REPORT

Mapping Agricultural Water Dynamics and Management Pathways in Kenya's Central Highlands

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CGIAR Sustainable Farming Program

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Contents

Introduction

Data-driven Approaches for Sustainable Water and Agriculture

The growing pressures of population growth, land use change, and climate variability are reshaping how societies interact with natural resources, particularly water (Abungba et al., 2022; Elmhagen et al., 2015; Rotich et al., 2022). Agriculture remains the single largest consumer of freshwater worldwide, accounting for close to 70% of withdrawals, and this dependence underscores the urgent need for smarter water management (Gupta et al., 2020). Without innovative approaches, competing demands across food production, domestic use, and ecosystems will intensify, threatening both livelihoods and environmental sustainability (Ladson & Finlayson, 2002; Obiero et al., 2024; Van de Giesen et al., 2001).

Agriculture is central to Kenya's economy and food security, contributing significantly to national GDP and supporting the livelihoods of most rural households (Ochieng et al., 2016; Recha, 2019; World Bank Group, 2018). Yet the sector is highly vulnerable to water scarcity and climatic variability. With more than four-fifths of cultivated land dependent on rainfall, crop yields fluctuate with shifting precipitation patterns, and recurrent droughts and floods intensify risks to both farmers and ecosystems (Kogo et al., 2021; Ochieng et al., 2016).

Recent advances in data science and geospatial technologies have opened new frontiers for managing water in agriculture. Tools that integrate in situ climate records and remote sensing provide insights into water availability and demand, thereby linking hydrology and agriculture (Bhaga et al., 2020; Owusu, Kagone, et al., 2024; Thenkabail et al., 2009). Such innovations shift decision-making from a reactive to a proactive approach, empowering planners, policymakers, and farmers to optimize water allocation, identify stress hotspots, and adapt production systems under changing conditions. This project uses the Scale Invariant Water Accounting Plus (SIWA+) framework to provide water accounts that quantify inflows, outflows, and consumption at multiple scales; and the Securing Water Use in Agriculture (SWAG) tool, which focuses on crop-level dynamics, estimating crop water requirements and highlighting areas of water over-use in irrigation (i.e. surplus) or water stress (i.e. deficit). An additional component under the SWAG tool assesses the potential of small water storages to supplement deficits (Owusu, Matheswaran, et al., 2024). Together, the outputs generate insights that are critical for understanding potential water limiting constraints (i.e. scarcity and overuse) to agricultural production and identifying agronomic practices and interventions to support climate resilience, guiding investment decisions, and informing policy in agricultural water management.

Building Upon Earlier Work in the Central Highlands Ecoregion Foodscape (CHEF)

This work builds upon the earlier work conducted by (Owusu, Matheswaran, et al., 2024) in support of The Nature Conservancy (TNC) program in the Central Highlands Ecoregion Foodscape (CHEF) under the Excellence in Agronomy (EiA) initiative (Owusu, Matheswaran, et al., 2024). The CHEF program seeks to transform central Kenya into a regenerative foodscape, where agricultural practices improve soils and water resources while conserving biodiversity.

Earlier work under CGIAR Excellence in Agronomy demonstrated the potential of combining SIWA+ and SWAG in Kenya's CHEF region. That study provided the first integrated baseline of water accounts and crop water deficits in the region. However, it relied solely on remote sensing data for the former, and for the latter, it was limited to a single year (2021) and relatively coarse evapotranspiration (ET) inputs. The present study under the Sustainable Farming Science Programme, builds on this foundation with four major advances:

- Updated SIWA+ water accounting: By incorporating bias-corrected precipitation and river discharge data, the updated framework delivers more accurate and reliable water accounts and basin closure fractions. These results are now available not only for the 11 counties that make up the CHEF foodscape but also the CHEF region as a single unit.
- Extended and higher-resolution SWAG analysis: The crop water deficit and surplus assessment now covers a five-year period (2019–2023) and uses 30 m resolution Simplified Surface Energy Balance (SSEBop) (G. B. Senay et al., 2020) evapotranspiration (ET) datasets, allowing for a far more detailed analysis of spatial and temporal dynamics.
- Practical decision-support outputs: New workflows produce monthly indicators of the leading deficit and surplus crops, clarifying which production systems are most consistently stressed and when. These insights can then directly link to opportunities for intervention, such as targeting irrigation, promoting drought-resistant varieties, or improving on-farm water management.
- Integration of storage solutions: A storage assessment tool (SAT) has been added to simulate the performance of small-scale water harvesting structures (e.g., ponds of about 1,000 m³ in volume),

identifying where localized storage could buffer monthly deficits and improve reliability for farmers (G. Senay & Verdin, 2004). Studies demonstrate that supplemental irrigation volumes of about 100–150 mm, applied strategically at critical crop stages, can substantially stabilize crop yields and reduce rainfall-induced variability across semi-arid regions (Gadédjisso-Tossou et al., 2018). Likewise, on-farm experiments show that even modest applications of supplemental irrigation (60–90 mm per season) from small (approximately 150m^3) manually dug ponds significantly increased sorghum yields by up to threefold when combined with nutrient management (Fox & Rockström, 2003; Vico et al., 2020). The 1,000 m^3 pond capacity aligns with these findings and is grounded in typical crop water demand estimates for maize in semi-arid climates, while also balancing construction feasibility and safety on one hand and storage efficiency on the other. A maize crop over a 90-day growing period requires approximately 400–500 mm of water (Allen et al., 1998; Gadédjisso-Tossou et al., 2018; G. Senay & Verdin, 2004). Under these conditions, and accounting for seepage and evaporative losses, a 1,000 m^3 pond can provide roughly a quarter of the full seasonal water requirement for a half-hectare field, or enough water to supply 100–150 mm of supplemental irrigation during key growth stages such as tasselling and grain filling, when rainfall deficits most affect yield. When applied over smaller plots which are common among smallholder farms in Africa (Giller et al., 2021), the same storage volume can meet more than half of the crop's seasonal demand. In Kenya, where rainfall is typically intense and concentrated within a few months of the year, such storage interventions can capture excess runoff during peak rainfall periods and sustain rainfed agricultural productivity during subsequent dry spells. The storage assessment tool also considers pond overflow to the downstream areas — providing insights on the environmental flow impacts of potential ponds on catchment hydrology (G. Senay & Verdin, 2004)

By combining these advances, the study in the CHEF region under Sustainable Farming Science Program delivers an updated and more nuanced understanding of agricultural water dynamics. It strengthens the evidence base for policymakers, planners, and development actors to design interventions that not only respond to immediate water stress but also support long-term resilience in Kenya's central highlands for both water sustainability and food security.

Central Highlands Ecoregion Foodscape (CHEF)

Central Kenya is widely recognized as the country's agricultural heartland, producing a large share of staple foods, cash crops, and horticultural exports that feed both domestic and regional markets (Figure 1) (Owusu, Matheswaran, et al., 2024; Pender & Ehui, 2006; Recha, 2019). Mount Kenya itself, Africa's second-highest peak and a UNESCO World Heritage Site, remains the most prominent feature of this landscape, providing water through the Ewaso Ng'iro and Tana rivers for agriculture, wildlife, and millions of households across the country (Ojany, 2008; Wamucii et al., 2025). It also functions as one of Kenya's most important water towers, supplying rivers that sustain farming, ecosystems, and urban centers downstream (Ojany, 2008; Wamucii et al., 2025).

The CHEF region spans eleven counties: Samburu, Laikipia, Meru, Isiolo, Nakuru, Nyandarua, Nyeri, Murang'a, Embu, Kirinyaga, and Tharaka-Nithi (Figure 1). Rainfed croplands dominate much of the area, while forested landscapes in Nyeri, Embu, and Kirinyaga play a key role in regulating water flows. With nearly a quarter of the nation's cropland concentrated in less than a tenth of its land area, the region's productivity is vital. Still, it is also highly exposed to climate variability, water scarcity, and land-use pressures. Sustainable management of water and land in the CHEF landscape is therefore not only central to the resilience of local communities but also to the stability of Kenya's broader agricultural economy.

Figure 1. Central Highlands Ecosystem Foodscape (CHEF) region and counties (*Owusu, Matheswaran, et al., 2024*)

Tools and Approaches

This work builds on earlier applications of IWMI's data tools as documented in the Excellence in Agronomy (EiA) use case report for the CHEF region (Owusu, Matheswaran, et al., 2024). Two complementary tools are central: the Scale Invariant Water Accounting Plus (SIWA+) framework and the Securing Water Use in Agriculture (SWAG) tool. A brief overview of both tools is provided here, but for full methodological details reference is made to the EiA CHEF use case report (Owusu, Matheswaran, et al., 2024).

Scale Invariant Water Accounting Plus (SIWA+) Tool

SIWA+ is an adaptation of the Water Accounting Plus (WA+) approach (Karimi et al., 2013; Owusu et al., 2025). The framework generates water accounts for any defined boundary—such as a basin, sub-basin, county, or administrative region by estimating inflows, outflows, storage changes, and consumption. A key output is the Water Resource Base Sheet, which summarises water accounts per annum for the study area. From this, one of the central indicators is the Basin Closure Fraction (BCF), which measures the degree to which water demand is approaching or surpassing available supply.

$$BCF = \frac{Utilized\ flow + Reserved\ flow}{Exploitable\ water} \tag{1}$$

High BCF values, especially above the threshold of 70% indicate high stress and risk of over-allocation, while lower values suggest more flexibility for additional use (Falkenmark & Molden, 2008).

Bias Correction of Precipitation and Discharge data for SIWA+

Accurate rainfall estimation is critical for hydrometeorological research. In many regions, in-situ gauge networks are sparse and often have gaps in their records (Akpoti et al., 2024; Mekonnen et al., 2023). Remote sensing products help fill these gaps by providing broader spatial and temporal coverage, but they are prone to systematic biases (Kimani et al., 2018). Integrating the two through bias correction using ground observations enhances the reliability of precipitation and discharge inputs, thereby strengthening water accounting by reducing errors in inflow and outflow estimates (Kimani et al., 2018; Omondi et al., 2021; Yonaba et al., 2024).

In the previous EiA study, precipitation data from the Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS) (Funk et al., 2015) and discharge data from VegDischarge (Akpoti et al., 2024) were used in SIWA+. While CHIRPS offers excellent spatial and temporal coverage and performs well in East Africa (correlation of 0.81 with in situ gauges; Mekonnen et al., 2023), its rainfall estimates, like those of other global remote-sensing products, carry uncertainties when compared with ground-based gauges. Similarly, VegDischarge, despite reasonable performance statistics (R^2 = 0.68, NSE = 0.68, KGE = 0.61; Akpoti et al., 2024), tends to underestimate low flows. To address these limitations, in situ data from rainfall and discharge stations obtained from Centre for Training and Integrated Research in ASAL Development (CETRAD) (Figure 2) was used to bias-correct both datasets. For rainfall, only eight gauges out of 19 stations identified had continuous records from 2012, and these were used for bias correction of monthly CHIRPS data. For discharge, although measurements were available from 44 stations, only six had data extending beyond 2010 and these were therefore included in the bias correction of monthly VegDischarge data.

Five bias correction methods were evaluated— Random Forest, Delta Quantile Mapping, Delta Method, Quantile Mapping, and Linear Scaling. Random Forest produced the best results and was therefore used in the final bias correction of CHIRPS precipitation and VegDischarge input data for the updated SIWA+ analysis. Full details on the in-situ data, the bias correction methodology and results can be found in Yeboah et al. (2025) The bias corrected precipitation and discharge data were used in running SIWA+ for the CHEF region from 2012 to 2021 at 100m-scale applied across the CHEF region, to develop an improved overview of water availability (flows) and water use (consumption).

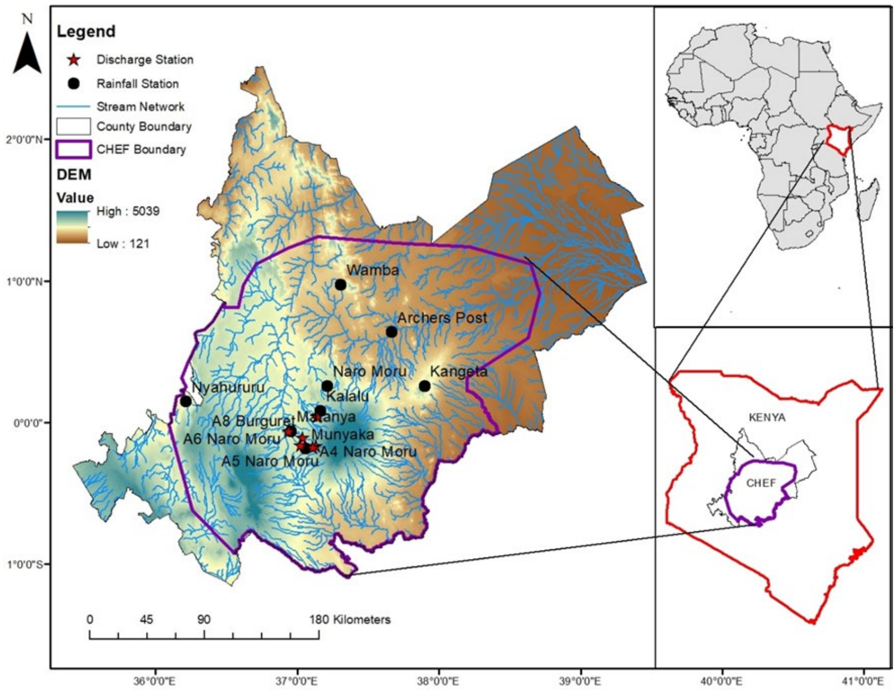

Figure 2. In situ precipitation and discharge stations used in bias correction of remote sensing precipitation and modelled discharge of the CHEF region

Securing Water Use in Agriculture (SWAG) Tool

The SWAG tool (Figure 3) analyses water use and water availability to determine where and how much water deficits and surpluses occur. With respect to the former, a storage assessment/water harvesting potential is then carried out to determine if small on-farm storage can buffer deficits, while with the latter, recommendations for water savings and, if possible, reallocation are made.

