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Climate-Resilient Solution for Drinking Water Management Through Atmospheric Water Harvesting: A Systematic Case Study of Atmospheric Water Generation Deployment in Zambia Using Monte Carlo Simulation and Sensitivity Analysis

Ekolle Ndinde Eya*, Tochukwu Ambrose Ngwu, Tochukwu Michael Odoh, Ibrahim Ayinla Mahmud, Deborah Osayie Abashiya, Chukwu Uzo Ogonnaya, Emmanuel Ebubechukwu Oguh, Dapo Amupitan Oluwayomi

Department of Research, EKCÖLAB, 00237, Buea, Cameroon

*Correspondence: ekolleeya@gmail.com

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ABSTRACT: Southern Africa, specifically Zambia, was still faced with the challenge of water scarcity coupled with climate variability, which posed a significant threat to access to safe potable water. Due to the lack of adequate supply systems, there was a growing need for decentralized and climate-resilient systems. One alternative system was Atmospheric Water Generation (AWG); however, the existing literature on AWG usability was largely centered on machine specifications, with limited insight into its feasibility within specific climatic and demographic contexts. Accordingly, this study assessed the community-scale feasibility of AWG deployment in Zambia by integrating climate variability, population demand, and uncertainty into a unified planning framework. Monthly temperature and relative humidity data were integrated with ward-level population statistics and manufacturer performance specifications of an HPT3000 AWG unit. Monte Carlo simulation (MCS) was applied to propagate uncertainty in climate, demand, and system performance, while seasonal risk indices were used to quantify reliability. Relative humidity ($r = 0.95$) and temperature ($r = -0.24$) demonstrated significant influence, generating 17–29% of the minimum potable water demand per ward. The output dropped by more than 80% during dry months due to seasonal variation, implying strong climatic sensitivity, while MCS showed a 52.1% probability of failing to meet 10% of the baseline potable water demand. The findings demonstrated that AWG was unsuitable as a sole water source but could potentially be used as a climate-conditioned auxiliary system when strategically positioned to complement risk-based, decentralized water planning under hydro-climatic uncertainty.

KEYWORDS: Water resource management; atmospheric water generation; climate change; Monte Carlo simulation; sustainability; public health.

1. Introduction

Access to safe drinking water remained one of the most enduring global public health challenges, as an estimated 2.1 billion people still lacked safely managed potable water services. This deficiency caused more than 2 million deaths annually due to waterborne diseases such as cholera, typhoid, and diarrhea [1–3]. This crisis was further aggravated by climate change, which altered rainfall regimes, increased evapotranspiration and drought frequency, and exposed nearly 4 billion people to conditions of extreme water stress [4]. Southern Africa was among the regions highly prone to climate-driven water insecurity due to its strong dependence on rain-fed systems and limited adaptive capacity [5]. This situation was evident in Zambia, where frequent droughts and rising temperatures reduced surface water availability and increased pressure on groundwater resources [6 ,7]. Furthermore, national statistics in Zambia indicated that less than half of households had access to reliable and safe drinking water, with significant deficits among rural communities [8 ,9]. Projections of declining precipitation and temperature increases exceeding 2°C by mid-century further threatened agricultural production, ecosystems, and domestic water supply systems. These trends highlighted the need for climate-resilient, decentralized water supply technologies capable of functioning under increasing hydro-climatic uncertainty [10].

Atmospheric Water Generation (AWG) emerged as a potential alternative for decentralized drinking water provision through the extraction of moisture from ambient air via condensation or adsorption–desorption processes [11]. Experimental and numerical studies showed that AWG system performance was primarily dependent on temperature, relative humidity, airflow rate, and refrigeration cycle characteristics [11–16]. Recent assessments reported productivity efficiencies of up to 60–70% under favorable climatic conditions [16], while market analyses indicated rapid global growth driven by increasing water scarcity and technological advancement [17].

However, existing research on AWG was predominantly machine-centric, with most studies focusing on thermodynamic optimization [13, 14], refrigerant performance [15], or laboratory-scale efficiency testing under controlled climatic conditions [16]. Only a limited number of studies evaluated AWG feasibility under real climatic variability, and virtually none integrated demographic demand, climate uncertainty, and spatial deployment planning at the community scale. Consequently, insufficient evidence was available to guide decision-makers and policymakers regarding where, when, and under which risk conditions AWG systems could meaningfully supplement drinking water supply. Moreover, because AWG performance was highly uncertain under variable humidity, temperature, energy constraints, and per capita demand, probabilistic modeling was necessary to quantify these uncertainties and constraints. Probabilistic approaches such as Monte Carlo simulation and sensitivity analysis were widely applied in hydrological risk modeling and climate-impact assessments [18–20], yet their application to AWG-based potable water supply remained underexplored. Without explicit uncertainty and sensitivity analysis, previous studies implicitly assumed deterministic system behavior, limiting their relevance for climate-resilient planning.

