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Intra-seasonal rainfall and piped water revenue variability in rural Africa

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ABSTRACT

Rainfall patterns influence water usage and revenue from user payments in rural Africa. We explore these dynamics by examining monthly rainfall against 4,888 records of rural piped water revenue in Ghana, Rwanda, and Uganda and quantifying revenue changes over 635 transitions between dry and wet seasons.

Results show operators experience revenue variability at regional and intra-seasonal scales. Revenues fall by an average of 30 percent during the wettest months of the year in climate regimes with consistent wet season rainfall. However, seasonally stable revenues are observed in areas where consecutive dry days are common during the wet season, potentially reflecting a dependency on reliable services. We also find changes in tariff level, waterpoint connection type, and payment approach do not consistently prevent or increase seasonal revenue variability.

Local revenue generation underpins delivery of drinking water services. Where rainfall patterns remain consistent, piped water operators can expect to encounter seasonal revenue reductions regardless of whether services are provided on or off premises and of how services are paid for. Revenue projections that assume consistent volumetric demand year-round may lead to shortfalls that threaten sustainability and undermine the case for future investment. Intra-seasonal rainfall analysis can enhance rural piped water revenue planning by offering localised insight into demand dynamics and revealing where climate variability may increase dependency on reliable services.

1. Introduction

Current climate models predict increases in frequency and intensity of drought and heavy rainfall events and decreases in mean precipitation almost everywhere in Africa, with medium to high confidence (Gutiérrez et al., 2021). However, local rainfall trends and socio-climatic interactions are likely to manifest in mixed patterns (Conway and Schipper, 2011), and the converging impacts of climate change will vary across the continent. In rural areas, rainfall patterns influence water usage and threaten the stability of revenue generation. Remote and *in situ* monitoring systems can generate warning signals (Armstrong et al., 2021), but improved understanding is needed to inform resilient water investments in rural Africa. We analyse seasonal revenue dynamics of six small-scale piped water operators in rural Ghana, Rwanda, and Uganda over a four-year period to address three research questions. First, how does seasonal rainfall influence revenue from user payments for rural piped water services? Second, which rainfall metrics are useful for characterising seasonal revenue variability? Third, do tariff level, connection type, and payment approach influence seasonal revenue patterns?

2. Rainfall and rural water services

2.1. Seasonal revenue variability

For more than a century, piped water services in the Global South have been planned and financed under an urban paradigm transferred from the Global North (Braadbaart, 2012). A core assumption of this model is that a household connected to a piped network will collect and use consistent volumes of water from that connection each month of the year, with infrastructure and tariffs designed accordingly. Yet evidence from across sub-Saharan Africa shows rural households have access to and use multiple water sources of varying service levels for different domestic and productive activities, some of which they pay for and some they do not, and they change the sources they use throughout the year depending on availability of seasonal surface or rainwater (Elliott et al.,

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2019, Hoque and Hope, 2018, Smits et al., 2008, Thompson et al., 2001). Rain-fed sources such as domestically harvested rainwater can be more convenient and reliable than primary water supplies during wet seasons and are often accessible without payment or at a lower price point after an initial capital investment is recovered. Households that utilise rain-fed sources can therefore spend less time and money on water collection during wet seasons (Kelly et al., 2018) and may even experience enhanced resiliency to supply shocks (Elliott et al., 2019, Kohlitz et al., 2020).

However, seasonal demand dynamics can threaten financial and operational viability of rural water services. Several studies conducted in Africa and Asia suggest domestic use of rural handpumps and piped schemes alike can fall by 20 to 30 percent during wet periods (Armstrong et al., 2021, Elliott et al., 2019, Kulinkina et al., 2016, Thomson et al., 2019). When payments for professional water services are based on volumetric usage, seasonal reductions in water use means revenues are more irregular with implications for operational sustainability. Seasonal revenue variability for handpump services has been documented in several sub-Saharan countries (Foster and Hope, 2016, 2017, Kelly et al., 2018), but its severity and extent related to piped water services across the continent is not well understood.

2.2. Rainfall dynamics

Despite the growing body of evidence demonstrating seasonal use of multiple water sources, little is published about how rural households respond to spatial and temporal variations in seasonal rainfall and how this demand response poses a revenue threat to water services within different climate regimes. Except for a few studies that combine longitudinal rainfall and water use data (Armstrong et al., 2021, Kulinkina et al., 2016, Thomas et al., 2019, Thomas et al., 2021, Thomson et al., 2019), most analyses draw on cross-sectional household surveys and utilise a binary, often subjective wet/dry monthly classification which hides presumably important intra-seasonal nuances about onset, duration, and intensity of dry and rainy periods (Wainwright et al., 2021). Water demand and revenue dynamics are likely driven by localised, weekly or even daily changes rather than whether a given month falls in a wet or dry season according to conventional definitions or is wetter or dryer than historical averages. This poses several questions pertaining to our study. In wetter climates, does a more consistent year-round prevalence of rainwater use lead to attenuated seasonal dynamics? Considering evidence that domestic withdrawals from boreholes decrease within a few days of heavy rainfall events (Thomas et al., 2019, Thomson et al., 2019), will less frequent but more intense rainfall lead to higher annual averages but more dramatic instantaneous falls in demand and revenue? Are households less likely to use seasonal sources as rainfall becomes more irregular and unreliable, particularly during rainy seasons (Kendon et al., 2019)? Will the revenue threat to rural water services increase or decrease as household use of rain-fed sources occurs over condensed time periods? Billions are spent on efforts to increase access and maintain drinking water services based on simple demand assumptions stemming from this knowledge gap. The revenue models upon which infrastructure investment decisions are made could be enhanced with improved understanding of how rainfall patterns influence water use and payment behaviours. This is a necessary precursor to assessing and addressing seasonal and climatic revenue threats to rural water services at local, regional, and global scales and to prioritising investments that maximise sustainability and equitability of outcomes.