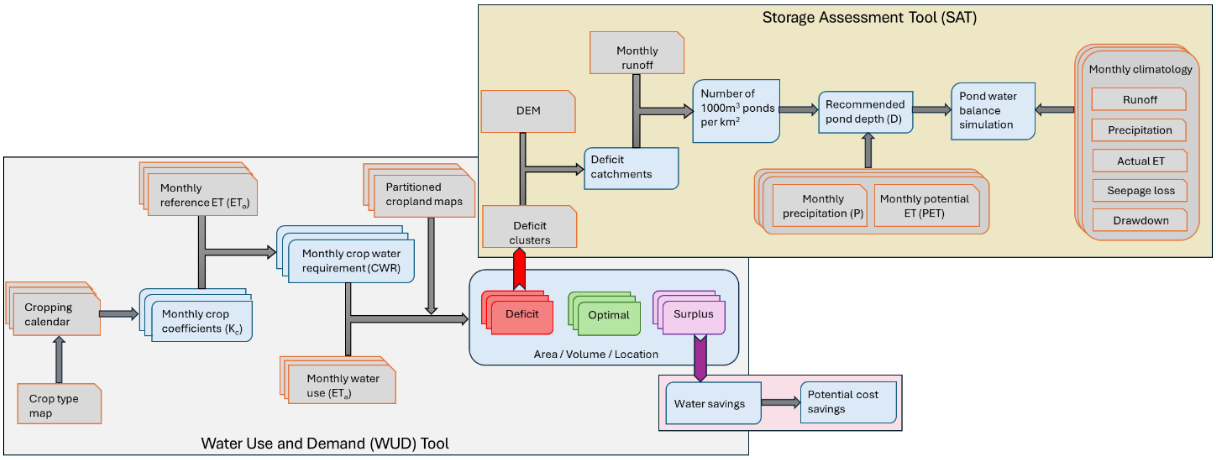

Figure 3. Securing Water in Agriculture (SWAG) Tool

First on water use and availability, crop water requirements (CWR) are determined by combining reference evapotranspiration (ET_o) with crop coefficients (K_c). This is then compared to actual evapotranspiration to determine whether crop water use faces a deficit (i.e. less used than needed), surplus (i.e. more used than needed), or optimal water. In this study, an extended and higher-resolution crop water balance assessment was conducted over a five-year period (2019–2023). The workflow generated monthly and annual indicators to identify leading deficit and surplus crops, clarifying which production systems are most consistently stressed and when.

An updated cropping calendar was shared with and validated by the National Irrigation Authority (NIA) of Kenya. Monthly crop water requirements (CWR) (Annex, Figure A 2) were then generated using crop coefficient (K_c) (Allen et al., 1998)(Allen et al., 1998) and reference ET from the Global Land Evaporation Amsterdam Model (GLEAM v3.6a) (Martens et al., 2017)(Martens et al., 2017) climatology (2003 to 2021) as:

$$\mathrm{CWR} = \mathrm{K}_c \times ET_o \tag{2}$$

Cropland was classified into water status categories by comparing monthly actual evapotranspiration (ET_a) to crop water requirements (CWR) using the ratio:

$$\frac{ET_a - CWR}{CWR} \tag{3}$$

Three classes were distinguished:

- **Water deficit:** ratio ≤ –0.2, rainfed and irrigated areas where available water falls short of meeting crop needs, leading to potential yield reductions due to moisture stress.
- **Water surplus:** ratio ≥ 0.2, areas with high blue ET where applied or available water exceeds crop demand, suggesting over-irrigation that may also reduce yields.
- **Optimal supply:** ratio between –0.2 and 0.2, where water availability is aligned with crop requirements, indicating optimal growing conditions. This also includes rainfed areas with ‘surplus’ water.

It should be noted that this ratio provides an indicative measure of relative water balance since apparent deficits or surpluses may arise not only from actual water stress or excess application but also from uncertainties in CWR estimation, which depends on generalized crop coefficients and may not fully capture local climatic or management conditions. Efforts to refine these estimates in this study included validation of the cropping calendar and crop coefficients by the National Irrigation Authority (NIA).

Statistics for areas and volumes of deficit and surplus supply were then extracted for both the CHEF extent, for individual counties, and for production types.

Storage Assessment

A storage assessment was undertaken to evaluate the feasibility of small-scale water storage, with the aim of exploring how small ponds could buffer crop water deficits through runoff capture and pond-level water balance simulations across catchments (G. Senay & Verdin, 2004).

Deficit Clustering and Catchment Delineation: An annual modal map of crop water deficit was derived, representing croplands that were persistently in deficit in the CHEF region across the five-year study period. Spatial clusters of deficit croplands (>10 pixels ≈ 0.1 ha) were identified, and for each cluster, the most downstream point was determined. The upstream catchment contributing flow to each deficit cluster was then delineated using a 90 m digital elevation model (DEM). These delineated units were compiled into a shapefile, which was used as the spatial area for subsequent storage assessment.

Runoff and Pond Number Estimation: Monthly runoff depth from VegET (G. Senay et al., 2023) for the delineated catchment during 2000–2021 was summarized as long-term climatological monthly means, and the 75th percentile across months was extracted to represent available supply. Given the underlying rationale that runoff generated in the rainy seasons can be harvested and stored in ponds to sustain water availability during subsequent dry periods, this 75th percentile was chosen because it corresponds either to high runoff during the minor rainy season (October–December) or to the low runoff during the major rainy season (March–May) in central Kenya. This provides a reliable representation of available supply for estimating typical storage potential as it captures substantial runoff while avoiding dependence on anomalously high values, aligns with seasonal rainfall patterns in central Kenya, and thus offers a more practical basis for storage assessment. The total available runoff volume for each catchment was then estimated by multiplying the runoff depth by the catchment area.

The potential number of 1000 m^3 ponds (NP) that could be supported by the runoff in each catchment was computed as:

$$NP = \frac{Runoff\ Volume}{1000} \tag{4}$$

Pond density (NP per square kilometer) was estimated as:

$$NP_{per\ km^2} = \frac{NP}{Catchment\ area} \tag{5}$$

Recommended Pond Depth: The recommended pond depth (D) for catchment (i) is defined as the minimum depth required to store net 1000 m³ of runoff while accounting for climatic aridity. This was determined using equations 6 to 8. First the difference between monthly potential evapotranspiration (PET_m) and precipitation (P_m) is estimated as:

$$d_m = \max\,(PET_m - P_m, 0) \tag{6}$$

where d_m is the monthly difference (mm). When negative, (i.e.: when precipitation exceeds PET), the max function sets d_m to zero. For each pixel, the maximum cumulative spell of consecutive positive monthly differences (D_{spell}) was determined to ensure that ponds are sized to buffer the most critical dry spell rather than just average or isolated dry months:

$$D_{spell} = \max\,(\sum_{m=k}^{l} d_m \mid d_m > 0\ for\ all\ m \in [k, l] \tag{7}$$

where k and l denote the start and end months of a consecutive dry spell where all differences (i.e.: $PET_m - P_m$) are positive.

The recommended depth per pond (in meters) is then defined as:

$$D =, 1 + \frac{D_{spell}}{1000} \tag{8}$$

The final recommended depth is rounded down to the nearest 0.25 m for practical construction. Because D_{spell} is non-negative, D has a minimum value of 1 m.,. The median value for the pixels in catchment was then assigned as the recommended pond depth for all ponds in a catchment D_i.

Pond Water Balance Simulation: A monthly water balance was simulated for each delineated catchment over a four-year period using repeated mean climatological sequences (rainfall, evapotranspiration, and runoff). The simulation captures the temporal dynamics of on-farm ponds and their hydrological interactions with cropland water deficits and downstream flow.

For each catchment$i$ and month m, the change in pond water level (H) was computed as:

$$\Delta H_{i,m} = R_{i,m} + P_{i,m} - ET_{i,m} - S_m - DF_{i,m} \tag{9}$$

Where:

$R_{i,m}$ = runoff inflow from the contributing catchment (m),
$P_{i,m}$ = direct precipitation onto the pond (m),
$ET_{i,m}$ = open-water evaporation over the pond (m),
S_m = seepage loss (m), assumed constant at 2.5 mm day^{-1} ≈ 0.075 m month^{-1} (G. Senay & Verdin, 2004),

$DF_{i,m}$ = drawdown flux (m), equal to the mean cropland water deficit for the corresponding cluster

The pond water level was then updated as:

$$H_{i,m} = H_{i,m-1} + \Delta H_{i,m} \tag{10}$$

To enforce physical limits on storage, the simulated level was capped at the maximum pond depth:

$$H_{i,m} = min(max(H_{i,m}, 0), D) \tag{11}$$

Overflow ($O_{i,m}$) was generated whenever the computed water level exceeded maximum pond depth:

$$O_{i,m} = max(H_{i,m} - D, 0) \tag{12}$$

In practice, this means ponds first satisfy their internal storage, and only after reaching capacity do they contribute to downstream flow via overflow.

Effect of withdrawals on runoff: To quantify what share of catchment runoff is intercepted by ponds, the retained fraction is calculated. This metric is important because it indicates the degree to which on-farm ponds alter or leave unchanged the broader water balance of the catchment. If most runoff is retained, ponds may substantially reduce flows to rivers. Conversely, if retention is low, the environmental impact of pond storage on downstream water availability is minimal.

Monthly retained fraction ($r_{i,m}$) per catchment (defined when monthly runoff > 0):

$$r_{i,m} = 1 - \frac{O_{i,m}}{R_{i,m}}, \ (R_{i,m} > 0) \tag{13}$$

Annual (cumulative) retained fraction(R_i): per catchment

$$R_i = 1 - \frac{\sum_m O_{i,m}}{\sum_m R_{i,m}} \tag{14}$$

Basin-wide retained fraction (volume-weighted across polygons):

$$R_{basin} = \frac{\sum_i \sum_m O_{i,m} SA_i}{\sum_i \sum_m R_{i,m} SA_i} \tag{15}$$

Where, $R_{i,m}$ is the runoff entering ponds in catchment i in month m, $O_{i,m}$ is the overflow released downstream, and SA_i is the pond surface area. Equation (15) provides a basin-scale indicator of the share of total runoff that ultimately flows downstream after accounting for pond storage.

Results and Discussion

Improvements in Precipitation and Discharge data for CHEF Region

Following the application of the Random Forest bias correction to the CHIRPS product in the CHEF region, the precipitation estimates improved (Figure 4). The correlation coefficients increased from 0.52 to 0.87 in the uncorrected data to 0.93 to 0.98 after correction, indicating a stronger agreement with observed values. Similarly, the Nash–Sutcliffe Efficiency (NSE) improved considerably, rising from −0.94 to 0.40 before correction to 0.85 to 0.95 after correction. Correspondingly, the Root Mean Square Error (RMSE) values declined sharply from 34 to 134 to 9 to 46, demonstrating a substantial reduction in estimation errors and confirming the enhanced predictive capability.

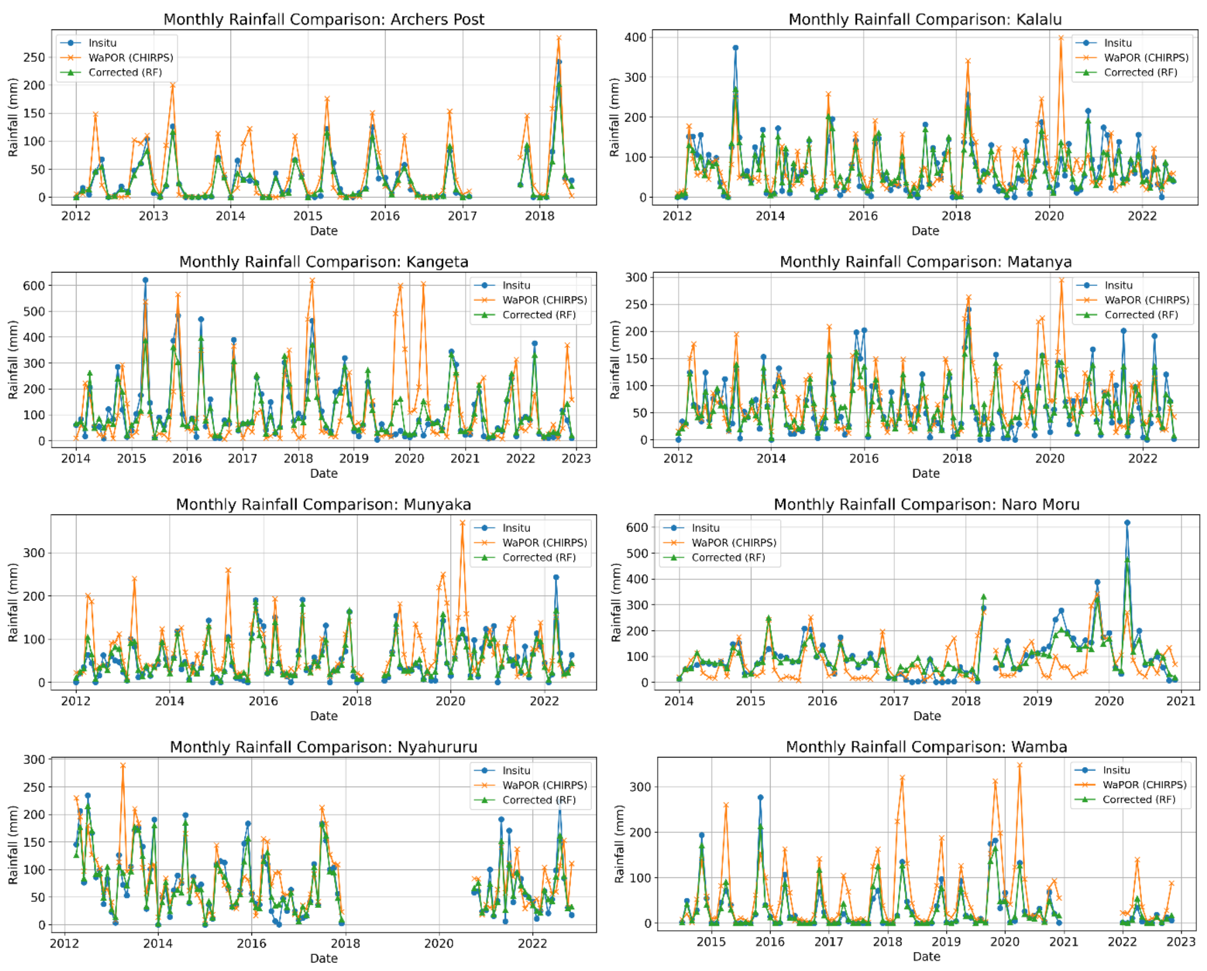

Figure 4. Time series plot of in situ and CHIRPS (before and after bias correction) monthly precipitation estimates