To address these gaps, this study evaluated the feasibility of decentralized AWG deployment across eight wards in Zambia using an integrated climate–population–demand modeling framework to estimate community-scale supply potential under realistic operating conditions. The novelty of this study lay in three key advances. First, it applied Monte Carlo–based uncertainty modeling and sensitivity analysis to evaluate AWG output under stochastic variability in temperature, humidity, population, production, and demand. Second, it conducted ward-level deployment analysis, shifting AWG assessment from machine-scale performance to community-scale drinking water planning. Third, it introduced seasonal risk indexing to identify periods during which AWG reliability was either maximized or constrained. By moving beyond deterministic, machine-level evaluations toward integrated climate–population–risk modeling, this work provided a systematic framework for assessing AWG as a climate-resilient drinking water intervention within a real-world national context.

2. Materials and Methods

2.1. Meteorological, population, and water production data.

Monthly mean temperature and relative humidity data for January–December 2023 were obtained from a publicly available climate database [21]. These variables were selected because AWG performance was primarily governed by ambient temperature and relative humidity [22, 23]. Ward-level population data were obtained from the 2010 national census compiled by the City Population platform [24], as complete ward-level disaggregation from the 2022 census was not publicly available at the time of analysis. These data were used to estimate community-scale drinking water demand. The daily water production capacity of the AWG system was obtained from the manufacturer's technical documentation [25]. Manufacturer specifications were used as baseline system performance inputs, consistent with prior AWG feasibility studies [26, 27].

2.2. Operating principle of the hpt3000 atmospheric water generator.

The HPT3000 AWG operated on a vapor-compression condensation mechanism, in which ambient air was drawn through a filtration unit and passed across a cooled heat exchanger. As the air temperature was reduced below the dew point, water vapor condensed into liquid form [22]. The collected condensate was subsequently treated using a multi-stage purification system consisting of particulate filtration, activated carbon filtration, reverse osmosis, and ultraviolet sterilization to meet potable water quality standards [28, 29], as shown in Figure 1. Overall, system performance depended primarily on parameters such as ambient temperature, relative humidity, air flow rate, and compressor efficiency [22, 23]. Technical specifications of the HPT3000 unit were provided by the manufacturer [25].

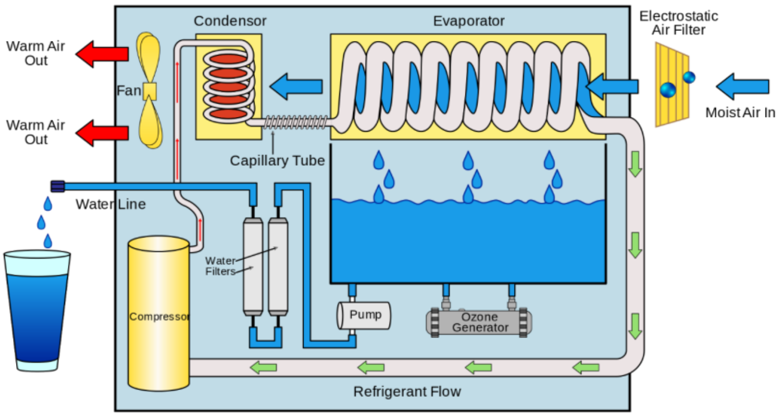

Figure 1. The working mechanism of Atmospheric Water Generator adapted from https://www.huprotec.com/about/

2.3. Water demand assessment.

Average household size in Zambia was taken as 4.8~5 persons per household based on national demographic statistics [30]. Daily per-capita drinking water demand was taken to be 2 L person^{-1} day^{-1}, consistent with minimum drinking water requirements in resource-limited settings recommended by WHO [31].

Total household drinking water demand was therefore estimated as:

$$D_h = n \times d \qquad (1)$$

Where D_h is household drinking water demand (L/day), n is household size (persons), and d is per-capita drinking water requirement (L/person/day).

2.4. Community-scale water coverage estimation.

The number of individuals that can be served by one AWG unit per day was calculated as:

$$P = \frac{W}{d} \qquad (2)$$

Where P is number of persons served (persons/day), W is daily water production of the AWG (L/day), and d isper-capita drinking water requirement (L/person/day). Community-level drinking water coverage was then estimated as:

$$C = \frac{P}{T} \times 100 \qquad (3)$$

Where; C is drinking water coverage (%), T is total ward population.

