

# 1 In Situ, Modeled, and Earth Observation Monitoring of Surface Water 2 Availability in West African Rangelands

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## 19 Abstract

20 Rangeland ponds are vital to the livelihoods of pastoral and agropastoral communities in Africa,  
21 providing an important source of water for livestock. However, sparse instrumentation across much  
22 of Africa makes it extremely challenging to monitor surface water availability in these areas. Model  
23 estimates of surface water, for example as used by the Famine Early Warning Systems Network  
24 (FEWS NET) Water Point Viewer, are one of the few operational tools available to monitor surface  
25 water stress across pastoral areas of the Sahel and East Africa. Water availability data from these  
26 models are difficult to validate. New methods using satellite data to classify surface water provide an  
27 opportunity to assess the performance of these tools. This study compares water availability estimates  
28 derived from Landsat and Sentinel 1 satellite imagery to in situ observations and model simulations  
29 of water availability in 22 ephemeral ponds located in the Ferlo region of Senegal. The Active-  
30 Passive Water Classification (APWC) algorithm detected surface water at each location. Over 2022  
31 and 2023, water was detected in pond locations annually at a frequency of 68.2% for all ponds and at  
32 frequency of 43.8% in ponds with a surface area less than 10,000 square meters (m<sup>2</sup>). The APWC  
33 results outperform global and continental surface water datasets in the Ferlo region. Seasonal water  
34 availability was captured in twelve ponds over the 2022 and 2023 seasons. The twelve locations can  
35 function as sentinel ponds to monitor local water availability. Study results demonstrate the viability  
36 of satellite methods to assess water availability in the region as well as the challenges to using  
37 satellite-based methods to estimate water availability in small ponds.

## 38 1 Introduction

39 Monitoring and forecasting rangeland water availability is critical to food security early warning  
40 systems in Africa. Rangelands feed more than half of Africa's livestock, providing a source of  
41 income to 268 million pastoralists and agropastoralists (Liniger and Mekdaschi 2019). Rangeland  
42 ponds are a vital source of water for pastoral livestock, directly contributing to household food  
43 security and health (Grace and Davenport 2021). However, many African rangelands are in arid and  
44 semi-arid regions. Thus, pastoral livelihoods are extremely vulnerable to climate shocks like drought.  
45 In August 2023, the United States Agency for International Development's (USAID) Famine Early  
46 Warning Systems Network (FEWS NET) projected that >65 million people in sub-Saharan Africa  
47 with large rangelands areas required urgent food assistance (FEWS NET 2023).

48 The operational FEWS NET Water Point Viewer (Senay et al. 2013) is one of the few resources to  
49 monitor the status of surface water across pastoral areas of Sahelian and East Africa. The FEWS NET  
50 Water Point Viewer applies a water balance model over 338 small ponds to assess water stress at  
51 each location (USGS, USAID, and FEWS NET, n.d.). Water stress is determined by comparing daily  
52 estimates of water depth at each location to its climatological median water depth (Senay et al. 2013).  
53 Daily estimates of stress are provided on the FEWS NET Water Point Viewer, available at  
54 <https://earlywarning.usgs.gov/fews/waterpoint/index.php>. Indicators like water stress are important  
55 tool for assessing drought impacts on livelihoods. FEWS NET uses estimates of surface water  
56 availability from the FEWS NET Water Point Viewer to assess water stress experienced by livestock  
57 herds. This information is complementary to the water requirement satisfaction index for rangeland  
58 areas, which provides information on pasture health over the growing season (Senay et al. 2013).  
59 Livestock is critical to pastoral livelihoods and therefore food security in rangeland areas of Africa.  
60 However, sparse in situ hydrologic data across much of Africa has historically limited our ability to  
61 assess the performance of surface water models in estimating water availability.

62 Surface water classification methods using satellite remote sensing provide an opportunity to assess  
63 surface water availability in data-sparse regions. Data from passive optical sensors (e.g., Landsat and  
64 Sentinel 2) have been used to create global and continental-scale maps of surface waterbodies  
65 (Carroll et al. 2016; Feng et al. 2016; Mueller et al. 2016; Pekel et al. 2016). However, map  
66 resolution is coarse relative to the size of pastoral ponds, and time series miss a substantial amount of  
67 data due to clouds and other sensor errors. Recent work in the Ferlo region of Senegal using Landsat  
68 and high resolution PlanetScope data to map waterbodies (Mishra et al. 2020) and on the WENDOU  
69 platform (Water ENvironment Dashboard for Observation in support of Users; SERVIR 2023) shows  
70 promise, but is not yet used to routinely assess water availability. Synthetic aperture radar (SAR) data  
71 from active microwave sensors have been used alone as well as fused with optical sensors to generate  
72 time series of surface water extent (Slinski, Hogue, and McCray 2019; Huang et al. 2018; Pulvirenti  
73 et al. 2011; Schumann et al. 2011), wetlands inundation (Bourgeau-Chavez et al. 2005; Chapman et  
74 al. 2015; Rebelo, Senay, and McCartney 2012), and flood maps (Brakenridge and Kettner, n.d.;  
75 Salamon et al. 2021), but are not routinely used to map surface water in most rangeland regions in  
76 Africa. SAR-derived surface water maps are higher resolution and less affected by clouds, but  
77 classification accuracy is affected by layover, floating vegetation, as well as sand and other reflective  
78 surfaces. Confusion between sparsely vegetated landcover and open water is a particular challenge  
79 for SAR-based water classification in rangeland areas. However, combining SAR and optical sensor  
80 data, for example using the Active-Passive Water Classification (APWC), reduces errors associated  
81 with the individual sensor datasets (Slinski, Hogue, and McCray 2019).