For the discharge data, the Random Forrest corrected VegDischarge improved in accuracy in the CHEF region (Figure 5). The correlation coefficient increased from a range of 0.46 to 0.71 before bias correction to 0.92 to 0.95 after bias correction. The Nash–Sutcliffe Efficiency (NSE) also improved significantly, rising from a range of −2.28 to 0.23 before correction, to a range of 0.80 to 0.88 after correction. Similarly, the Root Mean Square Error (RMSE) values decreased sharply, from a range of 0.34 to 1.55 before correction to 0.09 to 0.40 after correction, indicating a substantial reduction in prediction errors. These improvements confirm that the Random Forest bias correction effectively enhanced the reliability of VegDischarge data, improving its ability to capture temporal flow dynamics a nd closely align with observed discharge patterns across all stations.

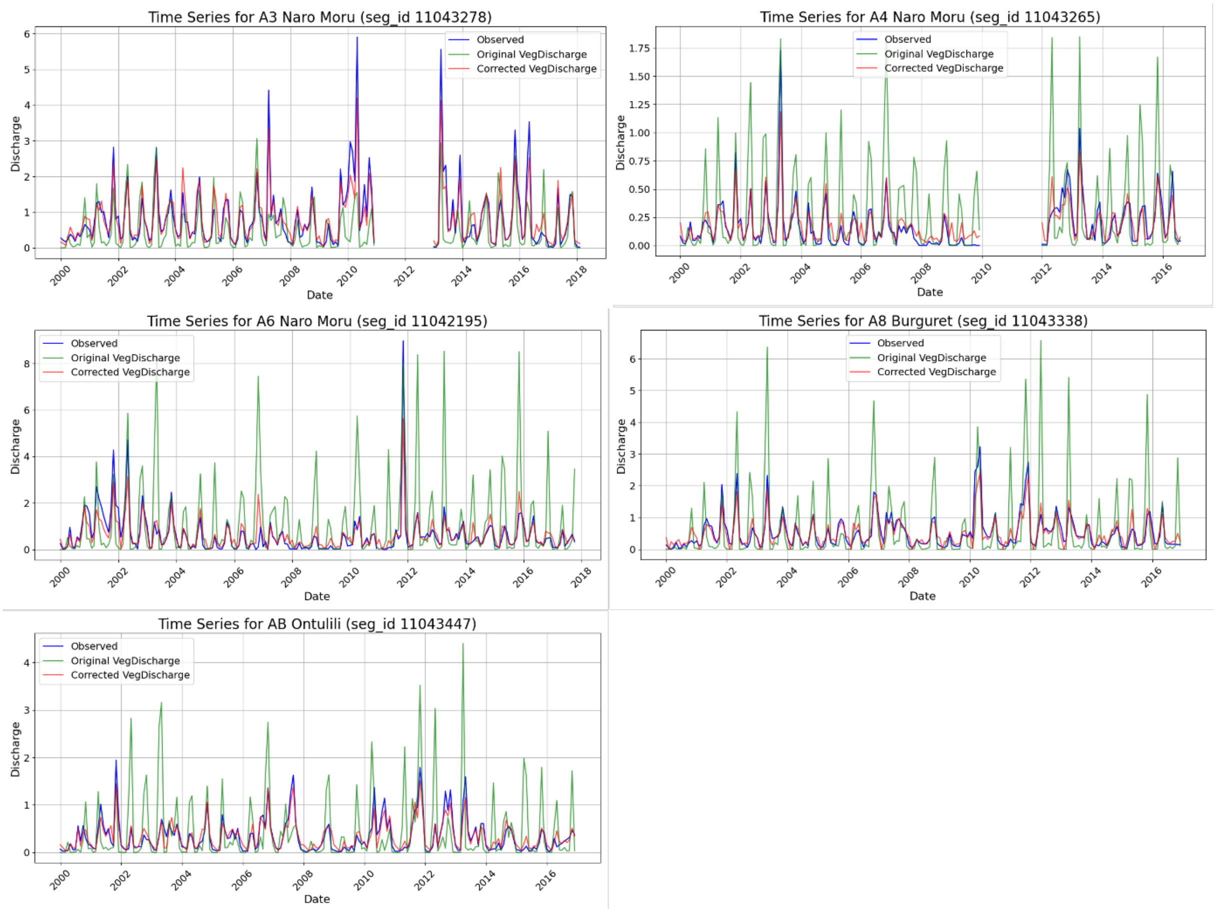

Figure 5. Time series plot of observed and VegDischarge (before and after bias correction) mean monthly streamflow estimates

Full details on the bias correction methods and results can be found in Yeboah et al. (2025).

Water Accounts and Basin Closure

The average water accounts for the CHEF area and, for comparison, Kenya between 2012 and 2021 are shown in Figure 6 and Figure 7 respectively. For the CHEF region, net inflow is partitioned into landscape evapotranspiration (≈37 km³/year) and exploitable water in streams and shallow aquifers (≈10 km³/year). Landscape ET represents the fraction of rainfall that is evaporated or transpired through interaction with land cover, soils, and vegetation. This water is consumed locally while exploitable water constitutes the portion of net inflow available for withdrawals or other downstream uses.

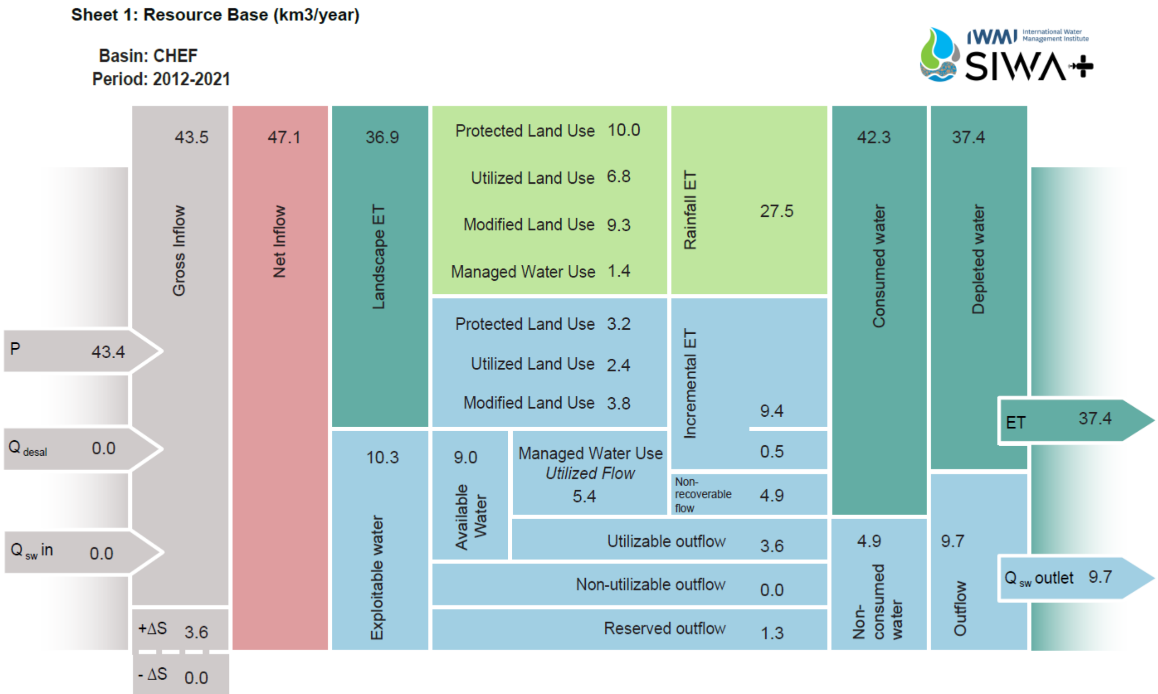

Figure 6. CHEF water accounts - average for 2012-2021 (km3/year)

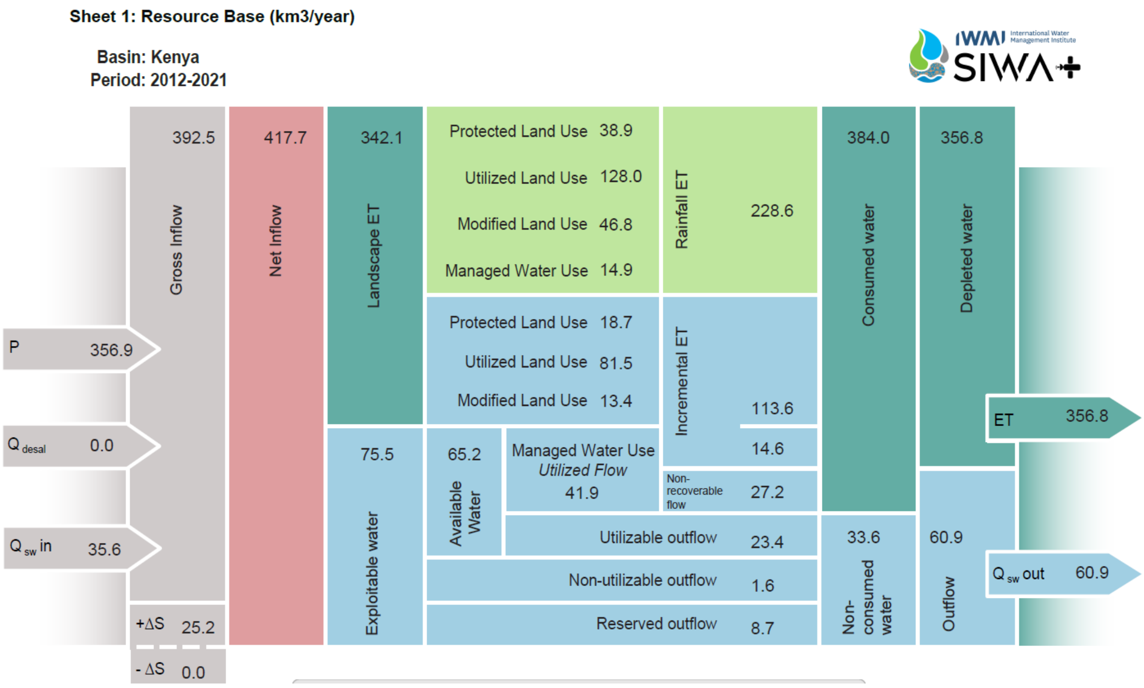

Figure 7. Kenya water accounts - average for 2012-2021 (km3/year)

From this exploitable component, the average available water is ≈ 9 km³/year. Of this, ≈ 5 km³/year is lost as non-recoverable flow, while ≈ 1.3 km³/year is maintained as reserved outflow to meet environmental flow requirements. After accounting for these allocations, the utilizable outflow amounts to ≈ 3.6 km³/year, representing the volume that remains available for further development such as irrigation, including agriculture and other uses within the basin.

Although the CHEF basin accounts for only about 9.5% of Kenya's total land area (5.2 million ha out of 55 million ha), it supports a disproportionately large share of the country's cropland (Annex, Table A 2). With 1.74 million ha under cultivation, CHEF contains roughly 23% of Kenya's cropland, making it more than twice as intensively farmed as the national average. From a water resources perspective, on average, CHEF contributes approximately 3.6 km³/year of utilizable water compared with 23 km³/year at the national scale, or about 15% of Kenya's total.

Table 1. Annual basin closure fractions for individual CHEF counties, the CHEF area and Kenya. Red shades represent higher basin closure while blue shades represent lower basin closure.