2.5. Monte Carlo simulation, uncertainty, risk, and sensitivity analysis.

Monte Carlo simulation was applied to quantify uncertainty in AWG performance arising from climate variability, system efficiency, energy availability, population growth, and water demand. System-level model simulations were implemented in Python. Probability distributions for temperature, relative humidity, population, and per capita water demand were derived from observed monthly data. A total of 10,000 random samples were generated to propagate uncertainty through the system, as reported in [18, 19]. The expected model output was estimated as:

$$E(X) \approx \frac{1}{N}\sum_{n=1}^{N} x_n \qquad (4)$$

Where $E(X)$is the expected outcome, x_n is the model output from the n-th simulation, and $N$is the total number of simulations (10,000). Baseline values for AWG production, population, and per-capita water demand were obtained by averaging across the eight wards. Uncertainty was introduced using multiplicative stochastic factors representing variability in climate conditions, machine efficiency, energy availability, population size, and demand (Table 1). Monte Carlo simulation was then used to estimate the probabilistic distribution of drinking water coverage. Population growth was incorporated using an annual growth rate of 2–3% over a 10-year planning horizon and treated as an uncertain input. Seasonal uncertainty was represented by separating wet (November to April) and dry season (May to October) climate conditions with distinct probability ranges for temperature and relative humidity.

System risk was quantified as the probability that drinking water coverage falls below 10%:

$$P(C < 10\%) \approx \frac{1}{N}\sum_{n=1}^{N} \mathbb{I}(C_n < 10) \qquad (5)$$

Where P(C<10%) is the true probability that the coverage is below 10%, C_n is drinking water coverage (%) in the n-th simulation and $\mathbb{I}$ is an indicator function equal to 1 when $C_n < 10\%$ and 0 otherwise. This threshold value is consistent with humanitarian WASH standards [32], where less than minimum drinking water needs (2-5 L/person/day) is considered a severe service failure and aligns with water security and reliability literature [33]. Sensitivity analysis (for the non-seasonal analysis) was performed by varying each input parameter by ±20% from baseline values while holding other variables constant to identify dominant drivers of AWG output and drinking water coverage [20]. Studies have shown that input uncertainty bands of up to ±40 % are realistic in water resource contexts, so ±20 % is conservative but plausible [34].

Table 1. Monte Carlo uncertainty variables used for the simulation.

Variables	Baseline Measurements	Baseline Values	Uncertainty Range
RH (%)	Average	64%	±15 %
Temperature(°C)	Average	24 °C	±10%
AWG Output (L/day)	Average	2331	-20% to + 10%
Energy Uptime (E)	Considered Stable	100%	70-100%
Population	Census (Average)	5,358	2-3% (Annual growth rate)
Drinking water needs (L/person/day)	Given base consumption	2	2-5

Uncertainty ranges for input parameters were derived from relevant climate, demographic, and engineering literature. Relative humidity and temperature variability ranges (±15% and ±10% [±2–3°C], respectively) were aligned with seasonal and intra-daily atmospheric variability reported for tropical and subtropical climates based on ERA5 reanalysis data [35]. Given the planning-level scope of this study, climatic influences on AWG production were represented as multiplicative performance factors rather than explicit thermodynamic calculations. Relative humidity variability (±15%) and temperature-induced performance variability (±10%) were applied to reflect moderate seasonal climatic fluctuations and their effects on condensation efficiency. These ranges were consistent with reported variability in AWG output under changing ambient conditions and avoided over-parameterization of the system-level Monte Carlo framework [36, 37].

AWG output uncertainty (−20% to +10%) reflected field performance deviations commonly reported in AWG evaluations compared with controlled ratings [27, 38, 39]. Energy uptime represented variability in rural grid reliability in Sub-Saharan Africa [40]. Population growth (2–3%) was consistent with World Bank population projections for Zambia, while per capita water demand (2–5 L/person/day) was bounded by Sphere and WHO minimum daily drinking water and basic needs standards [41, 32].

2.6. AWG risk index.

A seasonal AWG risk index was defined as the proportion of months in which the system failed to meet minimum drinking water demand for each ward:

$$AWG_{RI} = \frac{m}{M} \quad (6)$$

Where m is the number of months in which AWG production falls below minimum demand, and $M$is the total number of months in a year (12). Minimum monthly demand was defined as the product of ward population and per-capita drinking water requirement (2 L/person/day). A month was classified as a system failure when the average daily AWG output for that month was less than the minimum required potable water demand.