2.3. Behavioural determinants

Rural piped water service providers that are losing market share to alternative sources such as seasonal rainwater may seek to understand what aspects of their service households prefer, and what it would take to incentivise consistent year-round use. Improved understanding of how various determinants modify seasonal water source choice and payment behaviours of rural households can strengthen strategies for addressing the rainfall-related revenue threat. The importance of price, proximity, reliability, and water quality on rural households' decisions to choose one rural water source over another have been highlighted in the literature (Briscoe et al., 1981, Gross and Elshiewy, 2019, Mu et al., 1990, Wagner et al., 2019). Similar factors appear to affect payments for the services that operate and maintain water sources. Rural households are less likely to use and pay for water the further the source is from their residence, especially when alternative water sources are nearby (Koehler et al., 2015, Kulinkina et al., 2016). Faster maintenance response time (Hope (2015), Hope and Ballon, 2019, 2021), favourable and dependable service delivery arrangements (Hope (2015), Hutchings et al., 2017, Koehler et al., 2015, Koehler et al., 2018), and perceived water quality (Foster and Hope, 2016, Hope and Ballon, 2019, 2021) may increase user payments. An important interaction effect is that households often use water from seasonal sources that are lower in quality and cost for purposes other than drinking and cooking (Hoque and Hope, 2020, Pearson et al., 2016, Thomson et al., 2019, Tucker et al., 2014). Payment approach is also an important modifier of rural water user payments and revenues. Pay-as-you-fetch (PAYF) payments collected on a volumetric basis may generate more revenue overall and per volume than flat fees collected periodically (Foster and Hope, 2017). However, PAYF payments are also linked to higher rates of seasonal multiple water source use than flat fees across all socioeconomic classes (ibid.) and may be less resilient to seasonal variability (Armstrong et al., 2021).

The limited evidence that is available suggests rural demand for payment-based water services is prone to being exchanged for seasonal rainwater if the rainwater is less expensive, more convenient, more reliable, and an acceptable quality for non-consumptive uses. A key knowledge gap is whether reliable piped water services provided on household premises, which are at least as convenient as rain-fed sources during the wet season, can stabilise willingness to pay for the primary service and reduce seasonal revenue variability. We explore this question through an analysis of a multi-decadal operational dataset while also considering the potential modifying effects of tariff level and payment approach.

3. Methods

3.1. Quantifying seasonal revenue variability

Our empirical analysis draws on operational data from six rural piped water operators in Ghana, Rwanda, and Uganda. After extraction and cleaning, a total of 4,888 records of monthly revenue from user payments corresponding to geographic service areas of individual piped schemes spanning the years 2016 to 2019 are analysed. We exclude records from the analysis if fewer than twelve months are available for any service area. This approach ensures the analysis spans at least one annual rainfall cycle in each service area. We convert all monthly revenue records from local currency to 2019 US dollars per waterpoint by applying deflator factors and currency conversion rates at purchasing power parity for private consumption obtained from the World Bank Development Indicators database (World Bank, 2020) and dividing by the number of functional waterpoints in the service area for the corresponding month. This enables our analysis to consider the effect of temporal demand fluctuations on revenue. We assess seasonal revenue variability as percent change in the rate of monthly revenue per waterpoint between chronological dry and wet seasons, rather than in absolute magnitudes, to account for variation in scheme size and service population across the dataset.

Our seasonal classification utilises Climate Hazards Group InfraRed Precipitation with Station (CHIRPS) data (Funk et al., 2014) and adapts the methodology described by Liebmann et al. (2012). Recognising the implications of intra-seasonal rainfall dynamics for our research questions, our approach diverges from typical climatological analysis by classifying individual months as wet or dry relative to annual rainfall means instead of identifying onset and cessation of prominent wet and dry seasons and referencing long-term, multi-year means. Daily geospatial rainfall data corresponding to each service area over the range of dates present in the operational dataset (2016–2019) are extracted from the CHIRPS data. Rainfall levels are summed monthly to align with revenue records. For each service area and month, the monthly rainfall anomaly is calculated by subtracting the monthly average rainfall corresponding to the annual mean from the total rainfall for that month. We classify each month as wet or dry relative to the annual mean such that negative anomaly values represent dry months and positive anomaly values represent wet months. We then group records corresponding to consecutive dry or wet months together as seasons. This approach accommodates intra-seasonal rises and falls in rainfall which might have a critical influence on water use, but also allows erratic shifts which can distort revenue patterns. To compensate for this, we assume a threshold requirement that monthly rainfall is a defined percentage more or less than its local annual average for transitions between seasons to occur. We test the sensitivity of this threshold and find values of five percent or less apply to fewer than one month per year for the average service area and yield nearly the same seasonal patterns as when no threshold is applied, while threshold values of 15 percent or more apply to three months per year for the average per service area and conceal the intra-seasonal dynamics we hope to incorporate. We therefore adopt a moderate seasonal transition threshold requirement of ten percent of the local annual average rainfall in our methodology. Finally, we calculate the percent change in the average revenue generation rate from each dry season to the chronological wet season.