Embu	Isiolo	Kirinyaga	Laikipia	Meru	Murung'a	Nakuru	Nyandarua	Nyeri	Samburu	Tharaka-nithi	CHEF	Kenya
55%	75%	56%	69%	63%	60%	64%	48%	59%	64%	56%	65%	77%
57%	64%	63%	68%	64%	62%	59%	50%	63%	56%	56%	64%	64%
75%	76%	84%	79%	72%	95%	60%	65%	85%	74%	66%	79%	71%
56%	70%	60%	68%	60%	60%	63%	52%	59%	65%	53%	63%	67%
63%	78%	68%	78%	69%	70%	51%	55%	70%	75%	55%	71%	76%
70%	76%	71%	77%	74%	83%	65%	67%	72%	64%	61%	76%	77%
53%	64%	54%	62%	59%	57%	49%	43%	55%	55%	52%	59%	60%
52%	65%	54%	67%	58%	61%	61%	55%	60%	60%	50%	62%	60%
54%	66%	56%	65%	64%	62%	51%	49%	58%	57%	53%	63%	62%
64%	78%	71%	73%	75%	82%	62%	56%	72%	68%	59%	75%	79%
60%	**71%**	**64%**	**70%**	**66%**	**69%**	**59%**	**54%**	**65%**	**64%**	**56%**	**68%**	**69%**

Looking at BCF, average, the CHEF basin hovered near the critical closure threshold, with average annual BCF of 68 (Table 1). This mirrors the national pattern (69%), but within the area, closure intensity varied by county. Isiolo and Laikipia stood out as counties with high BCF on average, while Nyandarua and Tharaka-Nithi were relatively less constrained. In peak stress years (2014 and 2017), closure exceeded 75% basin-wide while in contrast, 2018 to 2020 were less water stressed years. These results suggest that overall, the CHEF area generally operates on the edge of closure, but with high variability from year to year. County-level variation is also notable: Nyandarua (54%) and Tharaka-Nithi (56%) averaged well below 70%, suggesting that even in dry years, these counties have more room for additional water development relative to the rest of the area.

Diagnosing Water Stress in Croplands

The analysis of cropland water status between 2019 and 2023 (Annex, Figure A 3 to Figure A 7) highlights monthly and interannual variability in both water deficit and surplus conditions. Deficit areas are largest during the dry months between Kenya's two rainy seasons (May to August) when rainfall is low. On the other hand, irrigated cropland areas with surplus can be seen, to a lesser extent, in the early and late months of the year (Figure 8). Similarly, the monthly volumes (Figure 9) show that water deficits consistently peak during this period with 2021 and 2022 recording particularly large deficit volumes exceeding 150 million m³ in some months. Water surpluses are also present but generally smaller in magnitude (< 100 million m³). Monthly cropland deficit areas ranged from ≈18,000 ha (in December 2019) to ≈450,000 ha (in May 2019). By contrast, surplus areas were consistently smaller, averaging ≈17,000 (in July 2022) to ≈98,000 ha (in April 2020) per month.

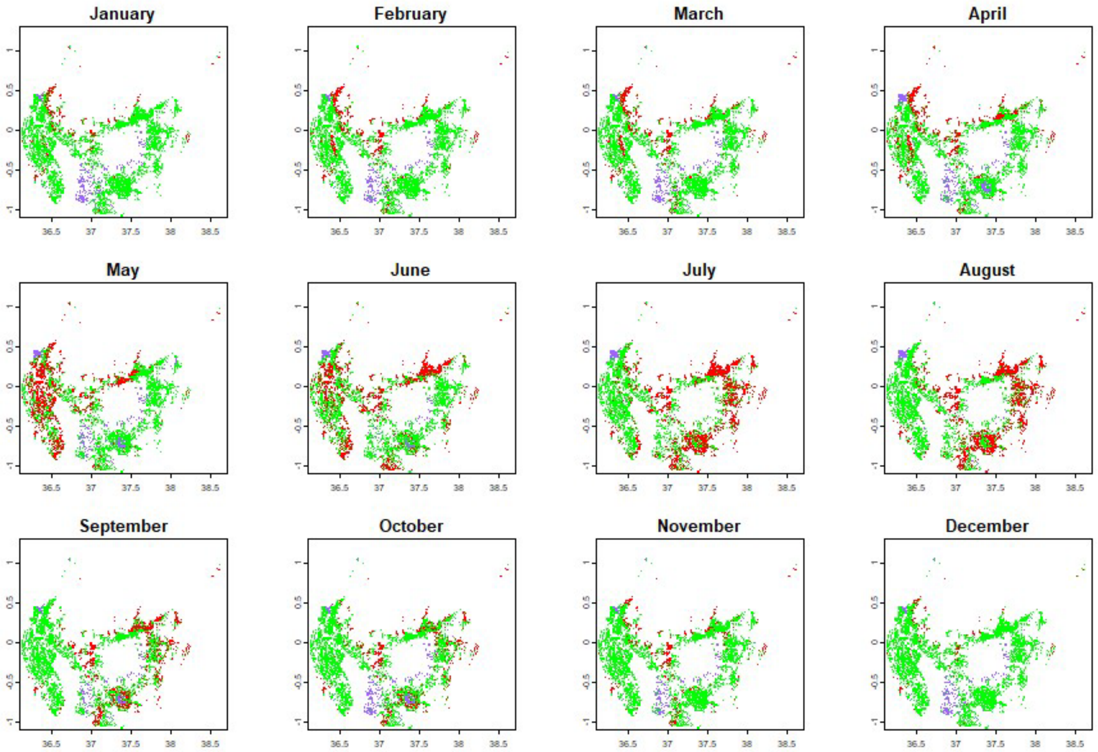

Figure 8. Cropland areas with persistent deficit (red), surplus (purple) and optimal (green) water status from 2019 to 2023 in the central highland regions of Kenya

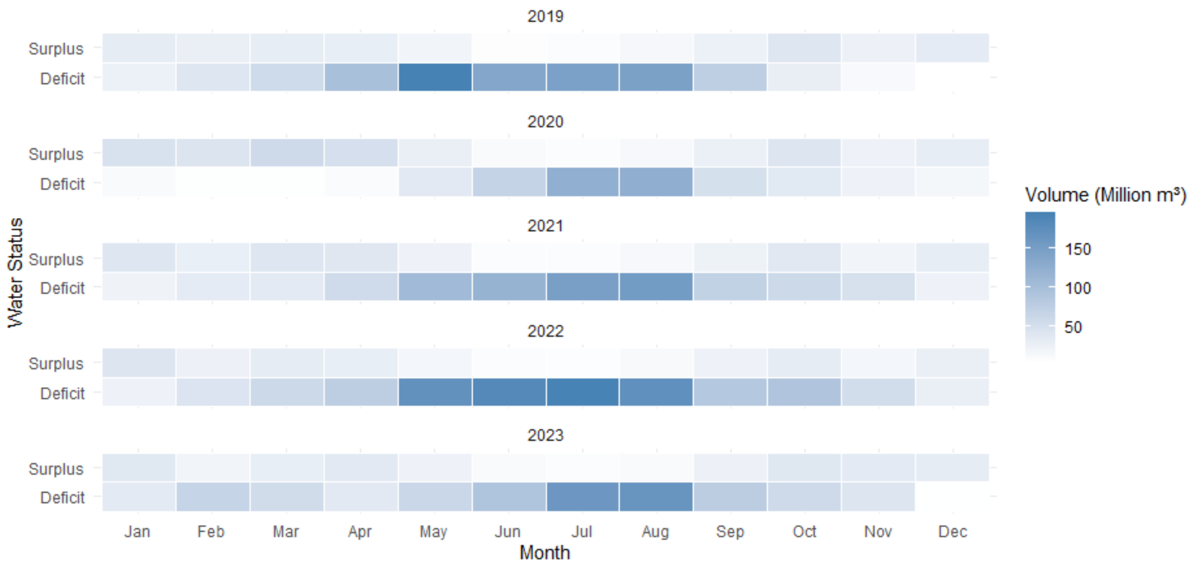

Figure 9. Volume of water deficits and surplus per month from 2019 to 2023 in the CHEF region

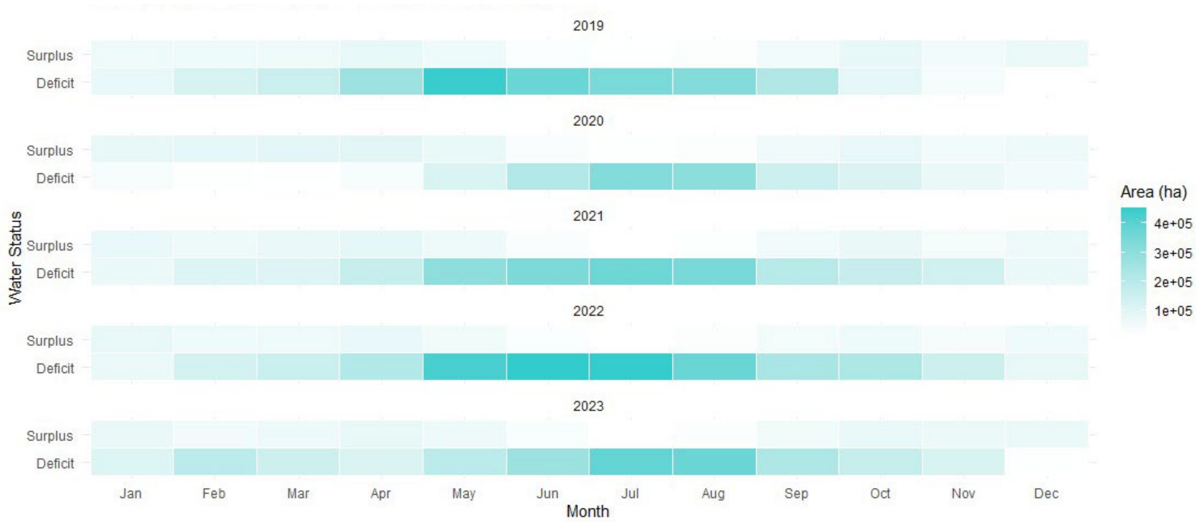

Figure 10. Area of cropland with water deficits and surplus per month from 2019 to 2023 in the CHEF region

The spread of cropland area affected (Figure 10) confirms that water stress dominates the agricultural landscape, with median monthly deficit areas several times larger than those under surplus conditions across all years. The largest deficit extents were observed in 2019 and 2022 while 2020 and 2023 showed comparatively lower but still substantial cropland areas under stress. Together, these results demonstrate that many of the agricultural systems in the CHEF region are water stressed, with pronounced peaks in mid-year that align with the main cropping period, while over-irrigation remain relatively limited in extent and volume.

Water Deficit by Production Type

Between 2019 and 2023, contrasts emerged between production zones experiencing water stress and those with excessive water use. The Ranching Zone consistently recorded the largest deficits for most of the year - an average area of 63,000 ha per month. During the mid-year months of July and August, the Marginal Cotton Zone is the cropping system most under stress, with around 78,000 hectares per month.

Table 2. Production types and areas persistently in deficit and surplus

Month	Top Deficit Production Type	Deficit Area (ha)	Top Surplus Production Type	Surplus Area (ha)
January	Ranching Zone	57,570	Tea - Dairy Zone	21,995
February	Ranching Zone	89,514	Tea - Dairy Zone	21,062
March	Ranching Zone	89,623	Tea - Dairy Zone	21,593
April	Ranching Zone	88,362	Tea - Dairy Zone	18,722
May	Ranching Zone	62,973	Coffee - Tea Zone	16,893
June	Ranching Zone	64,447	Coffee - Tea Zone	7,123
July	Marginal Cotton Zone	78,593	Wheat/Maize Zone	6,888
August	Marginal Cotton Zone	78,624	Cattle - Sheep - Barley Zone	5,399
September	Ranching Zone	46,954	Coffee - Tea Zone	16,723
October	Ranching Zone	46,825	Tea - Dairy Zone	21,297
November	Ranching Zone	59,331	Coffee - Tea Zone	18,314
December	Ranching Zone	28,954	Tea - Dairy Zone	20,452

In contrast, surplus conditions were concentrated in the perennial systems. Both coffee and tea in Kenya are traditionally rainfed crops, but supplemental irrigation is practiced in commercial estates and some smallholder areas to maintain yields during dry spells and mitigate the effects of climate change (Karuri, 2021; Mendes & Paglietti, 2015). The Tea–Dairy Zone dominated much of the year, particularly from January to April and again from October to December, with 18,000–22,000 hectares in surplus each month an average of approximately 14,000 ha per month. The Coffee–Tea Zone contributed surpluses in May, June, September, and November, ranging from 17,000 to 18,000 hectares monthly and accumulating also approximately 14,000 ha per month on average. Other zones, such as Wheat/Maize in July and Cattle–Sheep–Barley in August, contributed smaller amounts.