3. Results and Discussion

3.1. Climatic influence on AWG performance and implications for decentralized water supply

The results illustrated that the performance of AWG in Zambia was primarily constrained by climatic conditions, particularly relative humidity and, to a lesser extent, temperature. This trend was consistent with empirical evidence reported in earlier studies [17, 37], which indicated that the availability of atmospheric moisture strongly influenced condensation efficiency in AWG systems. The high sensitivity to humidity suggested that the application of AWG in semi-humid and seasonally dry regions such as Zambia was inherently climatically sensitive, and system performance could not be expected to remain consistent throughout the year. Across all eight wards, water production increased consistently during high-humidity months and declined sharply during dry, low-humidity periods, confirming that atmospheric moisture availability was a primary determinant of condensation-based water harvesting. This finding aligned with previous studies demonstrating that water vapor availability was directly proportional to relative humidity, a critical factor for condensation in atmospheric water harvesting systems [23, 37, 42]. The correlation matrix (Figure 2) further supported this observation, showing a very strong positive relationship between relative humidity and daily water production (r = 0.95), while temperature exhibited only a weak negative relationship (r = −0.24). These results supported the observed seasonal production pattern, characterized by peak production between January and March and reduced production during low-moisture months such as September.

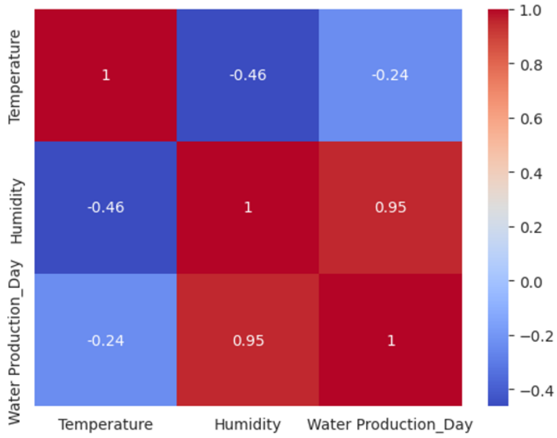

Figure 2. Correlation matrix of relationship between parameters.

Furthermore, relative humidity emerged as the dominant factor influencing AWG yield, with production exceeding 3,700 L/day in Chiyeke and 3,600 L/day in Milanzi when relative humidity was above 90% (Figure 3). In contrast, production fell below 700 L/day in several wards during dry months, indicating that seasonal variability alone could reduce output by more than 80%. This confirmed that AWG systems deployed without seasonal planning faced reliability challenges during dry periods and should be considered climate-sensitive infrastructure rather than uniform year-round solutions [37] (Table 2).

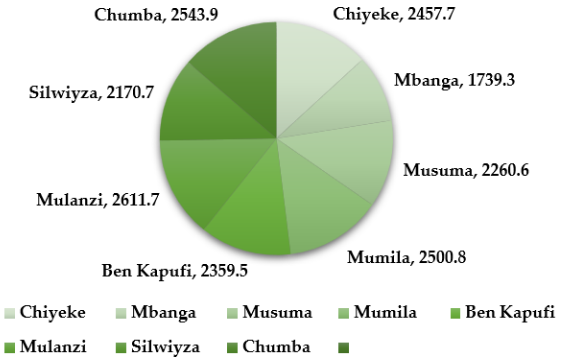

Figure 3. Pie Chart of average daily water production across all 8 wards.

Table 2. Summary of results in all 8 Wards.

Parameter	Chiyeke	Ben Kapufi	Chumba	Milanzi	Mbanga	Silwiyza	Musuma	Mumila
Humidity Min (%)	28.9	33.9	41.1	40.6	21.5	35.0	31.2	40.8
Humidity Max (%)	90.4	91.1	92.3	91.6	72.3	86.4	88.3	91.7
Temperature Min (°C)	21.9	19.7	20.1	21.3	20.8	18.4	19.1	20.1
Temperature Max (°C)	31.6	30.0	28.9	30.4	30.8	28.2	29.9	28.6
Water Production Min (L/day)	621.2	828.0	1204.6	1229.0	425.0	856.1	348.5	1141.2
Water Production Max (L/day)	3742.5	3488.0	3331.3	3644.5	3132.5	3261.7	3512.4	3309.1
Households (Min/day)	62	83	121	123	43	86	35	114
Households (Max/day)	374	349	333	365	313	326	351	331
Persons (Min/day)	311	414	602	615	213	428	174	571
Persons (Max/day)	1871	1744	1666	1822	1566	1631	1756	—

