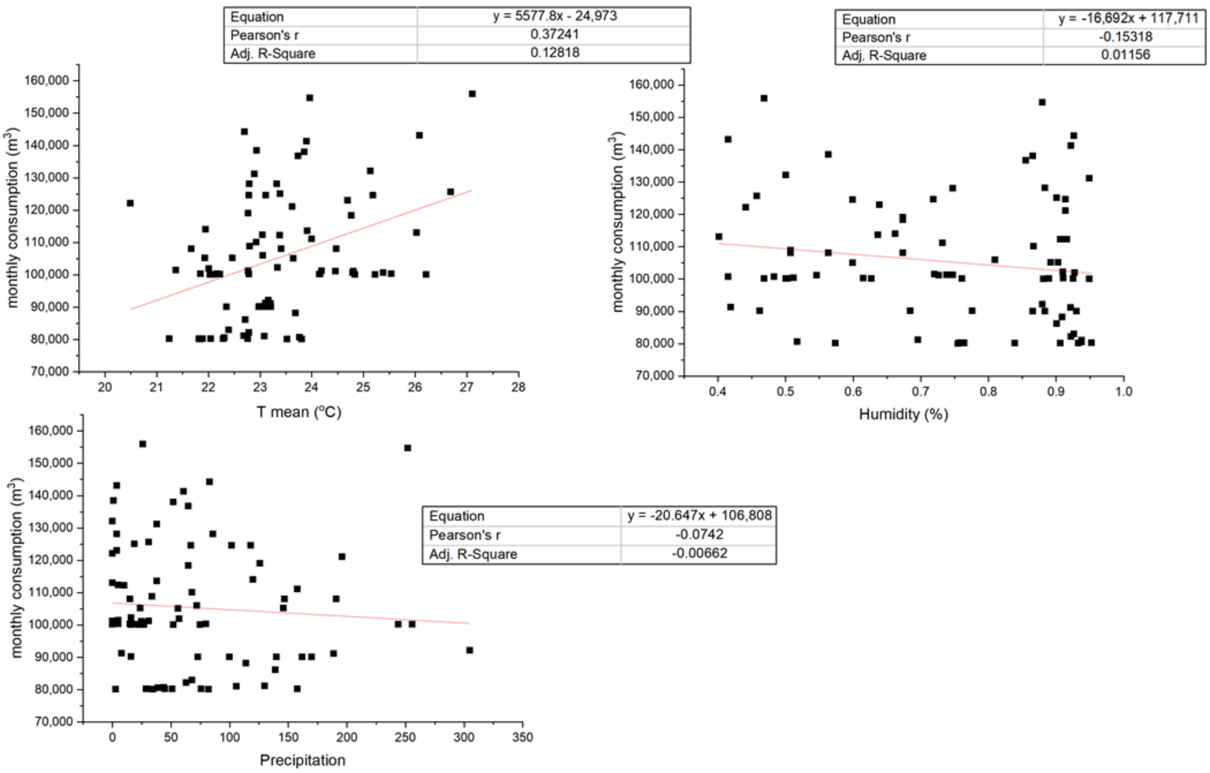

Figure 8. Monthly water consumption trendline of the climate variables of Arba Minch (2012–2020).

According to the scatter plot shown for Ziway (Figure 9), mean temperature, precipitation, and relative humidity are not correlated with monthly average water consumption. The Pearson's correlation coefficient value "r" is almost zero for all of the variables, which means that they do not have any relationship with each other. The R-square value, which indicates the proportion of the variation in the dependent variable, shows that precipitation and mean temperature explain less than 1% of the variability in water consumption. Alternatively, relative humidity variation affects monthly water consumption pattern variability by 3%. Reduced into single increments, each 1 °C increase in mean temperature causes an average increase of water consumption by 0.175%; each 1% increase in relative humidity causes a decrease of water consumption by 0.18%; and each 1 mm increase of precipitation decreases the monthly water consumption by 0.04%.