We identify anomalies in the data that appear to result from operational factors such as extended periods of service disruption, administrative changes to billing procedures or failure to collect user payments, inclusion of arrears in monthly revenue records, data recording errors, and infrastructure upgrades. Where possible, data are corrected based on discussion with operators. To further account for exogenous factors which exert an unknown effect on revenue, single months with no recorded revenue are assumed to represent true drops in demand while two or more consecutive months with no recorded revenue are assumed to reflect operational factors that should be controlled or minimised in the analysis and are excluded. The excluded monthly records are evenly distributed across dry and wet seasons and ultimately do not exert a directional effect on our results. We also identify extreme outliers in calculated seasonal percent change in revenue generation rate. Values greater than three standard deviations from the absolute value of the mean for each country are identified and considered for exclusion. This methodology only identifies exceptionally large increases in wet season revenue because revenues cannot decrease by more than 100 percent. These extreme outliers, which are found to be nonrecurring in individual service areas and therefore likely reflect operational factors rather than increased wet season water demand, are excluded. In total, we exclude 242 monthly records of no revenue and 45 chronological season transition pairs from the analysis. From the remaining dataset, we calculate mean percent change in monthly revenue per waterpoint between chronological dry and wet seasons across all service areas as well as those supported by each operator. Differences in means is evaluated via one-way ANOVA and homogeneous subsets are identified via Tukey's HSD.

3.2. Evaluating rainfall dynamics

We again utilise the CHIRPS dataset to evaluate several rainfall metrics in the geolocations of the observed piped water service areas which have potential to reveal intra-seasonal patterns in water demand and revenue. Daily rainfall estimates from 2016 to 2019 covering separate rectangular grids spanning the minimum and maximum latitudes and longitudes of the service areas in Ghana, Rwanda, and Uganda are extracted and manipulated for this purpose. We first generate plots of average monthly precipitation ("*monthly precipitation*") for each service area to compare the overall intensity and seasonal dynamics of the respective rainfall profiles. Following the methodology described by Liebmann et al. (2012) and advanced by Dunning et al. (2016) we use daily rainfall to calculate and plot the average annual dry season duration (*"dry season duration"*) for geographic grids corresponding to the observed service areas by identifying and subtracting the average dry season completion date from the average onset date. When two dry seasons are prevalent in the typical year, we generate separate plots for each. When no clear patterns emerge from observation of these two metrics that are based on monthly rainfall and seasonal timing, we calculate the cumulative number of instances of three, seven, and fourteen consecutive days with no precipitation during the main wet season ("*instances of dry days*") for each location. Although consecutive dry day metrics are more commonly used as indicators of drought intensity and frequency, recent climate models suggest future increases in dry period duration during the wet season over parts of Africa (Kendon et al., 2019). We apply these metrics to the three-month period of the main wet season in each country to illustrate intra-seasonal rainfall variability in the service areas. Durations of three, seven, and fourteen days are chosen to align with assumed household water storage practices. Rural African households that collect seasonal rainwater likely store and use it over several days. Dry periods of three consecutive days during the wet season are unlikely to disrupt this behaviour, but dry periods of a week or more may inhibit rainwater use. We quantify *instances of dry days* for each of these durations in 0.05-degree grids, assign values to a colour scale, and generate plots covering the geographic regions of the service areas. These plots are overlaid with markers indicating service area locations that experience "variable" or "stable" seasonal revenue based on a threshold of five percent, and we examine the plots for alignment or notable patterns.

3.3. Analysing behavioural determinants

Our data classification is aligned with previous work (Armstrong et al., 2022) which makes it possible to analyse the effects of tariff level, waterpoint connection type, and payment approach on seasonal revenue variability. The tariffs observed across the dataset are based on a volumetric water usage charge for all consumption levels, either per container or cubic metre, and do not contain a recurring fixed service charge. We convert all tariff levels to 2019 US dollars per cubic metre from local currency at purchasing power parity for private consumption. All records are further classified by waterpoint connection type: standpipes and kiosks are designated as off-premises connections and taps located in private homes or yards or dedicated for use at educational, religious, or healthcare facilities are designated as on-premises connections. Records corresponding to mixed schemes that include both on and off-premises connections are split into separate, geographically coincidental service areas so that all units of analysis share a common and static waterpoint connection type and operator. Payments across the observed service areas are collected from users who access off-premises connections by one of two approaches: the conventional PAYF approach, where users pay a standpipe or kiosk attendant when they collect water from the waterpoint, and the prepaid credit approach, where users prepurchase electronic credit that can later be redeemed at the waterpoint. For on-premises connections, users pay either by conventional billing based on metered usage during the previous billing cycle or by prepaid credit where water is purchased in bulk and dispensed via an electronic meter.