Temperature exhibited a consistent inverse relationship with water production, although its influence was less pronounced than that of relative humidity. Higher temperatures observed during dry months reduced the efficiency of the condensation process by increasing saturation vapor pressure and limiting air moisture release, except during periods when relative humidity was exceptionally high. These findings were consistent with [43], which reported that AWG performance was maximized under lower temperature and higher relative humidity, resulting in substantially higher water production. This combined effect explained the lowest yields observed in September across multiple wards and emphasized that both variables should be considered jointly when identifying suitable deployment zones and sizing AWG capacity [44].

At the community scale, a single HPT3000 unit could supply 17–29% of minimum drinking water demand, showing that AWG systems were insufficient as standalone solutions but could provide meaningful supplementary supply when integrated into decentralized water strategies [42, 45, 46]. Achieving over 90% coverage required 3–6 units per ward, emphasizing the need for strategic siting and scale optimization [47]. The results indicated that AWG feasibility in Zambia was primarily constrained by climate rather than technology. Effective deployment therefore depended on matching system capacity to seasonal humidity and population demand, highlighting the importance of climate-responsive, risk-based planning frameworks (Table 3).

Table 3. Water supply across all wards.

Wards	Total population of wards	Average No. of people that can be served per day (month)	Percentage of drinking water that can be served by a single HPT3000	No. of HPT3000 needed per ward to serve the total population
Chiyeke	5875	1229	20.9%	5
Mbanga	5021	870	17.3%	6
Musuma	5534	1130	20.4%	5
Mumila	4249	1250	29.4%	3
Ben Kapufi	4998	1180	23.6%	4
Milanzi	5532	1306	23.6%	4
Silwiyza	6614	1805	27.3%	4
Chumba	5041	1272	25.2%	4

3.2. Public health and policy implications

The demonstrated climate sensitivity of AWG systems had direct implications for mitigating water scarcity and public health in Zambia. Inadequate and unstable access to safe drinking water had been closely linked to high prevalence of waterborne diseases, malnutrition, and child mortality, especially among rural and peri-urban populations [1, 2]. The findings showed that AWG systems could not substitute centralized or groundwater-based supplies but could reduce reliance on unsafe surface water sources at the ward level during periods of appropriate atmospheric humidity, supplying between 17% and 29% of the potable water needed at the ward level. This supplementary contribution had the potential to reduce exposure to contaminated water and improve baseline hydration, which was critical for immune function and disease resistance [3]. However, the strong seasonal decline in production during low-humidity months implied that AWG deployment without climate risk planning could introduce new vulnerabilities instead of enhancing community resilience. During dry seasons, when traditional sources were typically most strained, AWG production became significantly reduced, limiting its usefulness as a health-protecting measure [37]. This supported the argument for considering AWG as a climate-conditioned technology for public health, whose utility relied on coordination with favorable seasonal conditions rather than year-round operation [11]. By incorporating AWG into decentralized water portfolios, rainwater collection systems, groundwater abstraction, and storage mechanisms, the health benefits could be maximized by mitigating seasonal supply shortages and acute exposure to unsafe water [27, 37]. However, the feasibility of such integration was strongly conditioned by the high energy demand of AWG operation. The HPT3000 required approximately 48 kWh per day, representing a substantial operational cost in rural and low-income Zambian settings where electricity access was limited and tariffs were relatively high. With only about 53.6% of households in Zambia having access to electricity, and just 34% in rural areas, this energy burden constrained the scalability of AWG as a public health intervention and reinforced its role as a supplementary rather than primary water source [48]. Consequently, AWG deployment without parallel consideration of energy availability and affordability risked transferring water insecurity into energy insecurity. These findings directly addressed the gap identified in the literature between machine-level optimization and community-scale feasibility. While previous studies emphasized thermodynamic efficiency, refrigerant performance, and laboratory productivity under controlled conditions [11−16], the present results demonstrated that climate variability and population demand fundamentally governed real-world practicality. The observed dependence on relative humidity confirmed experimental claims that AWG productivity could reach 60–70% efficiency under favorable conditions [16] but also showed that such efficiencies were not transferable across seasons or locations without risk-based planning. These findings collectively provided decision-relevant information to guide AWG optimization and policy planning to ensure equitable and sustainable water resource systems in Zambia, as well as other urban communities.