82 The overarching goal of this study is to assess the potential of the APWC algorithm to validate  
83 modeled representation of water availability in rangeland areas. Previous studies have demonstrated  
84 the algorithm's ability to estimate water stress in the Awash River basin in Ethiopia (Slinski, Hogue,

85 and McCray 2019) and for small waterbodies in rangeland areas of East Africa (Slinski et al. 2020).  
86 This study expands this work, comparing surface water classification results derived from the APWC  
87 algorithm to in situ observations and model simulations of surface water availability in West Africa.  
88 The specific objectives of this study are to answer the following research questions:

- 89 1. To what extent can indicators from high resolution remote sensing data be used to assess  
90 water availability in rangeland ponds of West Africa?
- 91 2. To what extent can these indicators be used to assess model representation of surface water  
92 availability?

93 To address the first research question, in situ measurements of pond water depth collected during  
94 2022 and 2023 in the Ferlo region of northern Senegal are compared to surface water classification  
95 results derived from the APWC algorithm. To address the second research question, model-simulated  
96 estimates of pond water depth during 2022 and 2023 for locations monitored by the FEWS NET  
97 Water Point Viewer in the Ferlo region of northern Senegal are compared to surface water  
98 classification results derived from the APWC algorithm. This study is the first to compare in situ data  
99 to satellite estimates of surfaced water availability in small ponds (< 10,000 square meters [m<sup>2</sup>]) in  
100 the Sahel. This comparison allows a robust assessment of the skill of satellite estimates of water  
101 availability in this data sparse region. This study is also the first to use satellite estimates of surface  
102 water area to assess the model estimates of water availability in the Sahel.

## 103 **2 Materials and Methods**

### 104 **2.1 Study Area**

105 The study area (Figure 1) is an approximately 35,000-square-kilometer (km<sup>2</sup>) area of the Ferlo  
106 Region, a semi-arid pastoral zone in northern Senegal. This region is part of the Sahelian climate  
107 zone (Tappan et al. 2016). Annual rainfall over the study area ranges from 250 millimeters (mm) in  
108 the north to 480 mm in the southwest [Figure 2(A)]. Nearly all rainfall in this region falls during  
109 June, July, August, September, and October [Figure (2B)] as part of the West African Monsoon  
110 (WAM). The onset of the WAM corresponds with the northern migration of the Intertropical  
111 Convergence Zone (ITCZ). Monsoon rainfall intensity has been linked to the ITCZ; large-scale  
112 atmospheric circulation features such as the Tropical Easterly Jet, the African Easterly Jet, and the  
113 low-level African Westerly Jet; as well as the Saharan Heat Low (Nicholson 2013). Monthly  
114 precipitation for most of the 2022 and 2023 rainy seasons was above average across the study area  
115 [Figure 2(B)].

116 The primary landcover of the Ferlo Region is the Sahelian shortgrass savanna (Tappan et al. 2016).  
117 Livelihoods in the region are largely dependent on resident and transhumance herds of cattle, sheep,  
118 and goats that graze on the savanna, with some rain-fed subsistence agriculture (World Food  
119 Program et al. 2011). The region is characterized by a network of natural and constructed ephemeral  
120 ponds that fill during the WAM. These ponds are an important source of water for livestock during  
121 the rainy season, when the pastureland greens up and herds are dispersed across the region. When the  
122 ponds dry at the end of the rainy season, herds are moved to areas with a year-round source of water  
123 such the Sylvo-Pastoral Reserves, which are managed pastoral areas in the Ferlo Region where high-  
124 yield boreholes have been installed.

125 Twenty-two natural ponds (shown on Figure 1) are included in this study. Action Contre la Faim  
126 (ACF) collected in situ water depth measurements from 12 ponds (denoted as “ACF ponds”), and the

127 FEWS NET Water Point Viewer simulated water depth for 10 ponds (denoted as “FEWS NET  
128 ponds”). Remote sensing-based estimates of surface water extent were generated over all 22 ponds.

129 The following subsections provide additional detail on in situ, modeled, and remote sensing-based  
130 estimates of water availability for the ponds. Figures 3 and 4 show dry season imagery for the ACF  
131 and FEWS NET ponds, respectively. Pond size inferred from these images indicate that these are  
132 small ponds, with pond diameters ranging from approximately 25 to 200 meters (m).

## 133 **2.2 In Situ Observations of Water Depth**

134 ACF installed staff gauges in 12 ponds within the study area during July 2022. The gauges were  
135 installed at the approximate deepest point of each pond [Figures 5(A) and 5(B)]. Data enumerators  
136 documented pond depth at the gauge and extent of each pond [Figure 5(C)] over the 2022 and 2023  
137 rainy season and until each pond dried up. Data were collected approximately every two weeks from  
138 July to December 2022 and approximately six days from June to December 2023. Photographs were  
139 taken of the gauge, showing the water level reading, and of the pond, from the same vantage point for  
140 each reading. The photographs were transmitted to the ACF country office in Dakar, Senegal, for  
141 logging of the water level readings and filing of the photographs. For three locations, the staff gauge  
142 had to be decommissioned due to vandalism. In two of these locations, the gauge was moved to a  
143 pond in the same general area. The third gauge was not reinstalled. Data from vandalized gauges  
144 were discarded, resulting in shortened datasets for the Belel Mouthiatédé, Loumbal Demak, and  
145 Weendou Lamma 2 ponds.