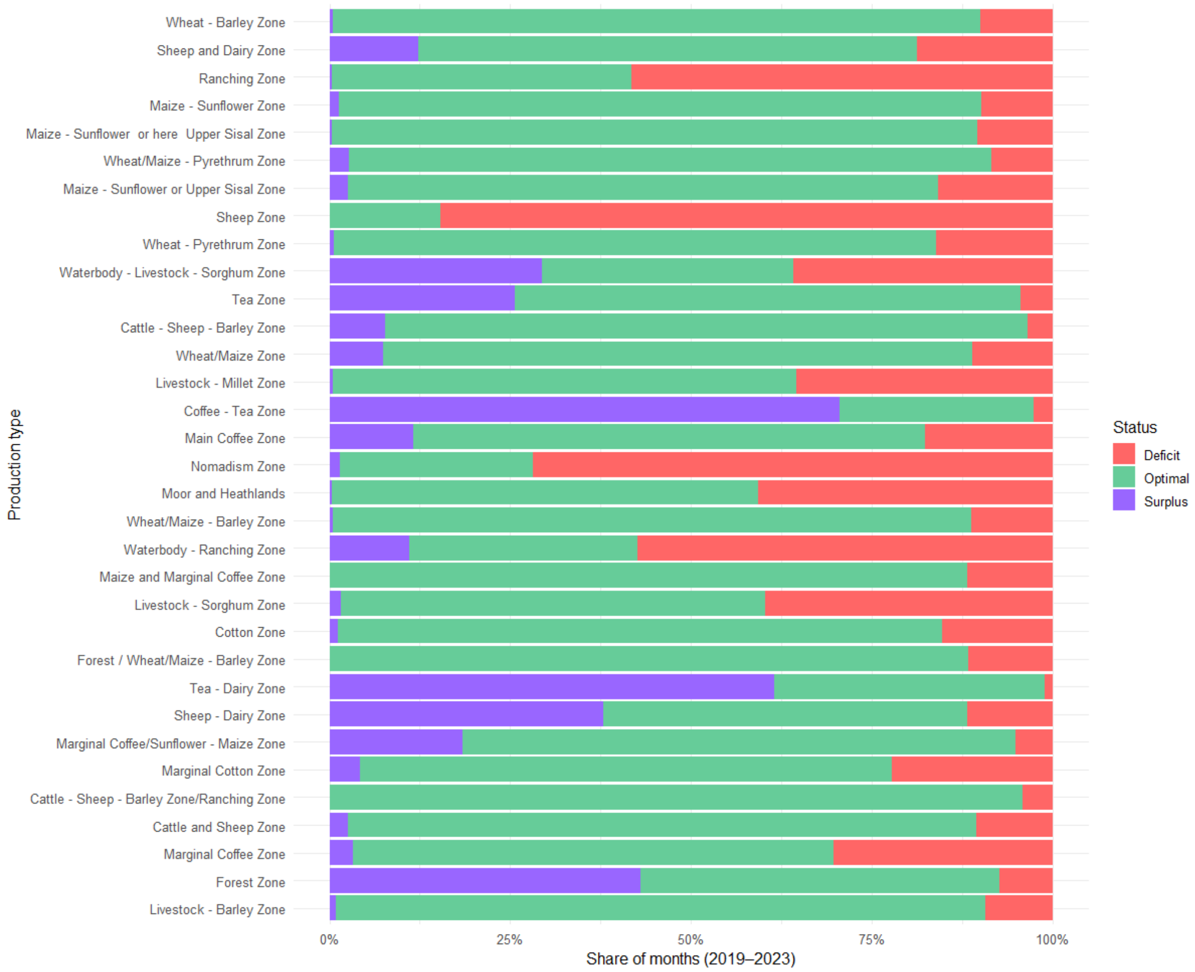

Figure 11. Water-status frequency by production type (2019–2023) showing the proportion of months over the five-year period that a production zone experienced water-deficit (red), optimal (green), or surplus (purple) conditions

Figure 11 shows the water status frequency for the production types in the CHEF region from 2019 to 2023. Most production zones experienced optimal water conditions for most months. However, consistent with Table 2, the Ranching, Nomadism, and Sheep zones are persistently deficit-prone, spending more than half of all months under water-stress conditions. In contrast, the Tea–Dairy and Coffee–Tea zones exhibit consistently high frequency (> 0.62) of water surplus months. Together, these results highlight the spatial differentiation between Kenya's water-stressed livestock-dominated zones and its moisture-rich perennial crop systems. The observed surplus in the Forest Zone does not indicate over-irrigation; rather, it reflects that these areas were classified as 'production types' in the land-cover and crop-type datasets, and their naturally higher evapotranspiration potential, driven by deep-rooted vegetation accessing deeper soil moisture or groundwater can appear as surplus when assessed using the same water-balance framework applied to cropland.

Storage Assessment

Catchment Delineation

An annual modal map of crop water status was generated for the CHEF region, summarizing dominant (most frequently occurring) water status of croplands across the five-year study period (Figure 12). The dominant class at each pixel represents the modal monthly crop water status values over 2019–2023.

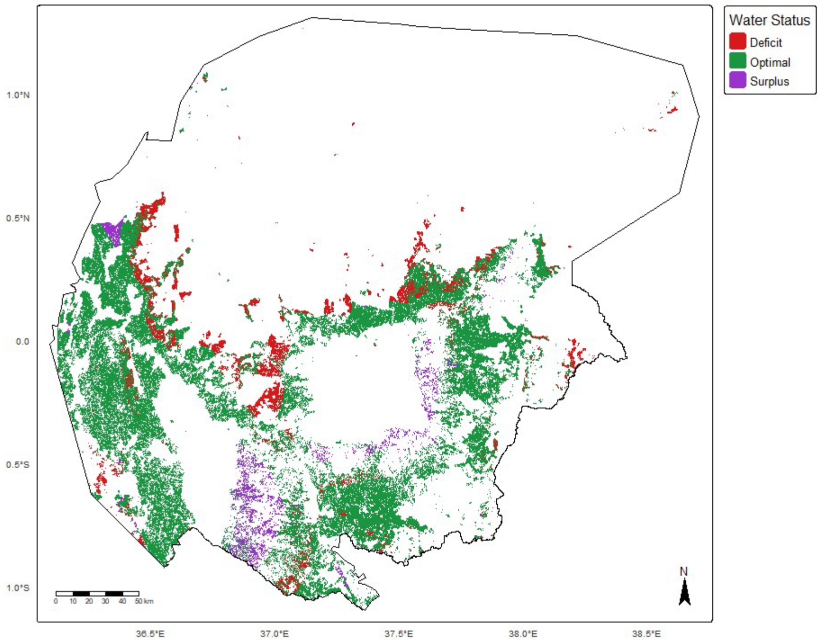

Figure 12. Annual modal map of crop water status showing persistent deficit, optimal, and surplus zones across the CHEF region

In total, 95 water stress cluster catchments were delineated across the CHEF region (Figure 13). These units represent hydrologically consistent areas linking water-stressed croplands to their upstream contributing zones and form the spatial basis for subsequent analysis of local water storage potential. NB: Some large water stress clusters did not yield delineated catchments, as their hydrological source areas extend beyond the CHEF domain and therefore fall outside the delineation boundary.

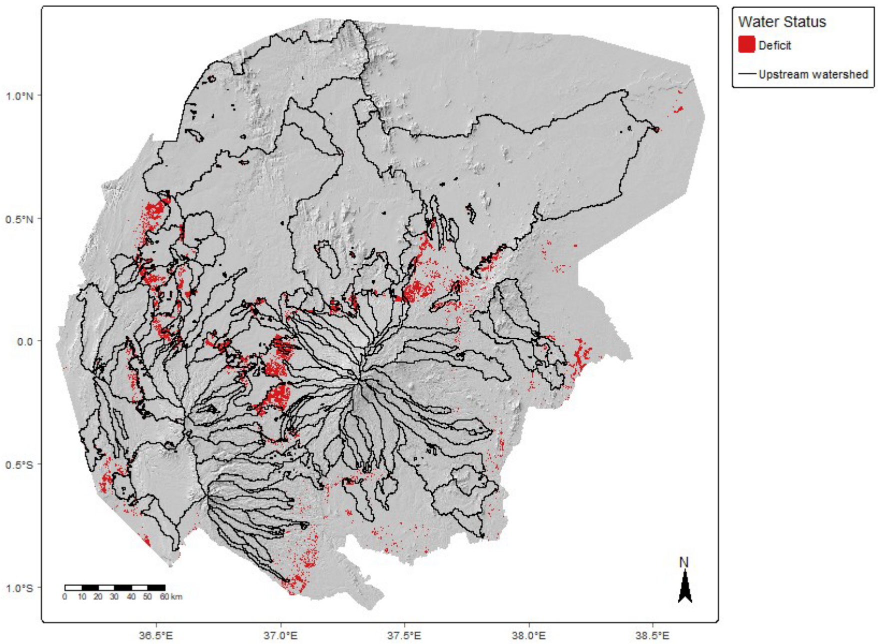

Figure 13. Spatial clusters of deficit croplands and their delineated upstream catchments derived from the 90 m DEM. NB: Some large deficit clusters did not yield delineated catchments, as their hydrological source areas extend beyond the CHEF domain and therefore fall outside the delineation boundary.

Potential number of ponds

Across the CHEF basin, the potential of 1000 m³ sized farm ponds varies among catchments (Figure 14a). The highest densities (>25 ponds km^{-2}) are concentrated around the high-elevation headwaters and mid-slopes of Mount Kenya, where small catchments with favourable slope conditions dominate. In contrast, lower densities (0–5 ponds km^{-2}) occur toward the western and northeastern lowlands, corresponding to larger, flatter catchments with relatively lower runoff generation potential. The frequency distribution of pond densities (Figure 14b) shows that most catchments can accommodate less than 10 ponds km^{-2}, while only a few reach above 20 ponds km^{-2}.

Recommended pond depths (Figure 15) exhibit a distinct north–south gradient. Deeper ponds (1.25 m) are predominant across the northern and northeastern catchments bordering the ASAL (arid and semi-arid land) region of Kenya, reflecting the need for greater storage to buffer higher evaporative demand. Shallower ponds (1.0 m) are recommended for the more humid southern and western slopes, where frequent rainfall and reduced evaporative losses favour smaller, more numerous ponds.

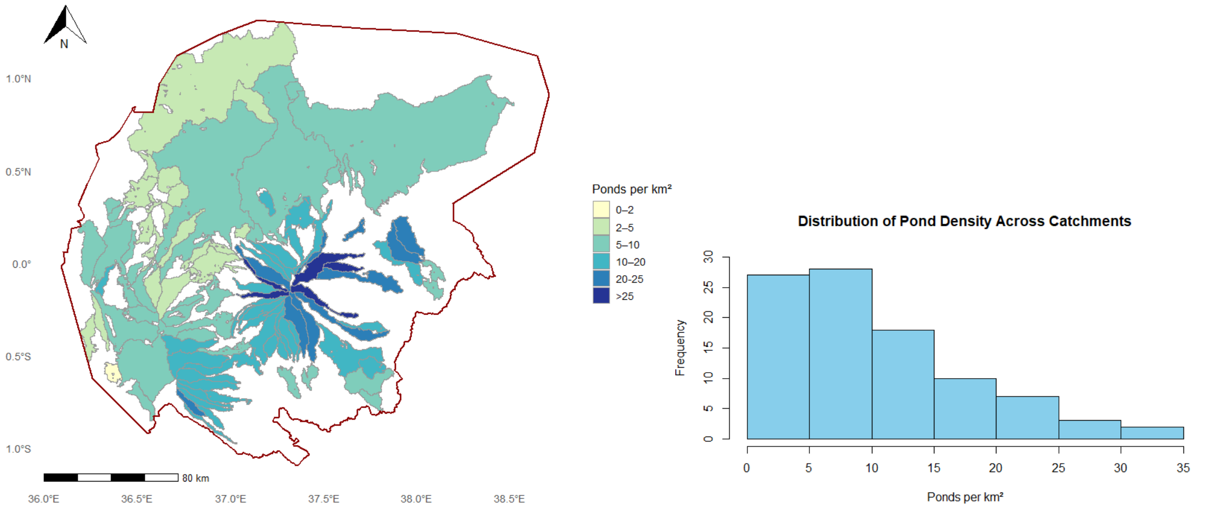

Figure 14. a. Potential number of 1000 m3 ponds per 1 km2 b. Frequency distribution of potential number of 1000 m3 ponds per 1km2

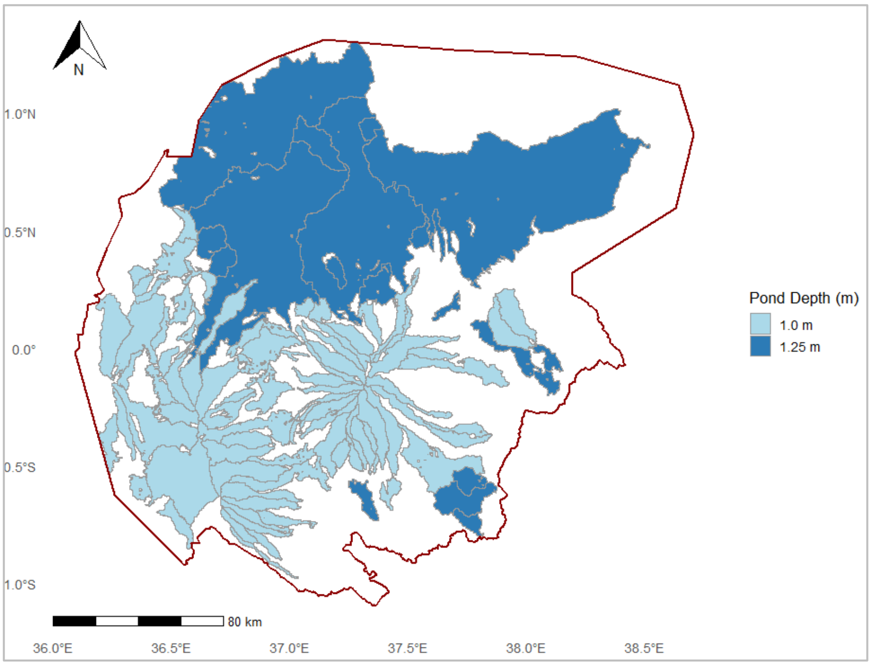

Figure 15. Recommended pond depth across CHEF catchments

CHEF-wide Water Balance Dynamics

The basin-wide simulations reveal strong seasonality in runoff generation and pond response (Figure 7 a and c). Runoff peaks during the long (April–May) and short (October–November) rains, reaching volumes above 2×10^9 m^3 month^{-1} (Figure 7a). Overflow volumes mirror this pattern (Figure 7c), indicating that most ponds fill rapidly during wet months and spill soon after reaching capacity. This correspondence suggests that the pond system behaves primarily as a hydrological buffer rather than a net sink: it intercepts and temporarily stores runoff but ultimately releases much of it downstream once storage thresholds are exceeded.