3.3. System performance under baseline and population growth scenarios.

The Monte Carlo simulations revealed that under baseline uncertainty, AWG coverage ranged from 4.3% to 25.1% (95% confidence interval), with a median of 9.8%. The probability of the system failing to meet 10% of drinking water demand was 52.1% (Table 3). Under increased population scenarios, the median coverage declined to 7.6% (range: 3.3%–19.8%), and the probability of failing to meet the 10% threshold rose to 77.3%. This substantial increase in failure probability, from 52.1% to 77.3%, highlighted population growth as the primary driver of AWG service inadequacy. The system's fixed production capacity made it inherently vulnerable to increases in demand. This finding aligned with broader research identifying population growth and increasing water demand as key drivers for alternative water solutions globally [49, 50]. The United Nations estimated that more than 2 billion people worldwide lacked access to clean drinking water, with freshwater sources declining as demand consistently increased due to population growth and industrialization [51].

This underscored the critical need to integrate demographic projections into water infrastructure planning. Research examining AWG performance in various contexts had demonstrated that demand-side factors often outweighed technical specifications in determining system viability [52]. The results also suggested that while the HPT3000 might be suitable for smaller communities, its application in larger populations was economically prohibitive due to the need for multiple units [45]. Previous economic analyses of AWG systems had shown that while net present value calculations could be positive in suitable environments (e.g., $5,964 over four years in Austin, Texas), the initial capital expenditure of $30,000–$50,000 per commercial unit presented a significant barrier to widespread adoption, particularly in communities that needed this technology most [51]. A comprehensive techno-economic assessment of AWG systems designed for rural applications demonstrated that while such systems could achieve positive net present value, the levelized cost (ranging between $0.17/L and $0.40/L) of water remained highly sensitive to energy inputs, with payback periods extending significantly under suboptimal conditions [53, 54]. This finding had direct implications for the population growth scenarios modeled in this study: as water demand increased, the marginal cost of supplying additional water through AWG units escalated non-linearly due to both the need for multiple units and potential deployment into less favorable microclimates.

3.4. Seasonal variability and its equity implications.

AWG output exhibited pronounced seasonal variability across all wards. Production peaked during the humid months of December and February, with daily service in Chiyeke and Milanzi exceeding 1,500 people. Conversely, output reached its minimum during the dry months of

August and September, with service in Mbanga falling to just 213 people. Seasonal uncertainty analysis yielded an aggregate failure probability of 57.3% (Table 4). Critically, the failure risk during the dry season (78.8%) was more than double that of the wet season (36.4%). The pronounced seasonal variability observed in this study was consistent with performance patterns documented in comparable regions, where AWG systems exhibited substantial reductions in output during dry months compared to peak wet season performance [26, 37, 42, 55]. Similarly, a recent experimental study conducted in Masdar City, Abu Dhabi, from July 2023 to January 2024 documented a 71% decrease in AWG performance during cooler months, with production reaching up to 927 L/day at 81% relative humidity during summer nights but declining sharply as temperatures dropped [56].

Table 4. Monte Carlo simulation and seasonal uncertainty results.

	Mean	STD	Min	5%	50%	95%	Max	Failure of coverage
Monte Carlo simulation results								
Water Production (L)	1831.9	305.1	1087.9	1364.6	1810	2368	2857.8	-
People Served	561	179	231	332	525	898	1348	-
Water Coverage (%)	10.5	3.3	4.3	6.2	9.8	16.7	25.1	52.1%
Monte Carlo simulation with population growth (2-3%)								
Future Population	6856	192	6530	6563	6852	7163	7199	-
Water Production (L)	1834.4	306.3	1089.1	1368.8	1812.7	2378.5	2971.5	-
People Served	559	178	230	330	523	2378	1341	-
Water Coverage (%)	8.2	2.6	3.3	4.8	7.6	13.1	19.8	77.3%.
Seasonal uncertainty water coverage in wet and dry season								
Wet Season Water Coverage (%)	11.7	3.5	5.7	7.2	11.1	18.6	24.7	36.4%
Dry Season Water Coverage (%)	8	2.7	3.2	4.4	7.5	13.3	19.1	78.8%

These results had profound equity implications. During dry seasons, the risk of water scarcity was disproportionately borne by vulnerable populations, particularly in remote areas of Zambia lacking alternative water sources. In water-stressed periods, reliance on unsafe sources increased, elevating the risk of waterborne illnesses and exacerbating existing social inequalities. Research on AWG deployment in challenging environments, including installations in South Africa and drought-affected regions of Africa, demonstrated that while AWG technology could not replace municipal water systems entirely, it could provide critical backup clean water when multiple commercial units were grouped together [45, 55]. These findings emphasized that AWG deployment strategies must be tailored to local seasonal climate patterns, with particular attention to periods of heightened vulnerability [17].

