Monitoring and Forecasting Kenya's Fluctuating Hydroclimate

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ABSTRACT: This study reviews Kenya's fluctuating hydroclimate (3°S–4°N, 35°–40°E) and evaluates products that describe its area-averaged daily rainfall during 2008–18, monthly evaporation during 2000–18, and catchment hydrology via gauge, satellite, and model hindcast/forecast. Using the correlation of rainfall as a metric of skill we found daily satellite versus model hindcasts achieved 75%, while model forecasts at 2–6-day lead achieved 55%–58%. The daily satellite versus model soil moisture had a significant correlation (84%), and model runoff versus gauge streamflow reached 61%. A 2-day delay was noted between rainfall and streamflow response in recent flood events; however, long-range predictability was found to be poor (35%). These outcomes were considered at a local workshop, and ways to sustainably improve the real-time reporting of key hydroclimate parameters for operational data assimilation were suggested as steps toward better monitoring and forecast services in Kenya.

KEYWORDS: Africa; Satellite observations; Surface observations; Regression analysis; Short-range prediction

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Kenya's economy is driven by agriculture, tourism, and diaspora remittances. The poverty rate is highest in the northeastern lowlands where droughts are common (Parry et al. 2012), yet localized floods impact the central highlands causing financial losses > 5% of GDP about once per decade [Ministry of Environment and Natural Resources (MENR); MENR 2002; Mogaka et al. 2006]. Of Kenya's estimated 30 B m³ of water reserves, 20 B m³ are from renewable surface water sources, the rest is supplied from groundwater and transboundary rivers [World Resources Institute (WRI); WRI 2007]. Water covers 2% of the country (Mango et al. 2010) and includes many large lakes (Mutimba et al. 2010) and runoff from five distinct mountainous areas. Water resources are concentrated in the central and western highlands that drain into the White Nile via Lake Victoria (WRI 2007).

Despite these resources, Kenya is a water-scarce country (Mango et al. 2010). Water availability has declined from 900 to 400 m³ per capita in recent decades (WRI 2007) with population growth of ~3% and abstraction exceeding recharge (Kandji 2006). Seventy percent of water demand is from agriculture [World Water Assessment Programme (WWAP); WWAP 2006] that includes grazing in arid zones (Mogaka et al. 2006). Although domestic consumption is 20% of demand, only a few urban centers have water service; about 30% of the population obtain their water from open sources that carry health risks (e.g., cholera). The future demand for water is projected to exceed supply (WRI 2007).

Managing weather-related risks requires sufficient data in Kenya and surrounding countries (Conway 2009). Kenya has 25 official meteorological stations (Ziervogel et al. 2008) and >100 volunteer gauges, but many reports are too late for global assimilation and satellite-model calibration. In neighboring Somalia and South Sudan only the capital cities are reporting. The dwindling number of online stations limits the initialization accuracy of short-range weather forecast models.

East Africa is prone to weather extremes with a variable climate and population exposure to vulnerability. In the past few years, the region has experienced significant drought and flood events (Zwaagstra et al. 2010). The most notable droughts were in 2000 and 2016, associated with the cool phase of El Niño–Southern Oscillation (ENSO). The flow of the Tana River at Garissa almost ceased for the first time since 1941. On the other hand, Kenya recorded 17 major flood events since 1961 that limited production.

River monitoring networks have the potential to mitigate the impacts of floods, but such gauges are operational for just a few rivers in Kenya, as evident in the Water Resources Agency (WRA) information system queried in 2019. Weather advisory bulletins are issued to the public by the Kenya Meteorological Dept (KMD), but lead times may be insufficient for effective action. Rainfall tends to be concentrated in March–May or September–November seasons but long-range predictions are constrained by unsteady forcing by Pacific ENSO and the Indian Ocean dipole (IOD), as shown below. Some work has linked rainfall with the equatorial Madden–Julian oscillation (MJO) (Kilavi et al. 2018) and to atmosphere circulations over the tropical Atlantic (Jury 2015). In neighboring countries of Uganda and Ethiopia the rains come in different seasons and favor Pacific La Niña (Jury 2014, 2017a), while Kenya's rainfall is bimodal and increases during El Niño.