Parameters from generalised estimating equations (GEEs) are estimated to evaluate the isolated effects of these factors on seasonal revenue variability. The GEE method (Zeger et al., 1988) is chosen over other linear regression approaches because monthly records are clustered by operator which violates the independence assumption. The method also fits well into our approach because it estimates populationaveraged effects when covariates are unknown or unable to be controlled (Muff et al., 2016). We run separate GEE models for all records as well as clusters corresponding to individual operators and groups of interest. All modelling is conducted in IBM SPSS (IBM SPSS Statistics for Windows, Version 27.0. Armonk, NY: IBM Corp) with chronological season transition pairs as repeated measures, service areas as subjects, and operator as a within-subject variable to adjust for clustering. We construct a continuous response variable from change in monthly waterpoint revenue between chronological dry and wet seasons (percent) and utilise tariff level, connection type, and payment approach as explanatory variables. Tariff levels (2019 $/m3 at PPP) are centred on the mean for all records included in each model and modelled as a continuous covariate. Connection type (on premises; off premises) is modelled as a categorical factor. Payment approach is correlated with waterpoint connection type because all service areas that utilise pay-as-you-fetch payments contain off-premises connections and all service areas that utilise monthly billing contain on-premises connections. Therefore, we include a transformed binary variable based on utilisation of prepaid credit (conventional payments; prepaid credit payments) in the models as a categorical factor. We run each model once with an unstructured correlation matrix and again with an autoregressive correlation matrix, the latter of which considers correlations to be highest for time-adjacent records and to systematically decrease with increasing time distance between records. The correlation matrix with the lowest quasi-likelihood of independence criterion (QIC) statistic is determined to be the best fit.

4. Results

Here we describe our most salient findings based on observation of seasonal revenue, evaluation of rainfall metrics, and analysis of selected behavioural determinants.

4.1. Seasonal revenue

The box plots in Fig. 1 illustrate dispersion of the average percent change in monthly revenue per waterpoint between a total of 635 chronological dry and wet seasons observed across all service areas as well as clustered by operator. Full descriptive statistics disaggregated by waterpoint connection type and payment approach are reported in Supplemental Table 1.

We observe a wide range of seasonal revenue change across the dataset (IQR 50 percent), with all operators experiencing wet season revenue falls in at least some service areas. Operator A in Rwanda and Operator B in Ghana experience overall negligible seasonal revenue variability, but Operator C in Ghana and operators D, E, and F in Uganda experience an aggregated average 30 percent reduction in revenue during wet seasons (IQR 27 percent). One-way ANOVA indicates all operator means are significantly different from each other ($p < .05$), but post-hoc tests reveal service areas supported by operators C, D, E, and F are in a homogeneous subset. Seasonal change in revenue is also statistically greater ($p < .05$) for Operator E than any of the other operators.

4.2. Rainfall

Plots illustrating *monthly precipitation* and *dry season duration* across the service areas in Ghana, Uganda, and Rwanda are provided in supplemental figures. These metrics do not reveal a clear explanation for the observed differences in seasonal revenue variability between service areas and operators. The *monthly precipitation* profiles in all three countries are similar yet the service areas in those countries see differing degrees of seasonal revenue variability. The service areas in Ghana and Rwanda that experience negligible seasonal revenue variability and therefore might be expected to align with muted rainfall dynamics are instead characterised by pronounced wet and dry seasons. Furthermore, we do not find evidence that *dry season duration* might correlate with falls in revenue during the wet season. Service areas in Ghana experience similar *dry season durations* but drastically different seasonal revenue variability, and service areas in Rwanda see a gradient of *dry season durations* yet all experience relatively stable seasonal revenues. Whether a region experiences relatively wetter or drier seasons, greater differences in mean rainfall between seasons, or longer dry seasons does not appear to influence the degree of observed seasonal revenue variability.

We do, however, find a notable stratification when *instances of dry days* during the main wet season are examined at the level of individual service areas (Fig. 2). Piped water service areas that typically experience revenue falls during wet seasons (red dots) appear to be in climate regimes characterised by consistently rainy wet seasons. In climate

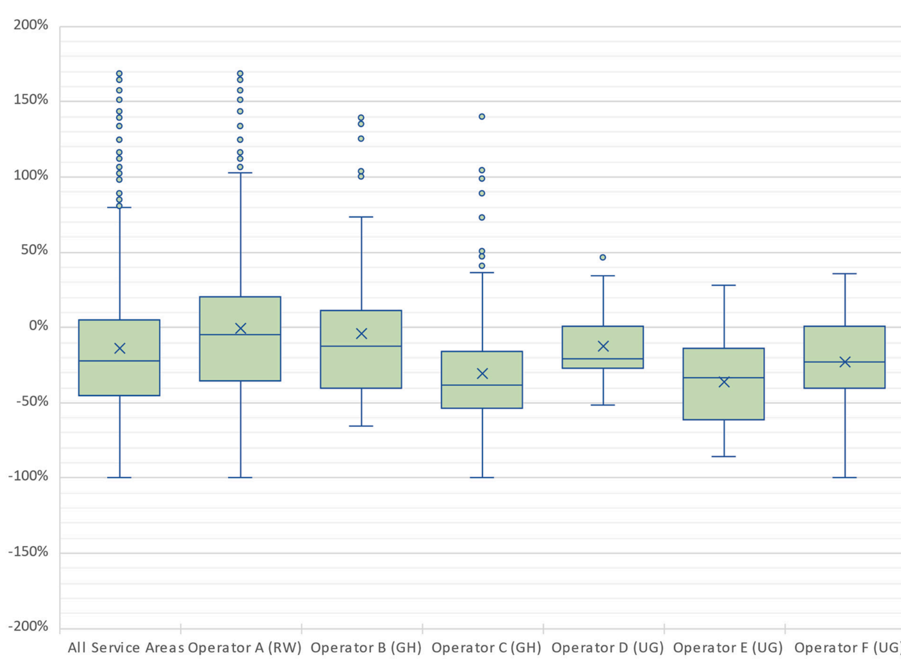

Fig. 1. Average percent change in monthly revenue per waterpoint in individual service areas between chronological dry and wet seasons. Box plot elements: mean markers, median centre lines, upper and lower quartile box limits, whiskers for minimum and maximum values within 1.5x IQR, and outlier markers.