The public health implications of AWG performance extended beyond water quantity. A longitudinal study evaluating AWG water quality across multiple installations found that while AWG-produced water consistently met WHO drinking water guidelines for chemical parameters, microbiological quality was highly dependent on maintenance frequency and environmental conditions [57]. During periods of low production, such as the dry season reductions documented in this study, stagnation in storage tanks and increased biofilm formation could lead to higher heterotrophic plate counts, thereby affecting water quality [58]. This suggested that the seasonal failure risk identified in our analysis (78.8% during the dry season) carried compound consequences: populations received less water, and the water they did receive could pose elevated health risks if storage and distribution systems were not designed to accommodate prolonged low-flow periods.

The selection of the 10% coverage threshold as a performance metric significantly influences the interpretation of system reliability. Sensitivity analysis examining threshold effects in water system performance assessment has demonstrated that failure probabilities are highly sensitive to threshold selection [59, 60]. For the systems analyzed in this study, increasing the threshold from 10% to 15% would elevate the aggregate failure probability substantially, while decreasing it to 5% would lower failure probability commensurately [59]. This threshold sensitivity has important policy implications: if AWG is positioned as an emergency backup system intended to provide only absolute minimum survival needs (approximately 2-3 L/person/day, or 5-7% of typical demand), the technology appears significantly more reliable than if it is expected to provide meaningful supplemental supply (10-15% of demand). This finding aligns with broader research positioning AWG as a crisis mitigation technology rather than a primary water source.

3.5. System performance and overall reliability.

The sensitivity analysis identified per capita water demand and population size as the most influential determinants of system performance. In contrast, water production rate and energy availability had a comparatively minor effect (Figure 4). This confirmed that the system was demand-limited rather than supply-limited under the tested conditions. This result corresponded with research on the water-energy nexus, which recognizes the inseparable interconnection between energy and water resources [52]. Advanced multipurpose AWG systems that integrated with building HVAC infrastructure demonstrated potential for significant efficiency gains [27]. A recent simulation study of a hospital building in Pavia, Italy, found that integrating AWG systems reduced primary energy consumption by 16.3% (from 231.3 MWh to 193.6 MWh), with additional benefits of 257 m³ of water production that could be used for photovoltaic panel cleaning, human consumption, or other technical needs [52]. Such integrated approaches, where the same energy input provided water harvesting, heating, and cooling simultaneously, represented promising pathways for improving AWG viability.

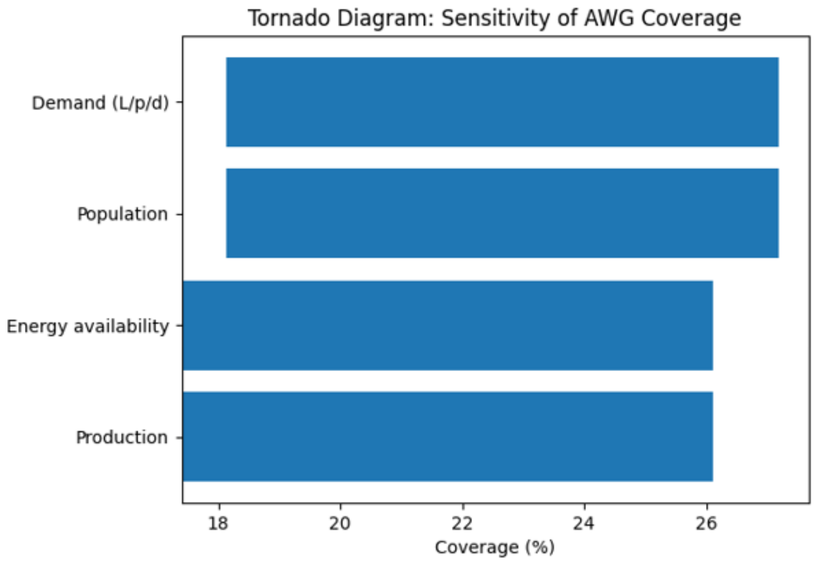

Figure 4. Sensitivity of AWG Coverage.