146 Observed water levels were scaled as follows:

147 
$$\omega_s = \frac{\omega_i}{\omega_{max}} \times 100 \text{ (Equation 1)}$$

148 where  $\omega_s$  (%) is scaled water depth,  $\omega_i$  (meters) is measured water depth for the target month ( $i$ ), and  
149  $\omega_{max}$  (meters) is the maximum measured water depth. Scaling converts water depth to a unitless  
150 value in the range of 0 and 100. A similar approach was used to convert satellite and modeled  
151 estimates of water availability to the same range, as described in the next subsections. Scaling  
152 facilitates comparison between the satellite, in situ, and modeled estimates of water availability.

## 153 **2.3 Satellite Remote Sensing-Based Estimates of Water Availability**

154 Water availability was estimated from satellite datasets following the APWC algorithm developed by  
155 Slinski et al. (2019). APWC uses the K-means clustering algorithm to identify water and non-water  
156 from SAR and optical datasets. K-means clustering is a simple unsupervised machine learning  
157 algorithm (Lloyd 1982). The APWC algorithm was chosen because it is a rapid, computationally  
158 light surface water classification method that has been shown to accurately identify water bodies in  
159 rangeland areas of Africa (Slinski, Hogue, and McCray 2019).

160 The APWC algorithm was implemented in Google Earth Engine (GEE, Gorelick et al. 2017) using  
161 datasets obtained from the GEE data collections. First, monthly median composite grids of Sentinel 1  
162 SAR brightness and Landsat-derived modified normalized difference water index (MNDWI; Xu  
163 2006) values were generated over the study area for 100 target months: October 2015 - January 2023.  
164 The MDWI is used in the APWC algorithm because it performs better than other water classification  
165 indices such as the normalized difference water index (McFeeters 1996) and the automated water  
166 extraction index (Feyisa et al. 2014). Pixels were then grouped into k number of clusters using the K-  
167 means clustering algorithm and the cluster associated with surface water was identified. The final

168 dataset consists of 109 monthly, 10-m resolution grids covering the study area with each grid pixel  
169 classified as “Surface Water,” “Not Surface Water,” or “No Data.” The following paragraphs provide  
170 additional detail on this study’s implementation of the APWC algorithm for surface water  
171 classification. The Supplementary Material (SM) contains a flow chart of the APWC methodology.

172 The MNDWI was calculated as follows:

173 
$$MNDWI = \frac{G-SWIR1}{G+SWIR1} \text{ (Equation 2)}$$

174 where  $G$  is the visible green band and  $SWIR1$  is the short-wave infrared 1 band from the Landsat 8-9  
175 Tier 1 Collection 2 surface reflectance (SR; Vermote et al. 2016) and Landsat 7 Level 2, Collection  
176 2, Tier 1 SR (Masek et al. 2006) datasets.

177 Each satellite has a 16-day return period. The Landsat 8 satellite orbit is in an eight-day offset with  
178 the Landsat 7 and 9. Thus, the combined Landsat 7, 8, and 9 SR datasets provide data over the study  
179 area every 8 days. Table 1 presents additional information on the satellite platforms and associated  
180 datasets used to derive MNDWI. The MNDWI composites were generated as follows: (1) the  
181 MNDWI was calculated for each Landsat scene available over the study area for October 1, 2015,  
182 through February, 1, 2023; (2) a cloud and cloud shadow mask, derived from bits 3 and 4 of the  
183 Landsat 7, 8, and 9 Pixel Quality Assessment Band (QA\_PIXEL), was applied to each scene; and (3)  
184 the 31-day median composite MNDWI grid was derived for each target month by taking the median  
185 pixel value of the masked Landsat scenes collected +/- 15 days around the 15<sup>th</sup> day of the target  
186 month. This method was followed for each month, with the following exception: cloud and cloud  
187 shadow contamination present over the south-central and southwest region of the study area during  
188 August 2022 was not identified in the QA\_PIXEL and was masked manually. This affected August  
189 2022 results for ACF ponds Weendou Howandou, Weendou Namma, and Weendou Mbayla. The  
190 FEWS NET pond locations were not affected.

191 Thirty-one-day median composite SAR brightness grids were derived from Sentinel 1A  
192 interferometric wide-swath ground range detected (GRD) data (Torres et al. 2012) with the vertical  
193 transmit-vertical receive (VV) polarization. Sentinel 1B data are not available over the study area.  
194 This study uses VV polarization because it performs better than vertical transmit-horizontal receive  
195 (VH) polarization at detecting water (Twele et al. 2016). Ascending and descending data are  
196 available for some regions. However, only ascending data are available for the study area. Table 1  
197 presents additional information on the Sentinel 1A platform and associated dataset. GEE applied the  
198 following preprocessing routines to the GRD images used in this study: orbital file application,  
199 border noise removal, thermal noise removal, radiometric calibration, terrain correction, and  
200 conversion of the detected backscatter coefficients to decibels. Pixel values represent the detected  
201 backscatter coefficient in decibels, which is also referred to as “brightness.” Consistent with the  
202 MNDWI composite calculation, 31-day median composite SAR brightness grids were derived for  
203 each target month by taking the median pixel value of the SAR scenes collected +/- 15 days around  
204 the 15<sup>th</sup> of the target month.