Average pond water levels (Figure 7c) rise steeply following the onset of rainfall. Levels decline moderately between seasons but rarely approach complete depletion. This persistent near-full condition of ponds indicates that, at the aggregate scale, available storage capacity far exceeds the monthly drawdown from crop water deficits (Figure 7d). The total deficit volumes per month confirm this, given that they are two to three orders of magnitude smaller than the corresponding runoff and pond inflow volumes.

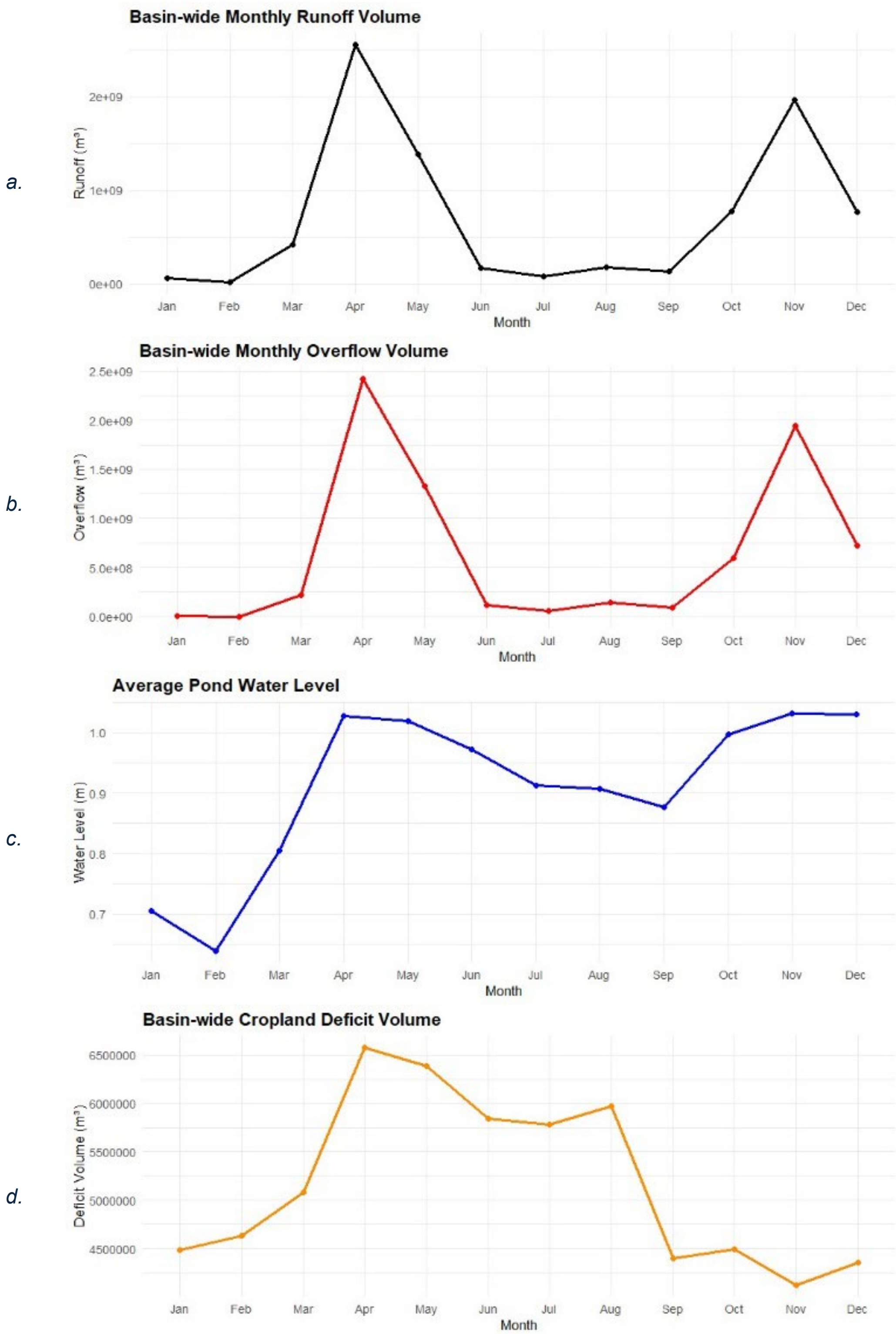

Figure 16. CHEF-wide dynamics: a. Total monthly runoff in catchments; b. Total monthly overflow from all ponds; c. Average pond water level across all ponds; d. Total cropland deficit volume (water demand/pond drawdown) of deficit clusters

Environmental Impact of On-farm Ponds

The analysis of retained fractions provides insight into the extent to which on-farm pond storage alters downstream water availability. The retained fraction quantifies the proportion of catchment runoff that is captured and held in ponds, rather than bypassing storage as overflow.

Monthly retention

At the monthly scale, retained fractions exhibit a strongly bimodal pattern inverse to the seasonal runoff (Figure 17). In many months, ponds either retain nearly all incoming runoff (retained fraction close to 1.0) or retain very little (fraction near 0). This reflects seasonal hydrology: during dry months, when runoff volumes are small relative to pond capacity, ponds effectively capture all inflow. Conversely, during wet months**,** ponds are frequently overwhelmed, resulting in high spill volumes and retained fractions close to zero.

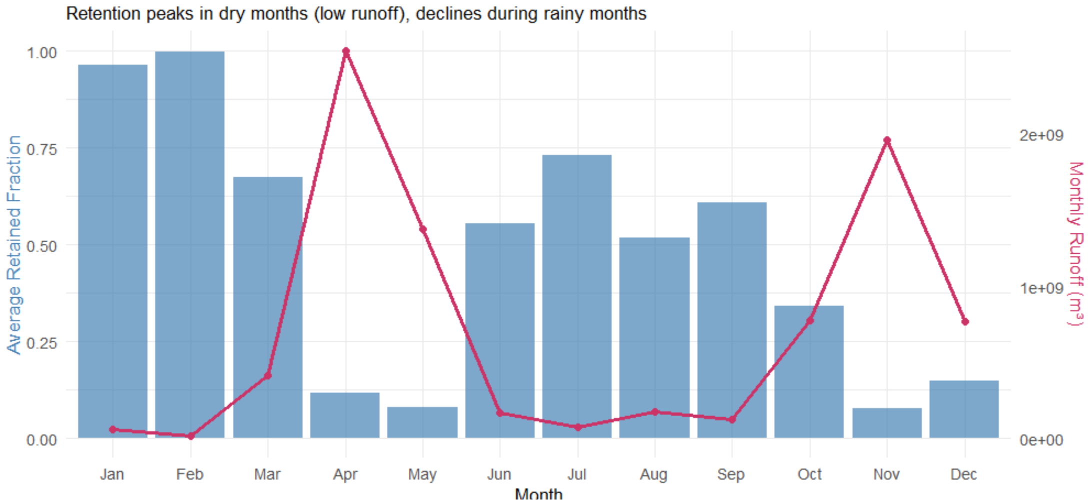

Figure 17. Average monthly retained fractions and total runoff across all catchments

Cumulative (annual) retention

When aggregated annually across the full 4-year simulation period, retention fractions are substantially lower (Figure 18). The majority of catchments retain less than 20% of their annual runoff, with only a small number of catchments reaching values greater than 0.5. The basin-wide, volume-weighted annual retained fraction was 0.13**,** meaning that across all catchments, ponds retained only about 13% of total runoff**,** while the remaining 87% was released downstream **as** overflow.

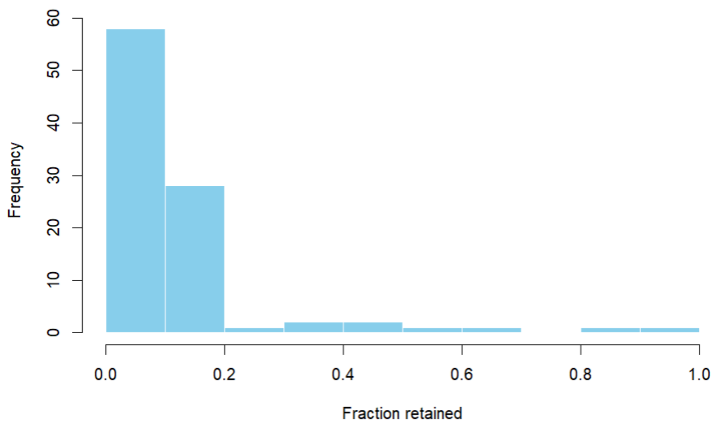

Figure 18. Histogram of cumulative (annual) retained fraction per catchment

Implications for downstream flows

While ponds provide meaningful temporary storage on a monthly basis, their cumulative effect on the annual, catchment-scale water balance is limited**.** Instead, ponds primarily buffer intra-seasonal variability, capturing small surpluses during dry months and spilling most water during wet months. As such, the pond system substantially modifies the timing of downstream flows. Because most ponds fill and spill only after local storage is satisfied, a significant portion of runoff is delayed within the landscape, flattening and lagging the basin hydrograph. Consequently, the hydrological effect of ponds is primarily temporal rather than volumetric—they delay runoff rather than deplete it (Figure 19).

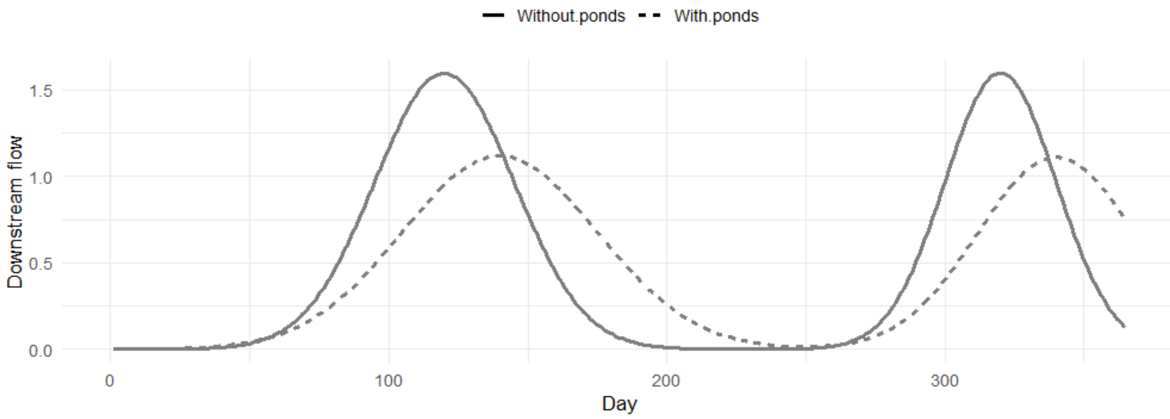

Figure 19. Effect of on-farm ponds on downstream hydrology

Although the volumetric impact on total downstream discharge is small, the environmental implications warrant further exploration. Even modest shifts in the timing, frequency, or duration of flow can alter key ecological processes such as sediment transport, nutrient delivery, and aquatic habitat connectivity (Bunn & Arthington, 2002; Owusu et al., 2022). In many dryland river systems, short-lived high-flow pulses act as critical ecological triggers—initiating fish migration, floodplain recharge, seed dispersal, and primary productivity. If these pulses are delayed, attenuated, or desynchronized from seasonal cues, they may disrupt ecological functioning even when total flow volumes remain largely unchanged. Understanding such timing-dependent effects in the CHEF region is therefore essential for assessing the broader sustainability of on-farm storage to meet water deficits.

There is also the potential that during intense rainfall events, excessive overflow result in localized flooding or erosion in adjacent areas if overflow structures are inadequate or poorly directed. Thus, understanding overflow dynamics is essential to ensure that pond placement and design do not inadvertently increase flood risks within the catchment.

Managing Water in CHEF Within Limits

CHEF is a strategic hotspot where water management decisions have nation-wide implications on food security, water resources and biodiversity. Addressing its deficits will require management approaches that balance hydrological and environmental limits with agricultural demands.

At the basin scale, there is little additional water to allocate, as CHEF is already nearly closed. At the farm scale, large areas of cropland are unable to meet their current crop water requirements, particularly during the critical growing season. Water stress is concentrated in the Ranching, Marginal Cotton, and Livestock–Millet zones, where seasonal shortages regularly exceed tens of thousands of hectares. By contrast, over-irrigation are mostly confined to perennial systems such as the Tea–Dairy and Coffee–Tea zones, and even there, the extent of over-irrigation is far smaller than the deficit areas. This indicates that the challenge in CHEF is not simply to mobilize “more water,” but to better match limited water supplies with crop demands through improved timing (water harvesting, storage, and redistribution), efficiency measures (soil moisture management, irrigation efficiency), and adjusting crop choices to align with water availability.

Within this hydrologically constrained context, the rationale for on-farm pond storage shifts from augmenting water supply to rebalancing its timing. Spatial analysis shows that the physical potential for pond development is widespread across CHEF. The highest densities of feasible 1000 m³ ponds (10–25 ponds km^{-2}) occur in the mid- to upper-elevation cropland belts, particularly along the eastern and southeastern slopes of Mount Kenya. In contrast, the northern and northeastern catchments, adjacent to the arid and semi-arid (ASAL) zones, are characterized by lower pond densities but deeper recommended storage (1.25 m) to offset greater evaporative losses. The storage simulations show that distributed ponds capture and hold a portion of surface runoff during wet months, reducing immediate downstream flow peaks, while releasing it gradually through use or delayed spill. As a result, pond systems primarily alter the temporal distribution of water, flattening the basin hydrograph and extending low flows, without substantially reducing total annual runoff. In practical terms, ponds enhance intra-seasonal water reliability, enabling farmers to bridge short dry spells and sustain crops during critical growth stages even in an almost fully allocated basin. However, it is essential to assess both the economic feasibility and overall viability of these approaches, as well as to identify potential socio-economic barriers that may hinder their adoption.