The calculated risk index (RI) demonstrated a complete failure to meet minimum daily drinking water requirements (2 L/person/day) throughout the entire year in all wards (Figure

5). Daily average output from the HPT3000 consistently remained below 5,000 L/day, confirming a persistent shortfall relative to baseline needs. Monitoring of AWG units over extended periods documented production declines, attributable to compressor efficiency losses, heat exchanger fouling, and sensor calibration drift [61]. These degradation effects were non-uniform across seasons, with dry season performance deteriorating more rapidly than wet season performance [55, 61]. Recent research applied established hydrologic performance indicators, including reliability, resiliency, and vulnerability metrics, to evaluate AWG systems across the United States, mapping efficiency at county-scale resolution to determine regional efficacy for supplementing potable water supply [62]. The combination of low baseline coverage, high seasonal failure risk, and a zero-reliability index for basic needs painted a clear picture: as a standalone system, the HPT3000 could not guarantee a minimum level of service for entire populations. Its role should be viewed as a supplementary source or a solution for small, critical facilities (e.g., clinics, schools, refugee camps, and military bases on and offshore) rather than as a primary source for whole communities.

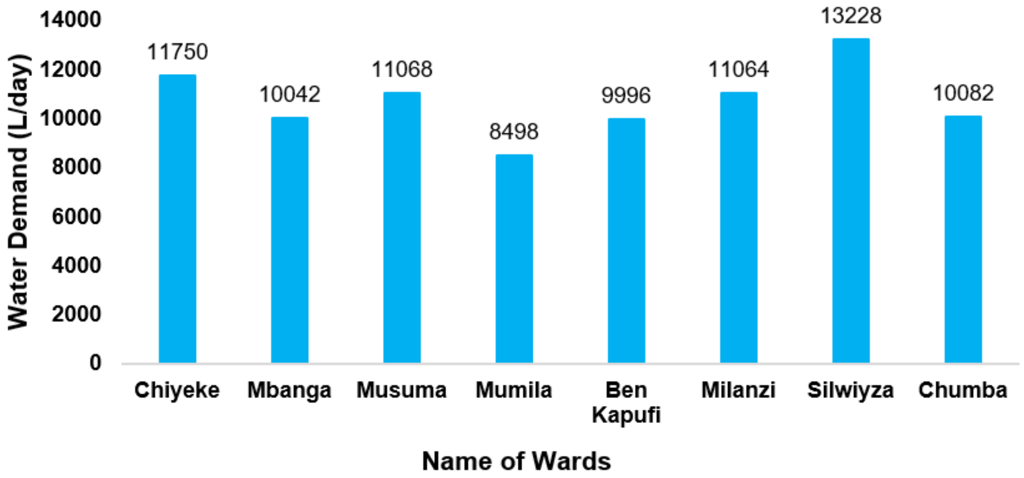

Figure 5. Minimum drinking water demand per ward.

4. Conclusions

This study focused on evaluating the viability of Atmospheric Water Generation (AWG) as a potential decentralized potable water source in Zambia by integrating climatic variability, population demand, and uncertainty analysis. The findings illustrated that AWG water production typically depended on relative humidity and marginally on temperature, further confirming the significance of air moisture in AWG water production. Water yields were higher in humid months and declined sharply during dry periods, with seasonal variability capable of reducing output by more than 80%. The results showed that a single HPT3000 unit could meet 17–29% of the minimum potable water requirement at a community level, and the energy requirement exceeded the affordability of the projected communities, confirming that AWG could not serve as a primary water source but could provide a significant supplement to decentralized water supply when properly planned and incorporated. This study also contributed to the literature on AWG by shifting the focus from machine-level performance evaluation to an integrated climate-population-risk framework. The incorporation of probabilistic analysis provided relevant information for decision-making on AWG reliability under seasonal and climatic uncertainty. Major limitations of this research included reliance on manufacturer-specified performance data, the use of short-term climate records, and the lack of water quality field measurements. Future research should incorporate long-term climate data, field validation, and techno-economic analysis to better inform policy and deployment strategies.

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Author Contribution

Ekolle Ndinde Eya conceived and designed the study. Ekolle Ndinde Eya and Tochukwu Ambrose Ngwu developed the methodology, collected and analyzed the data, and supervised the project. Writing of the original draft was carried out by Ekolle Ndinde Eya, Tochukwu Ambrose Ngwu, Tochukwu Michael Odoh, Ibrahim Ayinla Mahmud, Deborah Osayie Abashiya, Chukwu Uzo Ogonnaya, Emmanuel Ebubechukwu Oguh, and Dapo Amupitan Oluwayomi.

Data

Data and other materials for this work are available on request

Competing Interest

All the authors declare no conflict of interest.

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