205 Following derivation, the MNDWI and SAR brightness median composites were resampled to a  
206 common, 10-m resolution grid projected to the Universal Transverse Mercator 28 North (UTM 28N)  
207 coordinate system. Pixels were grouped into  $k$  number of clusters using the cascade simple K-means  
208 clustering algorithm, where the best  $k$  was selected following Caliński and Harabasz (1974). Finally,  
209 the cluster number associated with Lac de Guiers, an area of known permanent surface water in  
210 northern Senegal, was identified as the reference surface water cluster. Pixels with K-means output

211 matching the reference cluster number were classified as “Surface Water.” The remaining pixels  
212 were classified as “Not Surface Water” or “No Data.” This method produced a 10-m resolution  
213 surface water grid for each of the target months, with each grid pixel classified as “Surface Water,”  
214 “Not Surface Water,” or “No Data.”

215 There are several limitations to the APWC method. The APWC method requires a valid Landsat-  
216 derived MNDWI and SAR brightness value for pixel classification. This study uses 31-day  
217 compositing to minimize the impact of data gaps in individual Landsat and SAR scenes. However,  
218 sporadic data gaps remained in monthly composites of MNDWI due to clouds and cloud shadows.  
219 Additionally, Sentinel 1A scenes for portions of the study area are missing from the GEE archive for  
220 several dates, including July 2022, July 2023, and October 2023. The “No Data” label was applied to  
221 pixels where the MNDWI and/or the SAR brightness value for the target month was not available.  
222 Slinski et al. (2019) discusses additional method limitations, including errors of commission when  
223 water is incorrectly identified in both the MNDWI and SAR brightness datasets and errors of  
224 omission due to the presence of floating vegetation and tree canopy in pond areas.

225 The area of the surface water pixels associated with each pond was summed by month and scaled as  
226 follows:

$$227 \quad a_s = \frac{a_i}{a_{max}} \times 100 \text{ (Equation 3)}$$

228 where  $a_s$  (%) is scaled pond surface water area,  $a_i$  (square meters) is the total pond surface water  
229 area for the target month ( $i$ ), and  $a_{max}$  (square meters) is the maximum surface water area detected  
230 over the period assessed. Scaled surface water area results were compared to scaled observations of  
231 water depth to assess the performance of the water classification approach.

232 The APWC results for October 2015 through December 2023 were used to derive estimates of  
233 surface water occurrence at each location. Surface water occurrence for each calendar month was  
234 calculated by pixel as follows:

$$235 \quad occ_{i,m} = \frac{SW_{i,m}}{Obs_{i,m}} \times 100\% \text{ (Equation 4)}$$

236 where  $occ_{i,m}$  is surface water occurrence for pixel  $i$  and calendar month  $m$ ,  $SW_{i,m}$  is the count of the  
237 number of times surface water was detected for the pixel and calendar month, and  $Obs_{i,m}$  is the count  
238 of the number of “Surface Water” and “Not Surface Water” observations for the pixel and calendar  
239 month. “No Data” pixel classifications are not included in the calculation. 100% surface water  
240 occurrence indicates that surface water was detected in the pixel for all valid observations for the  
241 month while 0% surface water occurrence indicates that surface water was never detected.

## 242 **2.4 Model-Based Estimates of Water Availability**

243 Modeled estimates of water availability in ponds within the study area were obtained from the FEWS  
244 NET Water Point Viewer. Water availability estimates were generated using the water balance model  
245 described by Senay et al. (2013) as follows:

$$246 \quad \Delta D = P + R_{in} - R_{out} - E - S \text{ (Equation 5)}$$

247 where  $\Delta D$  (meters) is change in pond water depth, and  $P$  (meters) is satellite precipitation over the  
248 pond from the CHIRPS data (Funk et al. 2015) precipitation product.  $R_{in}$  (meters) is watershed runoff

249 into the pond estimated using the Soil Conservation Service Curve Number method (Cronshey 1986).  
250  $R_{out}$  (meters) is outflow from the pond that occurs when the water level exceeds maximum capacity,  
251 which is assumed to be 2 m for each pond.  $S$  (meters) is pond seepage, estimated to be a constant  
252 0.002 m/day.  $E$  (meters) is open-water evaporation from the pond, calculated as:

253 
$$E = 1.05 \times ET_o \text{ (Equation 6)}$$

254 where  $ET_o$  is climatological reference evapotranspiration calculated using the American Society for  
255 Civil Engineers formulation of the Penman–Monteith method (Allen et al. 1998). The model assumes  
256 that the pond has negligible inflow from groundwater. The surface area of each pond was delineated  
257 from ASTER satellite imagery and is kept constant over time in the model.

258 For the purposes of this analysis, modeled pond depth was transformed to scaled pond depth  
259 following Equation 1, consistent with the approach used to scale the observed pond depths.

260 Modeled estimates of water availability were obtained for the ten FEWS NET ponds shown on  
261 Figure 1. At the time of writing, modeled water depth estimates were not available for the ponds  
262 equipped with staff gauges. One additional location, FEWS NET pond SN08, is located within the  
263 study area but was not included in this analysis for data quality reasons; its behavior was an outlier  
264 relative to nearby pond SN51 as well as the rest of the ponds included in the analysis.