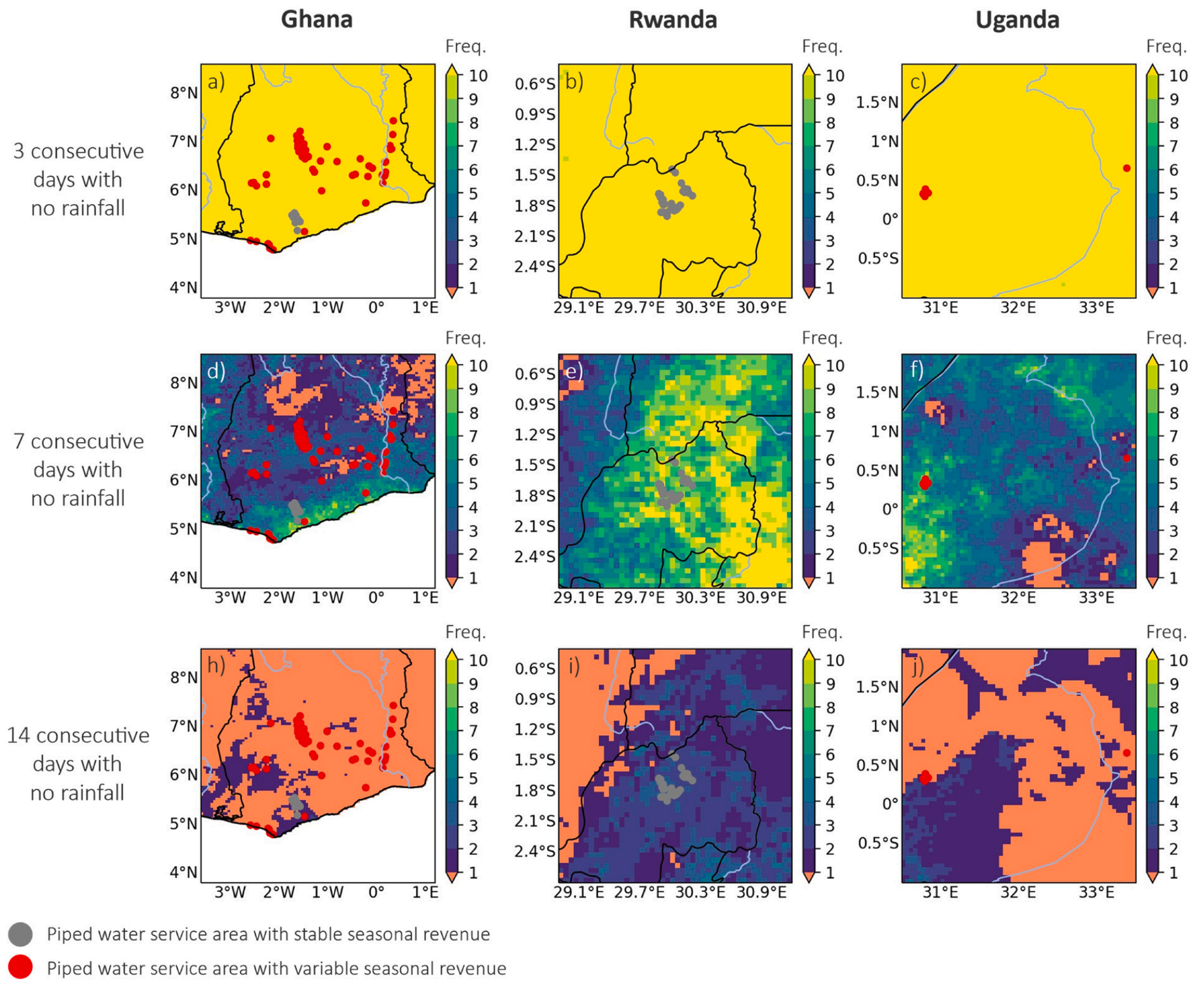

Fig. 2. Instances of consecutive days with no rainfall during main wet season in Ghana, Rwanda, and Uganda (2016–2019 cumulative). Grey markers indicate piped water service areas where average revenue variability of less than five percent is experienced between dry and wet seasons. Red markers indicate service areas where average seasonal revenue variability of greater than five percent is experienced. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

regimes where instances of 7 and 14 consecutive dry days during the wet season are more frequent, such as southern Ghana (panels d and h) and Rwanda (panels e and i), service areas appear to experience more stable revenue streams year-round (grey dots). This is especially notable when longer dry intervals occur during wet seasons (panels h and i).

4.3. *Tariff Level, waterpoint connection Type, and user payment approach*

Regression results corresponding to separate GEE models for service area clusters of interest are summarised in Table 1. Consistently better goodness-of-fit is observed when correlation across time-adjacent records is represented with an autoregressive correlation matrix. Reference cases correspond to service areas where only off-premises connections and conventional payment approaches are employed with tariff levels held constant at the mean value for the cluster. The models are constructed such that β values indicate the incremental effect of each parameter in relation to the reference case on percent change in monthly revenue per waterpoint between chronological dry and wet seasons. Tariff level increase is modelled as a main effect. The effects of on-premises connections and prepaid credit are modelled as interactions with mean-centred tariff level to control for the fact that the parameters are typically associated with higher user fees. Since Operator B does not utilise conventional payment methods, the reference case in Model 4 is based on off-premises connections where mean tariff levels are charged and paid for with prepaid credit. The isolated effect of prepaid credit is not able to be estimated in models 3 or 4 because prepaid credit payments are not utilised in the service areas supported by Operator A and conventional payments are not utilised in the service areas supported by Operator B.