The objective of this study is to optimize the monitoring and forecasting services of KMD and WRA, as part of a larger project (Aurecon 2019a,b,c). The review will provide context on Kenya's range of climates and consider how to best integrate products from the Global Data Assimilation System into existing resources, by statistical evaluations and feedback from a workshop conducted at Nairobi in December 2019. The methods support thematic outcomes: (i) mean climate, (ii) the monitoring system, (iii) short- and long-range forecasts, (iv) hydrological trends, and (v) recommendations for sustainable improvement.

Data and methods

Data. To gain insight on Kenya's range of climate, 1-km-resolution satellite land surface temperature and 5-km-resolution satellite-gauge rainfall were averaged during 2000–18 and mapped. Four types of data were gathered at two space–time scales: (i) interpolated gauge—from Climate Prediction Center v2 (CPC; Chen et al. 2008), Global Precipitation Climatology Center v8 (GPCC8; Schneider et al. 2014), and Climate Research Unit v4 (CRU4; Harris et al. 2014); (ii) satellite—Global Precipitation Monitoring (GPM; Huffman et al. 2009), Tropical Rainfall Measuring Mission (TRMM; Huffman et al. 2007), CPC morphed rainfall (CMORPH; Joyce et al. 2004), Climate Hazards Infrared Precipitation with stations (CHIRPS v2; Funk et al. 2014), net outgoing longwave radiation (OLR; Lee 2014); (iii) model hindcasts—from the European Centre for Medium-Range Weather Forecasts v5 (ECMWF5; Hersbach et al. 2020) and the Coupled Forecast System reanalysis v2 (CFSr2; Saha et al. 2014); and (iv) model forecasts—from the Global Forecast System v2 (GFS; Hamill et al. 2013) at 2-, 4-, and 6-day lead time and from ECMWF and CFS at seasonal lead time. Some of the satellite products are blended with gauges for calibration.

Temporal records were generated for daily data by averaging over the “highlands” (2°S–2°N, 35°–38°E) in the period 2008–18 ($N = 3,924$ days). The daily focus was on wet spells characterized by catchment rainfall, soil moisture and streamflow measurements at Mutonga and Garissa (cf. Fig. 1a). Soil moisture derives from AMSR2 satellite, ECMWF5, CFSr2, and NASA FEWS and Global Land Data Assimilation System v2 (FLDAS, GLDAS2;

Fig. 1. (a) Topography with “highlands” and “all” index areas for statistical analysis. The inset shows Kenya’s elevation vs mean rainfall at 50-km resolution. (b) MODIS satellite vegetation color fraction, averaged during 2000–17.

McNally et al. 2017; Rodell et al. 2004); and gridded streamflow reanalysis derive from the German Runoff product (GRUN; Ghiggi et al. 2019). Monthly data were averaged over “all-Kenya” (3°S–4°N, 35°–40°E) in the period 2000–18 ($N = 228$). In application the monthly analysis focused on dry spells characterized by potential evaporation and sensible heat flux (SHF) calibrated with station data (Dee et al. 2011). Previous work in Africa had determined that model SHF can be adjusted to fit A-pan measurements (Jury 2017b), to estimate moisture deficits.

GPM is a nowcast tool that relies on a multisatellite combination of infrared and microwave sensors blended with surface observations at 10-km and 30-min resolution. The in situ rain gauge network serves to calibrate the GPM product, but delayed reporting can undermine accuracy.

Methods. To evaluate the monitoring and forecasting products, statistical correlations were calculated: (i) temporally (time series, scatterplot) and (ii) spatially (field regression). Tables 1 and 2 list the Pearson-product values for daily rainfall and monthly evaporation, respectively. The degrees of freedom is deflated for autocorrelation such that $r > |0.30|$ (daily) and $r > |0.50|$ (monthly) is significant above the 90% confidence level.

From the temporal record of Kenya highlands daily rainfall, we identified flood cases on 3 March and 15 April 2018. The flood weather scenario was analyzed via regional wind maps of Modern-Era Retrospective Analysis for Research and Applications (MERRA-2; Rienecker et al. 2011) and GPM rainfall.