However, the widespread adoption of on-farm storage also introduces new management risks. When additional water becomes accessible locally, farmers may respond by expanding irrigation areas, over-irrigating, or shifting to more water-demanding crops. Such behavioural responses could raise overall consumptive use, effectively tightening basin closure and further reducing environmental or downstream flows. There is also the issue of whether even modest shifts in the timing alter key ecological processes such as sediment transport, nutrient delivery, and aquatic habitat connectivity. The small and shallow nature of typical on-farm ponds (≈1–1.5 m deep) makes them prone to rapid sedimentation, requiring regular maintenance and desilting to retain their buffer capacity. Rather than attempting to monitor each individual pond, management efforts should focus on monitoring aggregate storage development and flow responses at the catchment level to ensure that cumulative pond volumes remain within sustainable limits. This underscores the need to complement physical storage interventions with basin-scale governance, sediment management, and hydrological monitoring frameworks. In a basin that is productive but hydrologically near its limits, the value of ponds lies not in increasing withdrawals, but in stabilizing timing and reliability within the limits of the existing water budget.

This study has some limitations that should be considered when interpreting the findings. First, although precipitation and discharge datasets were bias-corrected using available in situ observations, the number and spatial coverage of stations remain limited. The study also relies heavily on other satellite-derived products such as land-use, and evapotranspiration, each of which carries inherent uncertainties related to sensor limitations, model assumptions, and spatial resolution. Again, the modelling assumes uniform farmer behavior and does not explicitly account for socio-economic diversity, adoption constraints, or potential rebound effects from additional water access. Finally, the storage assessments focus on physical feasibility and hydrological function; economic costs, governance factors, sedimentation dynamics, and ecological impacts are only qualitatively discussed. Field validation and higher-frequency monitoring will be essential to refine these estimates and assess the broader viability of pond systems and other water innovations in CHEF.

Based on the findings and limitations, forthcoming research in the CHEF basin will verify modelled water stress and over-irrigation by monitoring soil moisture directly on farms and measuring their impact on crop yields and farm incomes. Further, we will complement the current storage simulations with alternative water innovation strategies to overcome water stress such as the potential of solar irrigation for specific cropping systems. The study will evaluate for both type of interventions the sustainability, effectiveness, and financial practicality across various climate scenarios. The insights gained will contribute to developing a CHEF Water Investment Decision Support System (DSS). Collectively, these actions aim to turn hydrological understanding into investment and policy recommendations to overcome the water binding constraints for different agricultural cropping systems in CHEF.

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Appendix A.

Table A.1. Updated monthly crop water requirements of major production types in CHEF region

Crop	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Cattle - Sheep - Barley Zone	0.63	0.63	0.73	0.94	0.87	0.72	0.63	0.63	0.63	0.63	0.63	0.63
Cattle - Sheep - Barley Zone/Ranching Zone	0.71	0.71	0.79	0.94	0.89	0.78	0.71	0.71	0.71	0.71	0.71	0.71
Cattle and Sheep Zone	0.95	0.95	0.95	0.95	0.95	0.95	0.95	0.95	0.95	0.95	0.95	0.95
Coffee - Tea Zone	1.05	1.05	1.05	1.05	1.05	1.05	1.05	1.05	1.05	1.05	1.05	1.05
Cotton Zone	0	0	0.35	0.77	0.9	1.18	1.05	0.6	0.6	0	0	0
Forest / Wheat/Maize - Barley Zone	0.25	0.25	0.48	1.09	1.01	0.66	0.45	0.25	0.25	0.25	0.25	0.25
Forest Zone	1	1	1	1	1	1	1	1	1	1	1	1
Livestock - Barley Zone	0.48	0.48	0.63	0.94	0.83	0.6	0.48	0.48	0.48	0.48	0.48	0.48
Livestock - Millet Zone	0.48	0.48	0.71	0.83	0.98	0.74	0.63	0.48	0.48	0.48	0.48	0.48
Livestock - Sorghum Zone	0.48	0.48	0.78	0.92	0.83	0.78	0.75	0.48	0.48	0.48	0.48	0.48
Main Coffee Zone	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1
Maize - Sunflower or Upper Sisal Zone	0.18	0.18	0.28	0.73	0.89	0.7	0.53	0.3	0.18	0.18	0.18	0.18
Maize - Sunflower Zone	0	0	0.15	0.83	1.06	0.78	0.52	0.18	0	0	0	0
Maize - Sunflower or Upper Sisal Zone	0.18	0.18	0.28	0.73	0.89	0.7	0.53	0.3	0.18	0.18	0.18	0.18
Maize and Marginal Coffee Zone	0.55	0.55	0.7	1.15	1.15	0.79	0.79	0.55	0.55	0.55	0.55	0.55
Marginal Coffee Zone	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1
Marginal Coffee/Sunflower - Maize Zone	0.37	0.37	0.47	0.92	1.07	0.88	0.71	0.48	0.37	0.37	0.37	0.37
Marginal Cotton Zone	0	0	0.35	0.77	0.9	1.18	1.05	0.6	0.6	0	0	0
Moor and Heathlands	0.92	0.92	0.92	0.92	0.92	0.92	0.92	0.92	0.92	0.92	0.92	0.92
Nomadism Zone	0.95	0.95	0.95	0.95	0.95	0.95	0.95	0.95	0.95	0.95	0.95	0.95
Ranching Zone	0.95	0.95	0.95	0.95	0.95	0.95	0.95	0.95	0.95	0.95	0.95	0.95
Rocks and Glaciers	0.32	0.32	0.32	0.32	0.32	0.32	0.32	0.32	0.32	0.32	0.32	0.32
Sheep - Dairy Zone	0.95	0.95	0.95	0.95	0.95	0.95	0.95	0.95	0.95	0.95	0.95	0.95
Sheep Zone	0.95	0.95	0.95	0.95	0.95	0.95	0.95	0.95	0.95	0.95	0.95	0.95
Sheep and Dairy Zone	0.95	0.95	0.95	0.95	0.95	0.95	0.95	0.95	0.95	0.95	0.95	0.95
Tea - Dairy Zone	0.98	0.98	0.98	0.98	0.98	0.98	0.98	0.98	0.98	0.98	0.98	0.98
Tea Zone	1	1	1	1	1	1	1	1	1	1	1	1
Waterbody - Livestock - Sorghum Zone	0.67	0.67	0.67	0.82	0.97	1.03	0.85	0.78	0.67	0.67	0.67	0.67
Waterbody - Ranching Zone	1	1	1	1	1	1	1	1	1	1	1	1
Wheat - Barley Zone	0	0	0.3	1.07	0.93	0.59	0.16	0	0	0	0	0
Wheat - Pyrethrum Zone	0	0	0.15	0.84	1.04	1	0.44	0.18	0	0	0	0
Wheat/Maize - Barley Zone	0	0	0.3	1.12	1.02	0.55	0.27	0	0	0	0	0
Wheat/Maize - Pyrethrum Zone	0	0	0.2	0.96	1.09	0.83	0.45	0.12	0	0	0	0
Wheat/Maize Zone	0	0	0.3	1.21	1.18	0.7	0.4	0	0	0	0	0

Table A.2. Comparison of CHEF area to Kenya (Owusu, Matheswaran, et al., 2024)

Zone	CHEF area (ha)	Kenya (ha)	% CHEF: Kenya
Total area	5,206,386	55,089,235	9.5
Non-crop	3,469,710	47,488,602	7
Cropland	1,736,676	7,600,634	23
Rainfed	1,535,063	6,359,166	24
Total irrigated	201,613	1,241,406	16
Formal irrigation	45,544	361,854	13
Supplemental irrigation	156,069	879,552	18

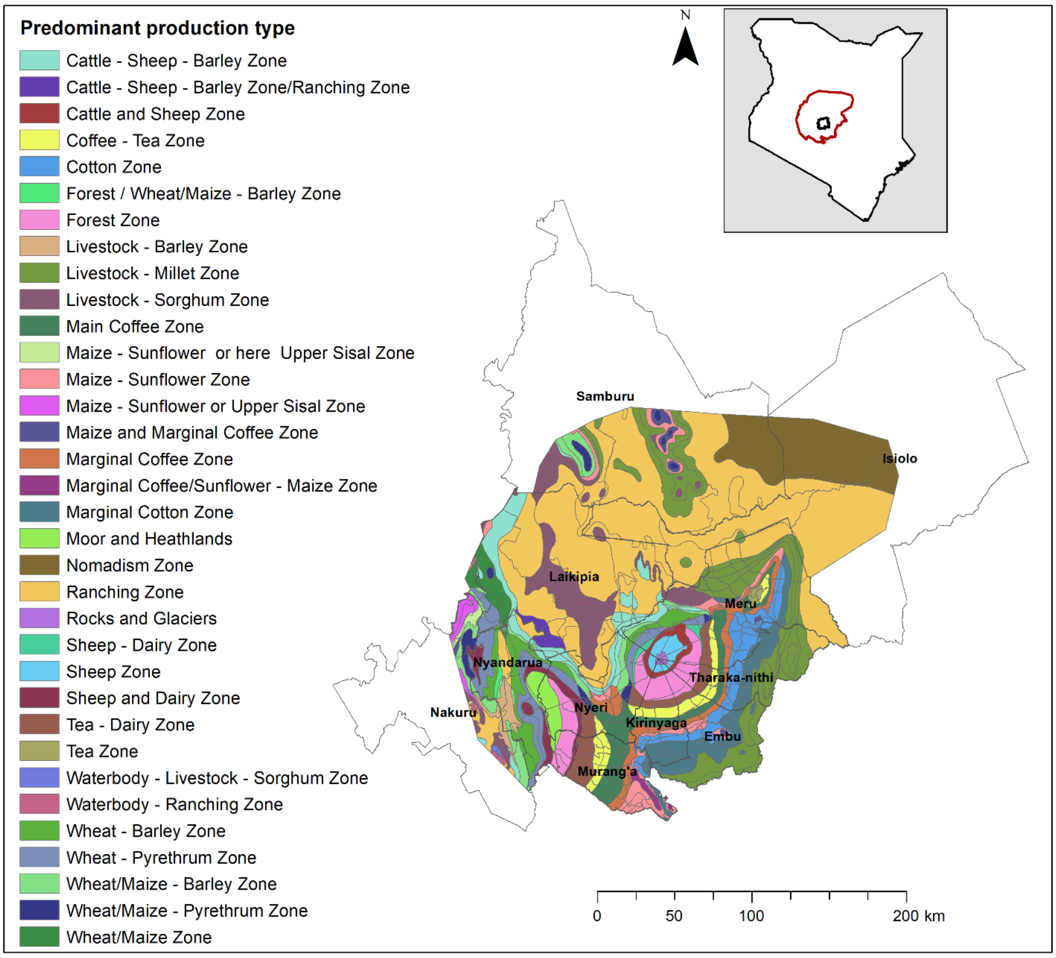

Figure A.1. Predominant production in the CHEF region (source: The Nature Conservancy (TNC)) (Owusu, Matheswaran, et al., 2024)