The estimated effects of the reference cases follow a similar pattern as the descriptive statistics. When all service areas are pooled together (Model 1), the reference case sees a 13.0 percent seasonal reduction in revenue ($p < .001$). However, seasonal revenue variability is not significant ($p \geq 0.05$) for operators A and B (models 3 and 4, respectively), and operators C, D, E, and F (models 5, 6, 7, and 8, respectively) each experience significant reductions in revenue during wet seasons ($p \leq 0.006$). When service areas supported by the latter group of operators are clustered together (Model 2), the reference case sees a 30.2 percent decrease in revenue during wet periods ($p < .001$).

Descriptive statistics for tariff levels associated with each operator are summarised in Supplemental Table 2. Tariff level increases significantly influence seasonal revenue ($p \leq 0.001$) for the three operators in Uganda (models 6, 7, and 8), further reducing revenue during the wet

Table 1
Modelled effects of tariff level increase, on-premises connections, and prepaid credit on percent change in monthly revenue per waterpoint between chronological dry and wet seasons [percent].

	β	SE	95 Percent Confidence Interval Lower	Upper	p
Model 1: All Service Areas (n = 635)					
Reference case (intercept)[1]	**−13.0**	**2.0**	**−17.0**	**−9.1**	**<0.001**
Tariff level increase[2]	−2.5	3.3	−9.0	4.1	0.463
On-premises connections[3]	1.0	5.5	−9.7	11.8	0.853
Prepaid credit[3]	6.2	4.7	−3.1	15.4	0.190
Model 2: Operators C (GH), D, E, and F (UG) (n = 272)					
Reference case (intercept)[1]	**−30.2**	**2.5**	**−35.1**	**−25.3**	**<0.001**
Tariff level increase[2]	0.5	3.5	−6.3	7.3	0.883
On-premises connections[3]	**−13.1**	**5.8**	**−24.5**	**−1.6**	**0.025**
Prepaid credit[3]	−8.6	5.6	−19.5	2.3	0.121
Model 3: Operator A (RW) (n = 328)					
Reference case (intercept)[1]	−0.4	2.7	−5.7	4.8	0.874
Tariff level increase[2]	−3.6	3.4	−10.2	3.0	0.282
On-premises connections[3]	2.4	4.9	−7.3	12.0	0.631
Prepaid credit[3]	–	–	–	–	–
Model 4: Operator B (GH) (n = 35)					
Reference case (intercept)[1]	−5.2	5.5	−16.1	5.6	0.343
Tariff level increase[2]	46.4	31.6	−15.5	108.3	0.142
On-premises connections[3]	−234.8	292.9	−808.8	339.2	0.423
Prepaid credit[3]	–	–	–	–	–
Model 5: Operator C (GH) (n = 189)					
Reference case (intercept)[1]	**−28.4**	**3.2**	**−34.8**	**–22.1**	**<0.001**
Tariff level increase[2]	−1.6	6.1	−13.6	10.5	0.796
On-premises connections[3]	−20.9	12.5	−45.4	3.5	0.094
Prepaid credit[3]	1.1	18.5	−35.2	37.4	0.952
Model 6: Operator D (UG) (n = 10)					
Reference case (intercept)[1]	**−7.1**	**0.0**	**−7.1**	**7.1**	**<0.001**
Tariff level increase[2]	**−24.6**	**0.0**	**−24.6**	**−24.6**	**<0.001**
On-premises connections[3]	**54.0**	**0.0**	**54.0**	**54.0**	**<0.001**
Prepaid credit[3]	**32.2**	**0.0**	**32.2**	**32.3**	**<0.001**
Model 7: Operator E (UG) (n = 56)					
Reference case (intercept)[1]	**−39.5**	**3.9**	**−47.2**	**−31.8**	**<0.001**
Tariff level increase[2]	**−10.2**	**2.5**	**−15.1**	**−5.2**	**<0.001**
On-premises connections[3]	5.4	6.2	−6.8	17.5	0.387
Prepaid credit[3]	2.5	4.4	−6.1	11.2	0.565
Model 8: Operator F (UG) (n = 17)					
Reference case (intercept)[1]	**−38.4**	**13.9**	**−65.7**	**−11.1**	**0.006**
Tariff level increase[2]	**−27.7**	**8.1**	**−43.5**	**−11.9**	**0.001**
On-premises connections[3]	**55.3**	**27.0**	**2.4**	**108.1**	**0.040**
Prepaid credit[3]	**11.5**	**1.1**	**9.4**	**13.7**	**<0.001**

[1] Reference cases correspond to service areas where only off-premises connections and conventional payment approaches are employed with tariff levels held constant at the mean value for the cluster.

[2] Tariff level increase is modelled as a main effect.