Debre Birhan's monthly water consumption and the three independent variable scatter plots show that relative humidity has a weak negative correlation, while precipitation and mean temperature have no correlation (Figure 10). A mean temperature increase of 1 °C causes an average increase of 0.29% in the rate of water consumption, and a 1% increase in relative humidity causes a 0.3% decrease in water consumption. The effect of precipitation was not statistically significant and smaller in magnitude; a 1 mm rise in precipitation results in a 0.014% drop in water consumption. The R-square value of the predictors are close to zero. As such, 10% of the variance in water consumption can be explained by relative humidity, while less than 1% of variance was explained by the precipitation and mean temperature variables.

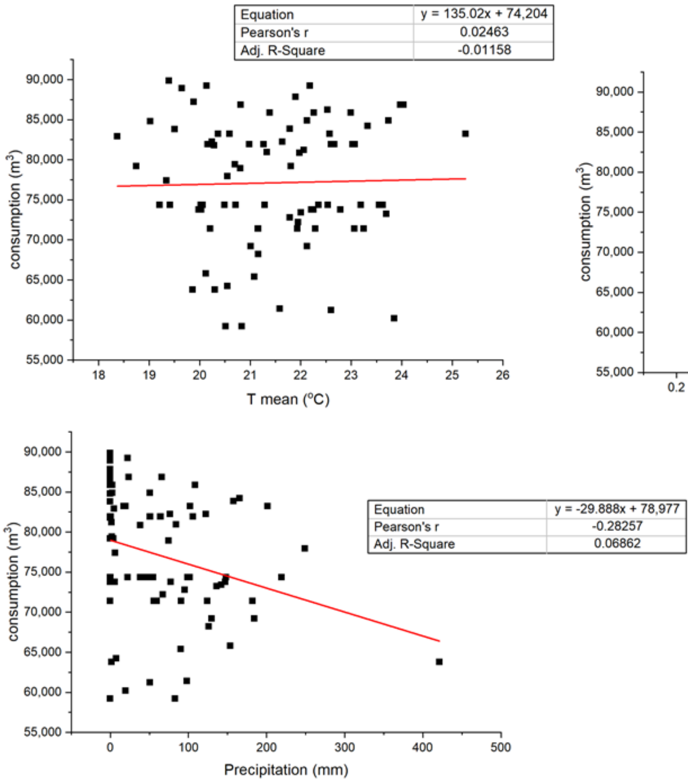

Figure 9. Monthly water consumption trendline for the climate variable of Ziway (2012–2020).