## 265 **2.5 Precipitation Data**

266 Water availability estimates at each location were compared to monthly rainfall estimates from the  
267 Climate Hazards Group InfraRed Precipitation with Station (CHIRPS) precipitation product.  
268 CHIRPS estimates rainfall by blending rain gauge data with satellite precipitation estimates from  
269 thermal infrared cold cloud duration statistics (Funk et al. 2015). The CHIRPS precipitation product  
270 has a  $0.05^\circ \times 0.05^\circ$  degree spatial resolution. The catchment area of the ponds used in this study is less  
271 than 2 km<sup>2</sup>. Therefore, catchment area precipitation was estimated as the precipitation associated with  
272 pixel overlaying the pond location.

## 273 **3 Results**

### 274 **3.1 Satellite-Based Surface Water Classification Results**

275 This study found that surface water was detected by the APWC method at each of the 22 pond  
276 locations. Figures 6 and 7 show surface water occurrence estimates for each of the ACF and FEWS  
277 NET ponds, respectively. Surface water classification of ponds was affected by the small size of  
278 some ponds. Over 2022 and 2023, water was detected in pond locations annually at a frequency of  
279 68.2% for all ponds and at frequency of 43.8% in ponds with a surface area less than 10,000 m<sup>2</sup>. The  
280 SM contains water classification results for each month and pond over the 2022 and 2023 seasons.

281 The satellite-based surface water classification results were also impacted by missing data. Partial  
282 results for July 2022 and 2023 are due to missing Sentinel 1A scenes and partial results for August  
283 and September 2022 and October 2023 are due to cloud cover and cloud shadows in Landsat scenes.  
284 The pixels affected by the missing data are classified as “No Data” on the surface water classification  
285 maps included in the SM.

286 Surface water classification results at twelve locations (Gowe, Loumbal Demak, Loumbal Peniol  
287 Naydé, Weendou Lamma 2, Weendou Mawndou Mbelogne, Weendou Soukoundou, SB38, SN39,

288 SN40, SN46, SN50, and SN51) identified surface water for three or more consecutive months during  
289 2022 and 2023. This allowed inference of seasonality (i.e., the seasonal progression of pond filling  
290 and drying at those locations).

291 The primary reasons that the APWC method failed to capture seasonality during 2022 and 2023 in  
292 the remaining ten locations are 1) the small pond size ( $< 10,000 \text{ m}^2$ ) and 2) the presence of  
293 vegetation. Seven of the locations (Bele Mouthiatédé, Weendou Mbayla, Weendou Namma, SN09,  
294 SN10, SN47, and SN48) are less than  $10,000 \text{ m}^2$ . Three ponds (Weendou Howandou, Weendou  
295 Ngueso Lombel, and Weendou Soukoundou) had substantial tree cover, e.g., as illustrated for  
296 Weendou Soukoundou on Figure 8. Algae or floating vegetation (Figure 8) may also have affected  
297 the detection of surface water at some pond locations. Additionally, the missing data for July 2022  
298 and 2023 limited the assessment of the timing of pond filling at the start of the season.

### 299 **3.2 In situ Water Depth Observations**

300 The in situ water depth observations show that all ACF ponds contained water during the 2022 and  
301 2023 rainy seasons (Figure 9). The timing of pond filling following the onset of the Ferlo rainy  
302 season and pond drying up lagging its end by one to three months (Figure 9). All ponds where  
303 observations were collected during July and August contained water by the first week of August.  
304 Pond depths reached near-maximum levels within a month of the first observation of water in the  
305 pond and maintained that level for most of the rainy season. The ponds progressively dried up from  
306 September to January, after the end of the rainy season. Bele Mouthiatédé dried up in September  
307 2022, but subsequently refilled and contained water until the end of October 2022. All other ponds  
308 contained water from the date of the first observation of water until the date of the first dry  
309 observation.

### 310 **3.3 Comparison of Satellite-Based Surface Water Classification Results to In situ Data**

311 The satellite-based surface water classification results for six ACF ponds (Gowe, Loumbal Demak,  
312 Loumbal Peniol Naydé, Weendou Lamma 2, Weendou Mawndou Mbelogne, Weendou  
313 Soukoundou,) were compared in situ measurements of seasonal water availability. These ponds were  
314 selected because the satellite-based surface water classification results allowed inference of the  
315 seasonal progression of pond filling and drying). Figure 10 compares scaled in situ measurements of  
316 water depth to scaled satellite estimates of water area for these ponds. The SM contains plots  
317 showing scaled and unscaled comparisons for all ACF ponds.

318 This study found good correspondence between the in situ measurements of water depth and satellite-  
319 based estimates of water area during the middle and end of the season (as depicted on Figure 10).  
320 However, early season comparisons for 2022 and 2023 cannot be made due to missing data for the  
321 month of July. Correlation or other statistical metrics were not calculated because of the small sample  
322 size. The SM contains plots showing unscaled depth measurements and surface water area for the  
323 ACF ponds.

### 324 **3.4 Comparison of Satellite-Based Surface Water Classification Results to Modeled Data**

325 The satellite-based surface water classification results for six FEWS NET ponds (SB38, SN39, SN40,  
326 SN46, SN50, and SN51) allowed inference of the seasonal progression of pond filling and drying.  
327 The satellite-based surface water classification results for these ponds were compared modeled  
328 estimates of seasonal water availability. Figure 11 compares scaled modeled estimates of water depth

329 to scaled satellite estimates of water area for these ponds. The SM contains plots showing scaled and  
330 unscaled comparisons for all FEWS NET ponds.