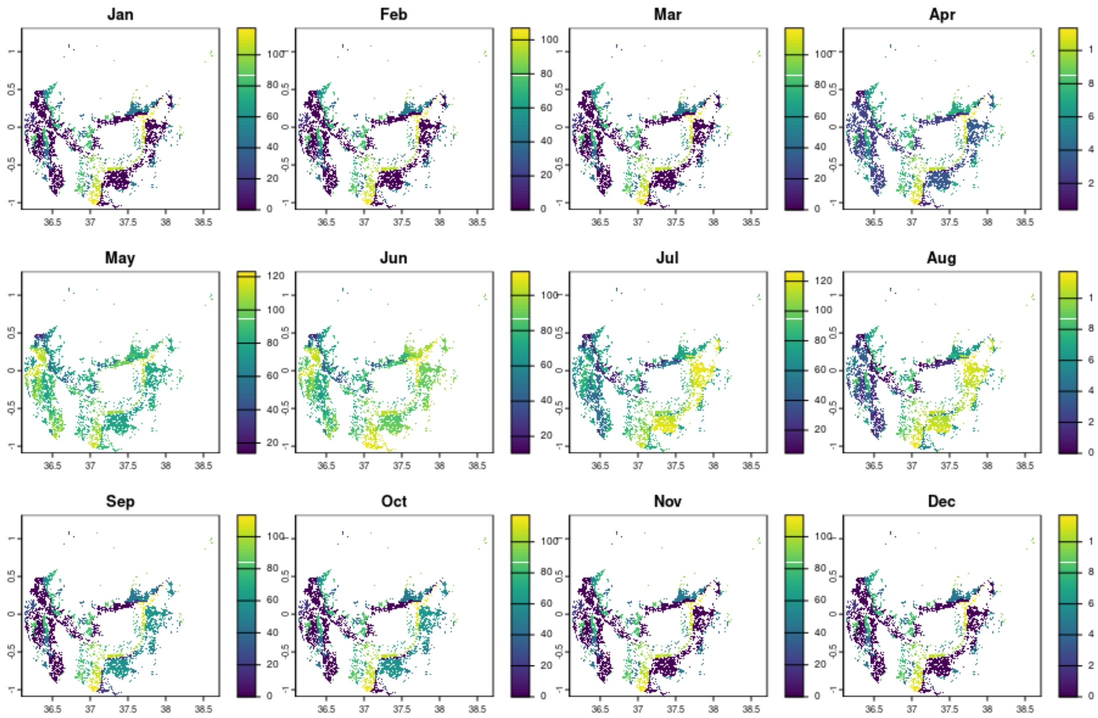

Figure A.2. Monthly crop water requirement (CWR) on CHEF croplands

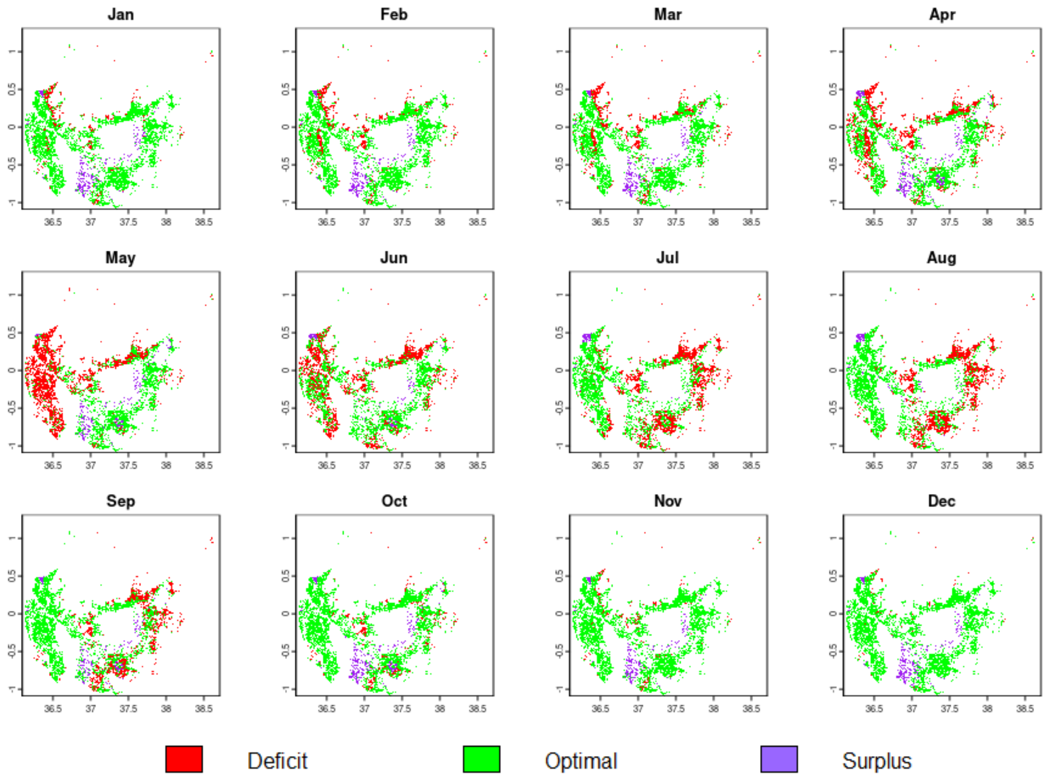

Figure A.3. Cropland areas with deficit (red), surplus (purple) and optimal (green) water status in 2019 in CHEF

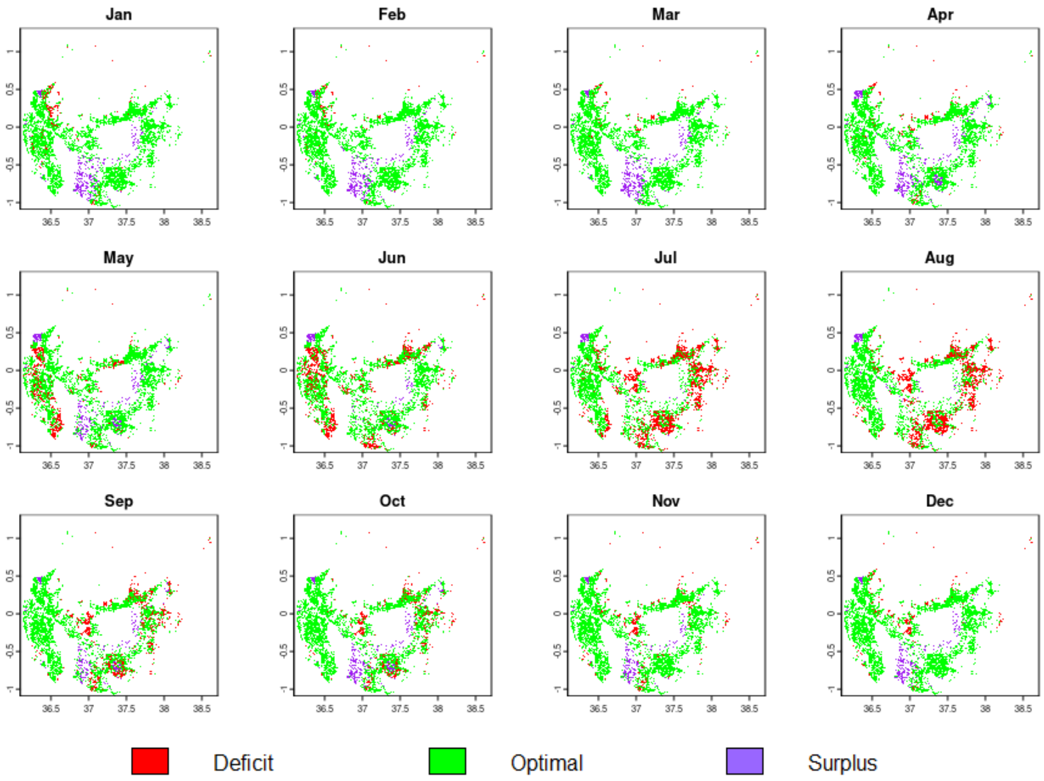

Figure A.4. Cropland areas with deficit (red), surplus (purple) and optimal (green) water status in 2020 in CHEF

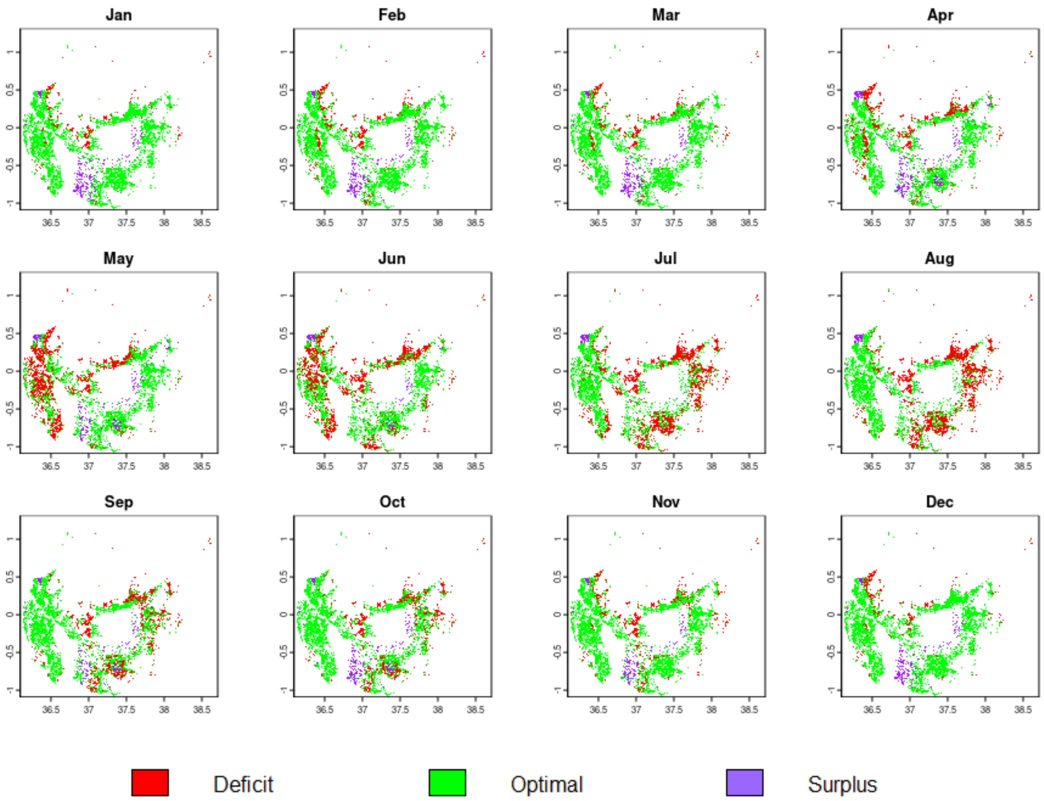

Figure A.5. Cropland areas with deficit (red), surplus (purple) and optimal (green) water status in 2021 in CHEF

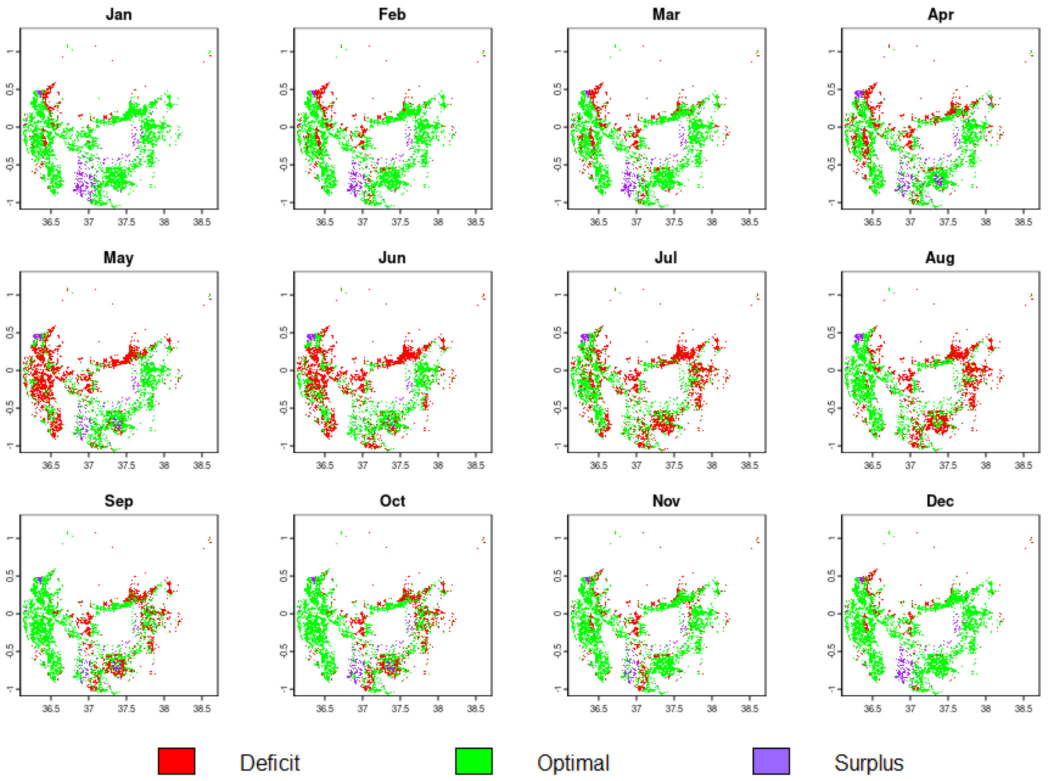

Figure A.6. Cropland areas with deficit (red), surplus (purple) and optimal (green) water status in 2022 in CHEF

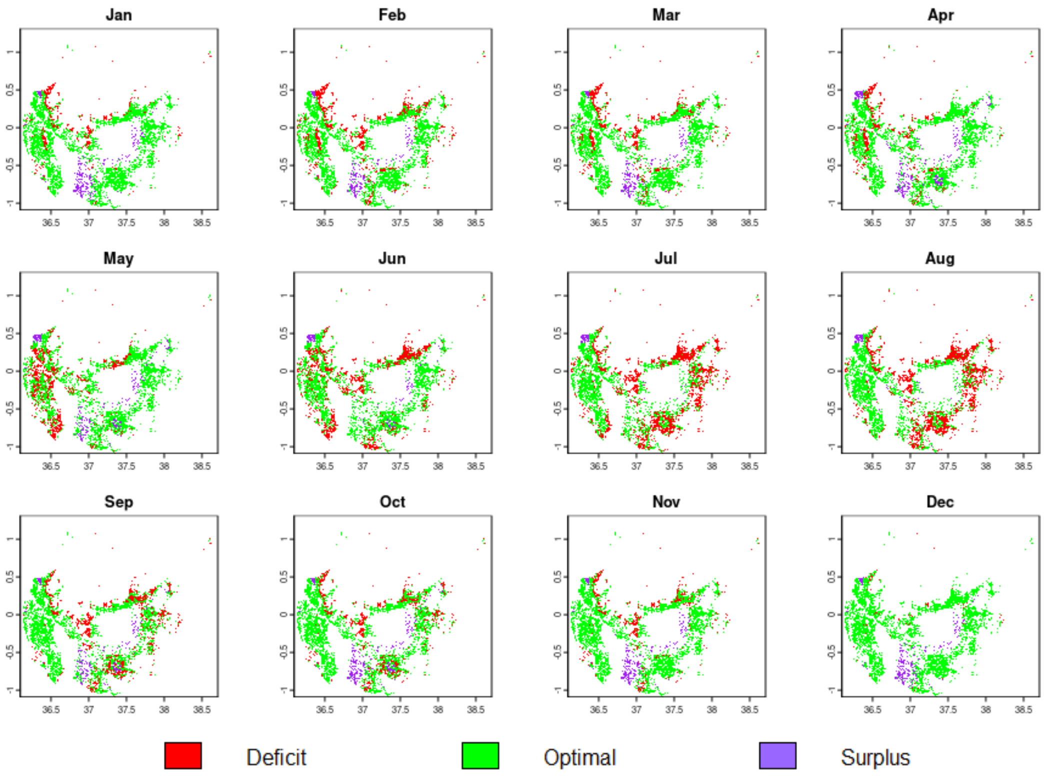

Figure A.7. Cropland areas with deficit (red), surplus (purple) and optimal (green) water status in 2023 in CHEF

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