Seasonal forecasts of Kenya highlands rainfall by coupled ensemble versions of the ECMWF and CFS2 models at 3-month lead time were compared with satellite–gauge products during 1980–2018. These outcomes were segregated into March–May and September–November seasons, and discriminated by observed (30–60-day) MJO and (3–5-yr) IOD indices.

Spatial trends were mapped in rainfall, streamflow, vegetation fraction, wind, and temperature fields; and placed in context of satellite estimated carbon monoxide and methane gas concentrations. Temporal trends for the all-Kenya area were analyzed from coupled climate model projections with RCP8 scenario, consistent with CMIP5 IPCC (2013) methodology. Regressions were fitted to the time series and the slope function and r^2 variance was computed.

Table 1. Evaluation of rainfall. The upper part of the table lists averages and standard deviations (mm day^{-1}); the lower part of the table lists correlations for *daily* rainfall averaged over the Kenya highlands during 2008–18, with $N = 3,924$. Greater values are in boldface.

	GPM	GPCC8	EC-5	CMORPH	CHIRPS2	GPCP3	CPC g	FLDASv	TRMM	CFSr2	GFS day 2	GFS day 4	GFS day 6
Avg	2.4	2.6	3.3	1.2	2.5	1.5	2.7	1.1	2.4	3.3	2.2	2.3	2.3
Std dev	3.9	3.9	3.7	2.1	4.2	3.3	4.3	3.0	3.8	4.2	3.2	3.1	2.9
2008–18	GPM	GPCC8	EC-5	CMORPH	CHIRPS2	GPCP3	CPC g	FLDAS	TRMM	CFSr2	GFS day 2	GFS day 4	
GPCC8	0.70												
EC-5	0.75	0.66											
CMORPH	0.90	0.67	0.74										
CHIRPS2	0.86	0.65	0.71	0.84									
GPCP3	0.85	0.61	0.65	0.83	0.89								
CPC g	0.65	0.85	0.63	0.62	0.62	0.56							
FLDAS	0.52	0.50	0.48	0.53	0.49	0.50	0.52						
TRMM	0.94	0.73	0.75	0.91	0.87	0.87	0.69	0.55					
CFSr2	0.71	0.62	0.76	0.72	0.71	0.64	0.58	0.52	0.70				
GFS day 2	0.55	0.48	0.62	0.57	0.54	0.52	0.44	0.39	0.54	0.66			
GFS day 4	0.56	0.50	0.63	0.56	0.54	0.52	0.47	0.41	0.53	0.68	0.77		
GFS day 6	0.58	0.53	0.65	0.59	0.58	0.53	0.51	0.46	0.58	0.67	0.66	0.74	

Table 2. Evaluation of evaporation. The upper part of the table lists means and standard deviations (mm day⁻¹); the lower part of the table lists correlations for *monthly* potential evaporation (pet) and proxies thereof: sensible heat flux (SHF), satellite net outgoing longwave radiation (OLR), averaged for all-Kenya during 2000–18, with *N* = 224. Greater values are in boldface.

	EC3 pet	MER SHF	EC5 SHF	Net OLR	FLDAS SHF	GLDAS pet	CRU4 pet	CFSr2 SHF
Avg	6.4	3.5	2.7	9.3	3.7	10.1	4.2	3.3
Std dev	0.80	0.70	0.47	0.44	0.71	1.39	0.43	0.65
	EC3 pet	MER SHF	EC5 SHF	net OLR	FLDAS SHF	GLDAS pet	CRU4 pet	
MER SHF	0.73							
EC5 SHF	0.77	0.91						
net OLR	0.73	0.68	0.60					
FLDAS SHF	0.55	0.91	0.81	0.65				
GLDAS pet	0.57	0.62	0.63	0.53	0.60			
CRU4 pet	0.72	0.36	0.53	0.27	0.10	0.20		
CFSr2 SHF	0.55	0.60	0.52	0.48	0.57	0.32	0.25	

Evaluating a diverse set of parameters and time scales yields guidance on the global tools available for monitoring and forecasting local drought and flood. These tools need to be integrated into KMD and WRA services to overcome deficiencies, following similar work in Zambia (Jury 2017b) and by Aurecon (2019a,b,c). Recommendations for sustainable improvements were fine-tuned during a local workshop.