331 Model simulations show all FEWS NET ponds containing water during the 2022 and 2023 season,  
332 with all ponds beginning to fill during July, drying up during April/May 2023, and containing water  
333 at the end of December 2023 (Figure 11). This study found good correspondence between the  
334 modeled estimates of water depth and satellite-based estimates of water area during the middle of the  
335 season (as shown on Figure 12).

336 Correspondence during the early season was mixed. For one location, SN38, 2022 season pond  
337 filling in the satellite-based dataset matches the model (i.e., both begin in July 2022). 2022 season  
338 satellite-based estimates of pond filling are earlier than model estimates at four locations (SN39,  
339 SN40, SN50, and SN51), with these ponds filling in June 2022. The discrepancy between the model-  
340 and satellite-based estimates of water availability in June 2022 at these locations may be due to  
341 model parameterization and/or underreporting of June precipitation in the CHIRPS product. The  
342 presence of June 2022 water in these ponds is not considered a water classification error because it is  
343 consistent across all locations in the eastern portion of the study area where satellite-based time series  
344 were successfully derived, e.g., ACF pond Weendou Lamma 2. The timing of pond filling could not  
345 be determined due to missing data for the sixth location, SN36, in 2022 and for all locations in 2023.  
346 It appears likely that unseasonal above-normal rains in June may have been poorly captured by the  
347 CHIRPS version 2. This may be due to a systematic under-representation precipitation variance; this  
348 issue should be less pronounced in CHIRPS version 3 (UCSB CHC, n.d.).

349 A major difference between modeled and satellite-derived time series of water availability is the  
350 timing that the pond dried up. As shown on Figure 12, the satellite-derived time series indicate that  
351 all ponds dried up or were near-dry by the end of December of each year. This is consistent with the  
352 in situ water depth observation time series. The water point model simulations retained water in the  
353 ponds past December. The longer retention of pond water in the model simulation may be due to a  
354 model parameterization error, e.g., the modeled pond surface area may be smaller than the observed  
355 pond capacity or the model could underestimate seepage. A larger pond watershed area could also  
356 increase overall pond depth and thus lead to larger and longer storage. It might also be due to  
357 underestimation of open-water evaporative demand ( $E$  in Equation 5). Underestimates of seepage ( $S$   
358 in Equation 5) are also possible.

#### 359 **4 Discussion**

360 Rangeland surface water is vital to the livelihoods of pastoral and agropastoral communities in  
361 rangeland regions of Africa. Modeling systems such as the FEWS NET Water Point Viewer  
362 described by Senay et al. (2013) provide one of the few resources to monitor the status of surface  
363 water across pastoral areas of the Sahel and East Africa. However, sparse in situ hydrologic data  
364 across much of Africa limit the ability to assess the performance of these models. Satellite remote  
365 sensing-based surface water classification methods such as the APWC algorithm have been shown to  
366 be a viable approach to assess water availability in the small ponds used by pastoral communities  
367 (Slinski, Hogue, and McCray 2019). The overarching goal of this study was to assess the potential of  
368 the APWC algorithm to fill this gap. The study demonstrates the viability of this approach for  
369 assessing surface water availability in the Ferlo region of Northern Senegal as well as the challenges  
370 to satellite-based estimates of water availability in small ponds. The main findings of the study are  
371 discussed below, by research question.

372 **4.1 Research Question 1: To what extent can indicators from high resolution remote sensing**  
373 **data be used to assess water availability in rangeland ponds of West Africa?**

374 Water occurrence derived from the APWC surface water extent estimates for 2015-2023 (Figures 6  
375 and 7) show that the APWC method successfully detected water at all 22 pond locations. 2022-2023  
376 annual detection frequencies for small ponds (less than 10,000 m<sup>2</sup>) and for all ponds are 43.8% and  
377 68.2%, respectively. The APWC results outperformed water occurrence products produced by the  
378 Global Surface Water Explorer (Pekel et al. 2016) and the Water Observations from Space (WofS)  
379 (Halabisky et al. 2024). Both datasets are 30-m resolution products derived from Landsat data. The  
380 Global Surface Water Explorer identified water in three of the 22 locations and WofS identified  
381 water in 19 of the 22 locations. 2022-2023 annual detection frequencies from WofS for small ponds  
382 and all ponds are 37.5% and 65.9%, respectively.

383 Mishra et al. (2020) derived annual detection frequencies for 867 small ponds in the Ferlo region of  
384 Senegal for one year, 2018, from Landsat and PlanetScope data. The APWC-derived surface water  
385 classification performed better than the Landsat classification method used by Mishra et al. (2020),  
386 which reported annual detection frequencies of 21.6% for small ponds and 31.7% for all ponds.  
387 PlanetScope are high resolution (3-m) surface reflectance data. Mishra et al. (2020) reports that water  
388 classification from these data performed considerably better, with an annual detection frequency of  
389 97.3% for small ponds. This demonstrates PlanetScope's promise for monitoring surface water in  
390 small ponds like those in the Ferlo region. However, PlanetScope data can be challenging to work  
391 with, particularly for time series applications over large domains, due to calibration issues,  
392 inadequate data flags, and the large volume of data (Mishra et al. 2020; Wang et al. 2021; Mullen et  
393 al. 2023). More recent work by Mullen et al. (2023) using PlanetScope data to identify the seasonal  
394 dynamics of small ponds (<10,000 m<sup>2</sup>) in the Alaskan tundra indicate that the more advanced Dove-  
395 R and Super Dove platforms and updated processing algorithms (Planet Labs PBC 2023) reduce, but  
396 do not fully resolve these issues. Key advantages of the APWC algorithm are its computational  
397 efficiency, use of longer and stable datasets, and ability to be implemented in the GEE cloud-  
398 computing environment (Slinski, Hogue, and McCray 2019).