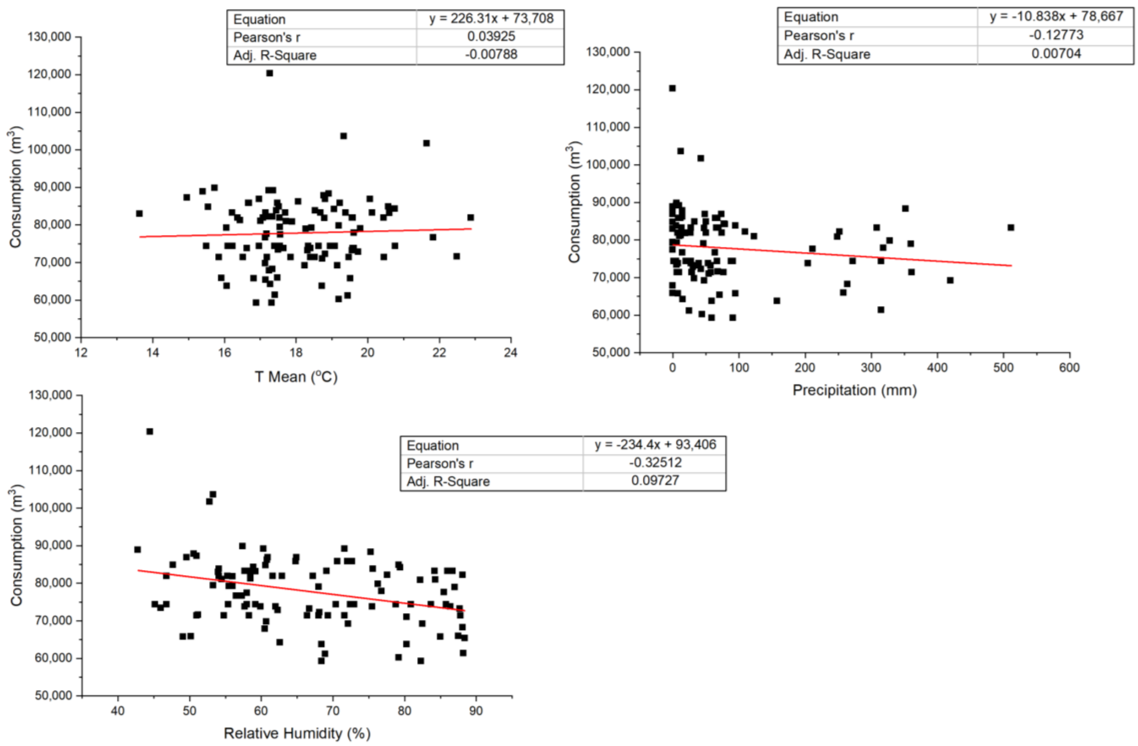

Figure 10. Monthly water consumption trendline for the climate variable of Debre Birhan (2012–2020).

4.8. Multiple Linear Regressions and Principal Component Analysis

4.8.1. Arba Minch

This study was conducted to determine whether climate variables reliably predict residential water demand. It was hypothesized that average mean temperature, precipitation, and relative humidity would impact the water demand. Results show that 14% of the variance in water demand can be accounted for by the three predictors. The sum result of the variables showed that F (3, 80) = 4.39 and $p = 0.007$—looking at the unique individual contributions of the predictors: the mean temperature (t = 3.31, $p = 0.01$), relative humidity (t = 0.38, $p = 0.7$), and precipitation (t = −0.091, $p = 0.93$). Therefore, the p-value for mean temperature is $p = 0.01$, which is less than 0.05, such that mean temperature is a predictor variable. In the multiple linear regression test analyzed for the test results, the p-values show that there is a significant relationship between the dependent and independent variables. This confirms that, although precipitation and relative humidity do not have a significant relationship with residential water demand, mean temperature does.

The general result of the regression equation is written as below:

$$\text{Water demand } (\text{m}^3/\text{month}) = -37{,}052 + 5935 \times \text{Mean Temp} + -2.8 \times \text{Precipitation} + 5307 \times \text{Humidity} \quad (4)$$

The results of the PCA on the three independent variables was able to identify the impact of the predictor variables on residential water consumption. According to the PCA output, only one factor has an eigenvalue above 1. Though only one PC explained 58.3% of the variability, the relative humidity and mean temperature variables (0.856 and −0.756) are incorporated component loadings in the PC and also have high loadings. The residential water consumption changes were caused mainly by the changes of the highest component loading value, which is relative humidity and mean temperature.

4.8.2. Debre Birhan

The result from the regression shows that 12% of the variance in water demand can be accounted by the three predictors, collectively: F (3, 104) = 4.86, $p = 0.03$. Looking at the unique individual contributions of the predictors, the mean temperature (t = 0.06, $p = 0.95$) and precipitation (t = 1.4, $p = 0.16$) had a value of $p > 0.05$ for both predictors. The contribution of one predictor, relative humidity (t = −3.51, $p = 0.001$), was proved to positively predict residential water demand. The p-values in the multiple linear regression test showed that there is a significant relationship between the dependent and independent variables. This suggests that precipitation and mean temperature variables do not have a significant relationship with residential water demand, but relative humidity has a significant relationship with the residential water demand.