[3] On-premises connections and prepaid credit parameters are modelled as interactions with mean-centred tariff level.

season. On-premises connections and prepaid credit payments are associated with significant revenue increases ($p < .05$) during the wet season for operators D and F (models 6 and 8, respectively). However, these results should be regarded with caution because the effects in each model are based on less than five percent of the service areas and seasonal transition records that comprise the full study dataset. When all records for the operators that experience seasonal revenue variability are clustered together (Model 2), tariff level increases and prepaid credit payments do not exhibit significant effects on seasonal revenue and on-premises connections are associated with a 13 percent revenue reduction during wet seasons ($p = .025$). We conclude from these results that tariff level adjustments, on-premises connections, and prepaid credit payments do not consistently mitigate seasonal revenue variability for the operators that experience it.

5. Discussion

Our findings underscore three implications for piped water revenue planning which can enhance the resiliency of infrastructure investments in rural Africa. First, piped water operators can expect to experience localised seasonal revenue reductions in areas characterised by consistent wet seasons. Second, seasonal revenue variability should be anticipated in these climate regimes regardless of whether waterpoint connections are located on or off premises and of how services are paid for. Third, intra-seasonal rainfall variability may lead to greater dependence on reliable, professional services in some sub-Saharan regions. We expand on these points here and address the limitations of our study.

Our first research question asks how seasonal rainfall influences revenue from user payments for rural piped water services. The results we present demonstrate seasonal shifts in rural piped water demand and quantify its impact on revenue generation in multiple sub-Saharan countries. We find operators that experience seasonal revenue variability collect on average 30 percent less revenue as demand falls during wet periods, the magnitude and direction of which agrees with seasonal water consumption patterns of rural households reported in the literature. Revenue projections that broadly assume consistent volumetric demand year-round may lead to shortfalls that threaten sustainability. To put the impact of this recurring deficit into perspective, the average annual financial loss due to nonrevenue water across sub-Saharan utilities is reportedly 34 percent (IBNET, 2020) which leads to substantial economic repercussions in the water supply sector (Liemberger and Wyatt, 2018). Furthermore, overestimating the ability of rural piped water services to generate revenue ultimately undermines the case for future investment. This study contributes to a more nuanced and accurate understanding of rural piped water demand and revenue dynamics relative to geospatial rainfall patterns, which can aid in effective resource allocation.

This study also informs approaches which might be adopted to address seasonal revenue variability. We pose a research question regarding the influence of several behavioural determinants on seasonal revenue patterns, including tariff level, connection type, and payment approach. While controlling for tariff level, we find on-premises connections are associated with similar levels of seasonal revenue variability as off-premises connections. This implies that upgrading rural piped water access from off-site to on-site, though potentially resulting in higher unit revenues (Armstrong et al., 2022), may not lead to more seasonally stable cash flows. Furthermore, we observe seasonal revenue reductions across all payment approaches included in our study and find prepaid credit payments are not consistently associated with less seasonal revenue variability than conventional payments. The tariffs in the study are based on volumetric water usage rather than fixed fees, which prevents examination of whether fixed fee payments stabilise seasonal revenue as prior evidence suggests (Armstrong et al., 2021). Revenue dynamics in this study are therefore expected to track with seasonal water demand with the most noticeable effect of payment approach being a temporal offset based on whether payments occur prior to, at the point of, or at some delayed frequency from water collection. It is plausible that users adjust seasonal water collection behaviours based on the frequency and way payments for services are collected, especially if they prepay days or weeks in advance of rainfall events. Furthermore, operators may make seasonal adjustments to their billing and payment collection practices depending on the modality by which users pay for services. Any of these payment and collection behaviours might intensify or mitigate seasonal revenue reductions. However, we do not find evidence to suggest the observed payment approaches have a predictable effect on seasonal revenue.

There may be a socioeconomic explanation for these inconsistent effects, which our dataset does not permit us to explore and is an area for future research. The seasonal water usage and payment behaviours of rural households in the observed piped water service areas may be influenced by a variety of factors such as cultural norms, education level, spending power and priorities, and perceptions of affordability. These factors likely interact with each other, and their influence may evolve over time. Yet even without thorough understanding of the underlying behavioural determinants of seasonal revenue variability, our findings motivate a close examination of the revenue assumptions that underpin widescale, capital-heavy investments in rural, piped on-premises connections and prepaid credit systems.

Our analysis indicates broad interventions aimed at incentivising water demand to reduce or eliminate the seasonal revenue threat to rural piped services may prove unsuccessful. Alternatively, ensuring availability of adequate financial resources throughout periods of reduced demand may the most effective way to mitigate the impact of seasonal revenue variability. We briefly highlight several promising approaches to this end, including cash flow planning, maintaining cash reserves, adjusting tariff rates on a seasonal basis, pooling financial risk, administering supply-side subsidies, and offering flexible loan repayment terms.

Cash flow planning is a logical and fundamental approach. Unlike financial shocks resulting from asset failures or natural disasters which are infrequent and somewhat unexpected, seasonal revenue variability occurs at a regular frequency and can be characterised. Planning can cushion shocks caused by interannual variability, and bulky expenditures such as capital maintenance projects or hiring new staff can be prioritised and sequenced to align with anticipated financial constraints.

Cash reserves are also generally recommended to compensate for revenue volatility of municipal water services (AWWA, 2018). However, the feasibility of rural African operators building and maintaining a reserve fund is low given the challenging economics (Hope et al., 2020) and recognised cost recovery constraints (McNicholl et al., 2019).

Seasonal tariff rate adjustments may be an effective financial management strategy recognising tariff margins during dry seasons can compensate for reduced demand during wet seasons (Andres et al., 2021). Although tariff level increases correlate with greater seasonal revenue falls for some operators in this study, our results do not present conclusive evidence that tariff variations consistently intensify or mitigate seasonal revenue variability. We therefore recommend tariff modifications be considered with caution.