399 Water classification maps included in the SM show that seasonality over the 2022 and 2023 seasons  
400 can be inferred from the surface water estimates for twelve locations: six ACF ponds and six FEWS  
401 NET ponds. The APWC-derived surface water area estimates for 2022 and 2023 for the six ACF  
402 ponds were then compared to in situ observations of water depth collected over the same period. The  
403 remote sensing-derived and in situ time series shown on Figure 10 indicate that the timing that water  
404 is available in the ACF ponds is generally consistent between the two datasets. The APWC-derived  
405 seasonality could not be directly compared to the results reported by Mishra et al. (2020) or the  
406 WofS datasets for 2022 and 2023.

407 Surface water classification at all locations was limited by data gaps due to missing SAR data and  
408 cloud/cloud shadow contamination of MNDWI data. Missing SAR data for July 2022 and 2023  
409 limited the assessment of water availability during the onset of the rainy seasons, when ephemeral  
410 ponds in the study area begin to fill. However, APWC-derived surface water extent estimates for this  
411 critical period are available in the longer dataset used to derive the occurrence maps (covering 2015-  
412 2023). Cloud cover and cloud shadows also impacted the surface water classification results, but are  
413 a minor limitation to the application of the APWC method in this region.

414 Surface water classification was also impacted by tree cover, algae, and floating vegetation.  
415 Classification in areas impacted by vegetation could be improved by including SAR data with longer

416 wavelengths in the APWC algorithm, which better penetrate vegetation. The NASA-ISRO SAR  
417 (NISAR) mission employs L-band radar, which has a longer wavelength than the C-band data  
418 provided by the Sentinel 1A sensors. The longer wavelength will help overcome this issue but is not  
419 likely to eliminate it entirely.

420 These results demonstrate that APWC method is a viable approach for assessing surface water  
421 availability in the Ferlo region of Senegal. The method was not able to generate surface water time  
422 series for all ponds, showing the importance of physical characteristics of the ponds such as size and  
423 presences of vegetation overlaying water surface as well as gaps in the satellite datasets, on method  
424 performance. However, seasonality is not expected to vary widely across the region. Therefore,  
425 changes to model parameters to improve performance at locations where the APWC method was  
426 successful may be extended to nearby locations where seasonality was not captured by the method.

#### 427 **4.2 Research Question 2: To what extent can these indicators be used to assess model** 428 **representation of surface water availability?**

429 The APWC-derived surface water area and modeled water depth time series shown on Figure 12  
430 indicate that, while the timing that the ponds fill and start to dry up is generally consistent between  
431 the datasets, there are two notable differences. The remote sensing-based dataset identified water in  
432 June 2022 for four locations (SN39, SN40, SN50, and SN51), while the model simulations showed  
433 pond filling starting in July 2022. In addition, the remote sensing-based dataset indicated that all six  
434 ponds dried up by December during the 2022 and 2023 seasons, while the model simulations showed  
435 the ponds containing water past December. The differences in the two datasets may be attributed to  
436 errors in model parameters (e.g., pond surface area, watershed area, maximum pond depth, etc.),  
437 model forcing data (e.g., precipitation, open-water evaporation, etc.), and/or surface water  
438 classification. Furthermore, the runoff estimation method could be a source of error and future efforts  
439 will evaluate the potential of using other techniques such as the saturation excess principles to  
440 simulate the rainfall-runoff process. Like the ACF ponds, missing SAR data for July 2022 and 2023  
441 limited the assessment of water availability during the onset of these rainy seasons, but APWC-  
442 derived surface water extent estimates for July are available in the longer dataset used to derive the  
443 occurrence maps. This assessment shows the utility of satellite remote sensing-based surface water in  
444 assessing model simulations of surface water availability in the Study Area. The method is subject to  
445 the previously mentioned challenges due to the physical characteristics of the ponds and data gaps in  
446 the satellite datasets.

#### 447 **4.3 Concluding Remarks**

448 Remote sensing-based surface water classification using high resolution satellite datasets provides an  
449 important opportunity to assess surface water availability in pastoral and agropastoral regions, where  
450 surface water is critical to community livelihoods. This study demonstrates the ability of the APWC  
451 method to generate surface water extent datasets for ponds in the Ferlo region of northern Senegal  
452 that can be used to assess the representation of water availability by the FEWS NET Water Point  
453 Viewer. This dataset is an important tool to assess the performance of hydrologic models that would  
454 not otherwise be available in data sparse areas like northern Senegal. Future work will assess to what  
455 extent the new surface water estimates can be used to tune model parameters to improve the  
456 performance of the FEWS NET Water Point Viewer. This may be done by comparing modeled  
457 estimates of surface water area to satellite-derived estimates. Future work will also assess  
458 improvement to satellite-based estimates of surface water area in the Sahel using datasets from new  
459 sensors, e.g. NISAR L-band data and PlanetScope Dove-R/Super Dove platforms.