Results

Mean hydroclimate. Kenya’s climate is placed in context using high-resolution topography, vegetation, rainfall, circulation, and temperature (Figs. 1a,b and 2a,b). Although Kenya’s east coast is warm and humid with average temperatures of 30°C (MENR 2002; Mutimba et al. 2010), most of the interior is semi-arid and receives rainfall < 700 mm yr⁻¹. In northern Kenya’s Turkana Valley mean daytime land surface temperatures exceed 50°C. The western highlands receive > 1,200 mm yr⁻¹, while the Rift Valley and lowlands are dry. Seasonal rainfall patterns depend on the equatorial trough and nearby west Indian Ocean monsoon that shifts southward in October–December and northward in March–May (Seitz and Nyangena 2009; Thornton et al. 2009). Rainfall varies from year to year partly due to IOD and Pacific ENSO sea temperatures, being wetter during El Niño (Conway 2009). Figure 2b reveals sharp land surface temperature gradients that underscore lowland–highland regimes.

Temporal variability is revealed by satellite-model time series in Figs. 3a–c. Lake Victoria and Lake Turkana share similar height fluctuations despite large differences in orographic rainfall (inset in Fig. 1a). Low lake levels induced by cumulative dry spells in 1992–95 and 2004–06 alternate with high levels in 1997–99 and the recent decade. While the lakes respond slowly to the regional water balance, the soil moisture over the Kenya highlands shows multiday fluctuations and erratic twice-yearly oscillations (Fig. 3b). Upward spikes at the beginning of wet seasons are followed by gradual reductions through infiltration and evaporation. The erratic behavior over the 3° × 4° highlands is evident in two models used in long-term forecasts (CFS2, ECMWF) which follow the AMSR2 satellite (Fig. 3b), indicating that coupled data assimilation systems are capable of monitoring large catchments with consensus. Comparison of GPM catchment rainfall and streamflow in April–June 2019 (Fig. 3c) shows a 2-day delay in flood events, offering a chance for mitigating action via an operational product with minor latency. Hence this part of the evaluation distinguished two climate regimes and showed that nowcasts from GPM satellite and CFS and ECMWF models achieve consensus.

Evaluation of rainfall and evaporation products.

This section considers the adequacy of the station network and the optimal gridded products for monitoring, to fill in any gaps. A brief inspection of Kenya's real-time monitoring network reveals ~20 rain and temperature stations currently online (Figs. 4a–c). The frequency of meteorological reports is adequate (Fig. 4d), but only 3 streamflow gauges were online (in 2020). Our validations compare satellite–gauge blended products with highlands averaged model hindcasts and forecasts (Table 1). Satellite-only rainfall estimates by CMORPH, GPCP3, FLDAS are drier ($<2 \text{ mm day}^{-1}$) while high-resolution model hindcasts by ECMWF5, CFSr2 are wetter ($>3 \text{ mm day}^{-1}$) than gauge-interpolated products from GPCC8, CPC. The satellite–gauge blended products are near consensus: GPM, TRMM, CHIRPS2 with an average of 2.5 mm day^{-1} and a standard deviation of 4.0 mm day^{-1} . Regarding soil water losses, the ECMWF5 model sensible heat flux (after calibration) is deemed a useful proxy for potential evaporation (Table 2). Its mean annual cycle peaks in January–February and September–October (Fig. 4e), and is about double the mean rainfall.

The daily rainfall evaluations in the period 2008–18 yielded significant correlations between the GPM product (Fig. 5a) averaged over the highlands and ECMWF5 hindcast ($r = 0.75$), and CFSr2 hindcast ($r = 0.71$; Table 1, lower portion, and Fig. 5b). Surprisingly, the GFS forecasts at –6-day lead time were slightly better than –2-day lead time ($r = 0.58$ vs 0.55). Correlations decline rapidly for smaller areas, in agreement with Roberts (2008, his Fig. 3d) that shows model skill in forecasting localized rainfall at 1-day lead time declines from 85% for a 500-km radius to 5% for a 10-km radius. For smaller catchments GPM rainfall monitoring is necessary to overcome the limited skill of operational model forecasts at individual grid points.