The general result of the regression equation can be interpreted as below:

$$\text{Water demand } (\text{m}^3/\text{month}) = 97{,}535 + 31 \times \text{Mean Temp} + 15 \times \text{Precipitation} - 323 \times \text{Humidity} \quad (5)$$

According to the PCA output, two factors have eigenvalues above 1, such that two PCs explained around 56% and 34% of the variability. The precipitation (0.921) and relative humidity (0.914) variables are incorporated in the first PC and have high loadings. Mean temperature (0.994) is the only high loading independent variable incorporated in the second principal component. The values with high loadings of the independent variables show which variables would have more effect on water demand from the PCA. According to the result of the regression analysis and PCA, the predicted variables have a significant relationship with the dependent variable. Accordingly to the PCA result, component one contains 56% of the variation of the relative humidity and precipitation variables. As such, these two variables highly explain the variation of water demand.

4.8.3. Ziway

Results from Ziway show that 8% of the variance in water demand can be accounted for by the three predictors, collectively: F (3, 80) = 2.44, $p = 0.07$. However, $p > 0.05$, which means that the model is not significant to predict the residential water demand according to any of the predictors: the mean temperature (t = 0.25, p = 0.79), precipitation (t = −1.79, p = 0.076), or relative humidity (t = −0.53, p = 0.59). In the multiple linear regression test, the p-values suggest that there is no significant relationship between residential water demand and selected variables. This indicates that none of the variables has a significant relationship with residential water demand. The regression analysis did not show clearly the interaction and relationship between the residential water demand and climate variables.

The general result of the regression equation can be interpreted as below:

$$\text{Water demand } (\text{m}^3/\text{month}) = 77{,}768 + 151 \times \text{Mean Temp} - 25 \times \text{Precipitation} - 4433 \times \text{Humidity} \quad (6)$$

PCA was conducted on the three independent variables to identify the predictor variables on residential water demand. According to the PCA results, two factors have eigenvalues above 1, such that there are two PCs that explained around 53% and 33% of the variability. Precipitation (0.894) and relative humidity (0.894) variables are incorporated in the first PC with high loadings. Mean temperature (0.999) is the only high loading independent variable incorporated in the second PC. The values with high loadings of the independent variables identify which variables would have much more effect on water demand from the PCA.

Collectively, the climate variables used for the multiple linear regression analysis explain the variance in residential water consumption in some case study towns. The spatial variation of the study areas has an influence on water consumption of the towns, which indicates that some particular variables have an impact on some specific areas, while some do not. Residual plots were also verified in order to check the goodness of a fitted model. Consequently, Arba Minch and Debre Birhan show random patterns with randomly distributed data points, while Ziway data points show some non-random pattern. In the regression analysis, the most consistently significant variables were mean temperature and relative humidity. This indicates that it would be better for the future study to include other non-climatic determinants such as socio-demographic influences. Basically, at seasonal and a monthly time scale, interannual variation in the climate parameters was shown to identify the important predictor of the seasonal water consumption. At a daily scale of water consumption, the influence of the climate variables on water consumption could explain with high precision the percentage of the variation in water consumption. Therefore, our result suggests that, although a significant amount of variance can be predicted by using monthly data, daily based data might explain the variation of water consumption in a more precise way.

5. Conclusions and Future Work

The investigation of weather influences on seasonal and interannual water consumption at three study areas is presented in this section. Three independent climate parameters (mean temperature, relative humidity, and precipitation) were chosen to assess and determine their relationship with residential water consumption rates in three study areas. Accordingly, climate variables specifically used in this study could have a significant impact on both seasonal and interannual water consumption.

The lowest water consumption occurs during "Kiremt" season, which is October–January for Arba Minch and Debre Birhan, while the highest consumption occurred for Ziway. The highest water consumption occurs during "Belg" season, which is February to May, for Debre Birhan and Arba Minch, but the lowest consumption occurs during "Bega" season (June to September) for Ziway. The maximum water consumption happens during March and the minimum in August for Arba Minch. For Debre Birhan, the maximum occurs around March to May and the minimum around October to December. The maximum occurs around December and January for Ziway, while the minimum is during the month of August. The geographical and altitude distribution within the country could be the main cause of the differences between the three climate variables. So, the differences in interannual and seasonal water consumptions are the consequence of climate variables.