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## 480 7 References

481 Figure 1: Location of the study area and ponds included in this study. Action Contre la Faim (ACF)  
482 pond locations are indicated by orange dots and Famine Early Warning Systems Network (FEWS  
483 NET) pond locations are indicated by green dots. Imagery: ©2023 TerraMetrics, Map data: ©2023  
484 Google.

485 Figure 2: Panel (A) (top) shows mean annual precipitation over the study area based on Climate  
486 Hazards Group InfraRed Precipitation with Station (CHIRPS) precipitation (Funk et al. 2015) for  
487 1993-2023. Panel (B) (bottom) shows boxplots of monthly CHIRPS precipitation for 1993-2023 and  
488 monthly 2022 and 2023 CHIRPS precipitation as green and yellow dots, respectively. The upper and  
489 lower boxplot hinges represent the first and third quartiles (25th and 75th percentiles), respectively,  
490 and the whiskers extend to the largest/smallest value no farther than 1.5 times the interquartile range  
491 from the upper/lower hinge. Monthly precipitation is calculated as the mean precipitation over the  
492 study area.

493 Figure 3: Dry season satellite images of the 12 Action Contre la Faim (ACF) ponds. Map projection:  
494 UTM 28N, Imagery: ©2023 TerraMetrics, Map data: ©2023 Google.

495 Figure 4: Dry season satellite images of the 10 Famine Early Warning Systems Network (FEWS  
496 NET) ponds. Map projection: UTM 28N, Imagery: ©2023 TerraMetrics, Map data: ©2023 Google.

497 Figure 5: Panel (A) (left) and Panel (B) (center) show photographs of staff gauge installation. Panel  
498 C (right) shows a photograph of staff gauge reading.

499 Figure 6: Percent surface water occurrence by month for the 12 Action Contre la Faim (ACF) ponds  
 500 from October 2015 to December 2023. 100% surface water occurrence indicates that surface water  
 501 was detected in the pixel for all valid observations for the month while 0% surface water occurrence  
 502 indicates that surface water was never detected.

503 Figure 7: Percent surface water occurrence by month for the 10 Famine Early Warning Systems  
 504 Network (FEWS NET) ponds from October 2015 to December 2023. 100% surface water occurrence  
 505 indicates that surface water was detected in the pixel for all valid observations for the month while  
 506 0% surface water occurrence indicates that surface water was never detected.

507 Figure 8: Panel (A) shows floating vegetation at the Weendou Namma pond. Panel B shows tree  
 508 cover at the Weendou Soukoundou pond.

509 Figure 9: Panel A (top) shows total monthly Climate Hazards Group InfraRed Precipitation with  
 510 Station (CHIRPS) precipitation (Funk et al. 2015) at each Action Contre la Faim (ACF) pond. Panel  
 511 (B) (bottom) shows in situ water depth measured at each ACF pond.

512 Figure 10: Comparison of scaled RS Area as percent of maximum measured and scaled In situ Depth  
 513 as percent of maximum measured for Gowe, Loumbal Demak, Loumbal Peniol Naydé, Weendou  
 514 Lamma 2, Weendou Mawndou Mbelogne, and Soukoundou ponds (Panels (A), (B), (C), (D), (E),  
 515 and (F) respectively).

516 Figure 11: Panel (A) (top) shows total monthly Climate Hazards Group InfraRed Precipitation with  
 517 Station (CHIRPS) precipitation (Funk et al. 2015) at each Famine Early Warning Systems Network  
 518 (FEWS NET) pond. Panel (B) (bottom) shows mean monthly water depth modeled at each FEWS  
 519 NET pond.

520 Figure 12: Comparison of scaled RS Area as percent of maximum measured and scaled Modeled  
 521 Depth as percent of maximum measured per month for SN38, SN39, SN40, SN46, SN50, and SN51  
 522 ponds (panels (A), (B), (C), (D), (E), and (F), respectively).

523 Table 1: Characteristics of the satellite platforms and associated datasets used by the Active-Passive  
 524 Water Classification (APWC) algorithm.

	<i>Landsat 7</i>	<i>Landsat 8/9</i>	<i>Sentinel 1A</i>
<i>Product</i>	Landsat 7 Level 2, Collection 2, Tier 1 surface reflectance (Masek et al. 2006)	Landsat 8-9 Tier 1 Collection 2 surface reflectance (Vermote et al. 2016)	Interferometric wide-swath ground range detected (GRD) (Torres et al. 2012)
<i>Band(s)</i>	Green: Band 2	Green: Band 3	VV receiver polarization

	(0.52 - 0.60 $\mu\text{m}$ )	(0.53 - 0.59 $\mu\text{m}$ )	
	SWIR (short- wave infrared): Band 5, (1.55 - 1.75 $\mu\text{m}$ )	SWIR: Band 6, (1.57 - 1.65 $\mu\text{m}$ )	
<i>Spatial Resolution</i>	30 meters	30 meters	10 meters
<i>Platform Return Period</i>	16-day	16-day	12-day
<i>Record</i>	Jan. 2015- Sept. 2021	Landsat 8: Jan. 2015- Dec. 2023  Landsat 9: Oct. 2021- Dec. 2023	Jan. 2015-Dec. 2023