Financial risk-sharing mechanisms such as insurance and derivatives are also sometimes adopted by water utilities in high-income countries to mitigate weather-related revenue threats (Alliance for Water Efficiency, 2014) and are gaining interest in rural areas of low- and middle-income countries (Koehler et al., 2018). Rainfall index-based crop insurance, which is conceptually similar and utilises a blended finance approach to mitigate climate risk for smallholder farmers, has also been applied in various forms across sub-Saharan Africa (Miranda and Mulangu (2016)). We observe revenue variability in some service areas but not in others suggesting financial risk may be pooled and reduced in an investment portfolio at some geographic scale. Although seasonal revenue variability is not eliminated when all observed service areas are combined (Model 1), there is less overall reduction in average revenue during wet seasons (13 percent overall revenue reduction compared to up to 40 percent experienced by individual operators).

Supply-side subsidies provided directly to service providers on a flexible or seasonal basis can provide a buffer against seasonal revenue shocks as well. Our results suggest this may be more effective at stabilising seasonal revenue than demand-side subsidies which aim to increase household connections or reduce the price users pay for water.

Finally, flexible loan terms, where repayments are based on percentage of water sales and therefore adjust to seasonal variations, can allow operators to avoid default during periods of reduced demand. This approach has been adopted with apparent success by the Cambodia Revenue Finance Facility (The Stone Family Foundation, 2018).

Our final research question asks which rainfall metrics are useful for characterising seasonal revenue variability. We find evidence that rural piped water revenue, hence demand for services, is relatively stable where *instances of dry days* during the wet season are more common. This type of intra-seasonal variability is a pronounced and localised rainfall feature across Africa (Kendon et al., 2019, Wainwright et al., 2021). Hydrologic instability is traditionally recognised as a threat to water security because it complicates the ability of water managers to ensure availability of adequate resources to all populations (Grey and Sadoff, 2007). Our findings further link rainfall patterns to water use and sustainability outcomes and demonstrate the importance of considering such patterns at local scales. The piped water operations observed in this study, particularly in southern Ghana and Rwanda, appear to exemplify a virtuous feedback loop of dependable services leading to consistent demand and revenue from user payments. However, such cases are rare in rural Africa and poor functionality with periods of downtime lasting for weeks is more the norm than the exception (Tincani et al., 2015). Where availability of seasonal rain-fed water sources are unpredictable, rural water users are not able to buffer daily water consumption from a secondary rain-fed source and are likely dependent on professional services. In an increasingly uncertain global climate, it is thus imperative that rural water services remain functionally reliable, financially viable, and affordable for all.

We identify several limitations to our study. The first is that our analysis is representative only at the scale of operations reflected in the multi-country dataset. Furthermore, the operational conditions of the individual piped water service areas and operators are not fully understood and therefore cannot be controlled via regression. Important covariates such as reliability of scheme performance, presence and condition of alternative water supply infrastructure, and changes in social and economic conditions are unknown. Such exogenous effects are more likely to manifest locally than regionally, introducing biases of unknown magnitude and direction. We therefore cannot rule out the possibility that observed differences in seasonal revenue variability across service areas are a result of contextual factors or operator-specific efficiencies. The original data are also prone to inadvertent recording errors and manipulation which can lead to imprecise or inaccurate results. This has been addressed through a systematic internal data validation and cleaning process involving dispersion and outlier analysis as described in the methodology. Lastly, the rainfall data are downscaled from the CHIRPS dataset to align with frequency and geolocation of operator data. Although the satellite-based estimates are validated against rain gauge data, ground truth observations are not available for the exact study locations.

6. Conclusion

Local revenue generation underpins delivery of drinking water services in rural Africa yet is threatened by seasonal rainfall and water usage patterns. We present evidence that intra-seasonal rainfall analysis can enhance rural piped water revenue planning by offering localised insight into water demand dynamics and revealing where climate variability may increase dependence on reliable services. The observed seasonal threat to rural piped water revenue in Ghana, Rwanda, and Uganda varies geospatially and appears to decrease with frequency of dry intervals during the wet season, which is a metric of rainfall variability. Our findings suggest piped water operators in rural Africa can expect to experience seasonal revenue reductions, an average of 30 percent across our dataset, in climate regimes where wet season rainfall is consistent. However, seasonal piped water revenue and hence demand for services appears stable where rainfall patterns are more erratic. On-premises connections do not consistently prevent falling demand and revenue during wet months when compared to off-premises connections at equivalent tariff levels. Likewise, we observe similar seasonal revenue falls among services that are paid for with traditional pay-as-you-fetch and monthly billing approaches as with prepaid credit.

Further research is needed to understand the contextual and behavioural determinants that influence rainfall-related revenue variability beyond those which were evaluated in this study, as well as how and why the phenomenon evolves over time. Future studies should explore rainfall and revenue variability at intra-seasonal scales, recognising climate impacts are likely to result from nuanced shifts in rainfall patterns as well as extreme weather events.

CRediT authorship contribution statement

Andrew Armstrong: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Project administration, Software, Validation, Visualization, Writing – original draft, Writing – review & editing. **Ellen Dyer:** Data curation, Software, Visualization, Writing – review & editing. **Johanna Koehler:** Supervision, Writing – review & editing. **Rob Hope:** Funding acquisition, Supervision, Writing – review & editing.

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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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.gloenvcha.2022.102592.

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