Mean temperature increases of 1 °C cause an average increase in the rate of water consumption of approximately 5.28%, 0.29%, and 0.175% for Arba Minch, Debre Birhan, and Ziway, respectively. This shows that Arba Minch is more sensitive to mean temperature increases, as demonstrated by the amount of water consumed relative to other case study areas. This is because the area is classified under one of the hottest in Ethiopia or "Kola" and found on an altitude 1300 m above sea level. Conversely, relative humidity and precipitation have a negative impact with weak magnitude on residential water consumption in the Arba Minch area. Ziway has a Pearson's correlation value R close to zero for the mean temperature variable. This implies that mean temperature does not have any relationship with residential water consumption. According to the scatter plot of the three climate variables and water consumption rates of Debre Birhan, relative humidity has a weak relationship with the residential water consumption.

Multiple linear regression models were used to explain how much variation in water consumption could be explained by weather variables for each study site. According to the regression results, residential water consumption is primarily influenced by mean temperature in Arba Minch. Relative humidity is the only independent variable with $p < 0.05$ for Debre Birhan and, thus, the dominant variable. Residential water consumption of Ziway is primarily influenced by other determinants (likely factors such as demographics, water availability, and socioeconomic status) rather than the climate variables under investigation within this study, because the *p*-value is greater than 0.05 for all the variables assessed in the multiple regression analysis.

The predictor variable analysis was performed using principal component analysis, which is one of the most common and frequently used variable selection methods used in multivariate analysis. Arba Minch has only one component factor (PC1), with mean temperature having 0.76 loading and relative humidity having 0.86 loading. Debre Birhan and Ziway have two component factors (PC1 and PC2) each; the first component has precipitation and relative humidity variables, and the second component has a mean temperature variable. Accordingly, Debre Birhan has a component loading of 0.92, 0.91, and 0.99 for precipitation, relative humidity, and mean temperature, respectively. Ziway has component loadings of 0.89, 0.89, and 0.99 for precipitation, relative humidity, and mean temperature, respectively.

The findings from this study demonstrate that the analyzed climate parameters have a significant relationship with the water consumption. Since the general objective of the study is assessments rather than comparison of the models, the results obtained from each method could be different. From the scatter plot and the multiple linear regression analysis, relative humidity is correlated with residential water consumption at Debre Birhan. In Arba Minch, mean temperature's correlation result is similar for both scatter plot and multiple regression. Since the number of the variables studied is small, it is not possible to select a few parameters as the dominant variable in principal component analysis. Instead, increasing the number of variables with other determinant variables would be a better way to obtain a precise result. Generally, in this study, we focused solely on the three climate variables' influences on monthly water consumption, but water consumption depends on other factors too, such as pricing, demographic, and conservation measures [43,44]. We found that the influence of temperature is stronger than that of relative humidity and precipitation at lower altitude areas such as Arba Minch. The influence of relative humidity is stronger at Debre Birhan, which might be due to the fact that relative humidity increases with altitude in the atmospheric boundary layer [45]. Since higher elevations in the troposphere usually have lower temperatures, relative humidity will be higher.

Because of the topographical distribution, Ethiopia is naturally exposed to climate variability, making the water consumption management and ability to estimate the impacts of climate on water consumption more complex. The main findings of this paper show that geographical distribution and other determinants are more important determinants of residential water demand, even though households in warmer cities consume more water that households in colder cities. Climate change has led global water availability to become more variable and unpredictable [46]. As such, the decision-makers and water managers need specific information on climate variables and their impacts on water management. Challenges to collect relevant data on water consumption include the perils of manual recording, limited water supply coverage, the intermittent water distribution system, and the prevalence of private hand-dug wells at the household's backyard. Specific and relevant information about the climate variables' impacts on water demand would enhance the water management system and also better evaluate and audit the water produced from the sources, since the unavailability of other data imposes it upon us to use a few climate variables to assess the relationship between the variables and water consumption. Recommendations for future research should include assessments that measure daily or monthly climate data as well as other factors such as demographic data, water price, availability of extra water sources in backyards (private hand-dug well), and water management measure issues. With these changes, more precise results can be obtained to identify which parameter is dominantly causing the changes in water consumption in each of the study areas.

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