Tana basin discharge from the GLDAS model was compared with daily measurements at Garissa from 1948 to 2014 (with some gaps). Figure 5c shows that the model product aligns with

Fig. 2. (a) Mean ECMWF surface wind vectors and CHIRPS2 rainfall (shaded). (b) MODIS daytime land surface temperature (°C) averaged during 2003–16.

Fig. 3. (a) Satellite altimetry levels for Lake Victoria and Turkana, of differing volume (2,420 vs 204 km³) and elevation (1,135 vs 360 m). (b) Comparison of daily Kenya highlands soil moisture: CFSr2 and ECMWF5 nowcasts vs AMSR2. (c) Comparison of catchment rainfall (0.5°N–0.5°S, 37°–38°E) and Mutonga streamflow, revealing ~2-day lag to runoff—highlighted by arrows in the flood event during 29 Apr–1 May 2019.

Fig. 4. (a) Map of daily rain gauges in GPCC8 (colored by reporting frequency). (b) Gauge influence on GPM merged daily rainfall averaged during 2014–18; the max value near Nairobi indicates 70% influence or 30% latency. (c) Temperature reports received via WMO-GTS in November 2018 (indicated by monthly maximum value). (d) Surface reports across Africa assimilated by ECMWF during January 2019 (avg daily sum per 5° grid) with green values indicating high density and timeliness. (e) Mean annual cycle of ECMWF potential evaporation and calibrated sensible heat flux averaged for all-Kenya.

Fig. 5. (a) Daily GPM rainfall, averaged over the Kenya highlands. **(b)** Scatterplots of daily rainfall over the Kenya highlands, comparing GPM satellite with (left) ECMWF5 and (right) CFSr2 (cf. Table 1). **(c)** Comparison of GLDAS model daily streamflow with the Garissa gauge on the Tana River (see photo in Fig. A1).

gauge ($r = 0.61$), although there are lengthy spells of offset. Recent streamflow validations for East Africa, using multisatellite rainfall in hydrological data assimilation models, have shown favorable results (McNally et al. 2016; Aurecon 2019a).

Floods and short-range forecasts. The March–May 2018 floods had major impacts, as most of Kenya’s river overflowed their banks, inundating farmlands and informal settlements. ECMWF and local KMD forecasts indicated a likelihood of floods at lead times too short for mitigating action (Wilkinson et al. 2018). Despite the damage, there was a subsequent increase of maize yield and groundwater resources, improved pasture conditions in northern Kenya following the lengthy drought, and more reliable hydropower electricity generation (Kilavi et al. 2018).

The weather scenario of the early March and mid-April 2018 floods reveals that equatorial “waves” and tropical cyclones near Madagascar led to a moist westerly low-level circulation (Figs. 6, 7). The time series (Fig. 6a,b, 7b) demonstrate consensus among the various rainfall products. In the early March case, the NE monsoon was strong and built up a NW cloud band linking

Fig. 6. (a) Comparison of rainfall products from February to May 2018 with an arrow pointing to the flood case. (b) Comparison of GFS 2–4-day lead-time forecasts (blue, left-hand Y axis) with ECMWF 30–60-day MJO-filtered rainfall (red, right-hand Y axis) over the Kenya highlands. Also shown is the 15 Apr 2018 flood scenario: (c) MERRA-2 775-hPa wind vectors with key weather features and (d) CHIRPS2 rainfall (mm day^{-1}).

Fig. 7. (a) The 3 Mar 2018 MERRA-2 850-hPa wind and GPM rainfall at the beginning of the floods. Key weather features are labeled. (b) Daily time series of GPM rainfall (dark blue) and FLDAS-vic runoff (light blue) over the Kenya highlands, with an arrow pointing to the case study. The red line represents ECMWF 30–60-day MJO-filtered rainfall. The Y axis has area-average runoff in log scale (black; mm) and rainfall in linear scale (blue; mm day⁻¹).

with Tropical Cyclone Dumazile (Fig. 7a). By contrast, the mid-April flood had SE inflow converging with westerlies from Uganda. Thus, quite different circulations can induce heavy rainfall.

To support operational short-range forecasts by numerical models a statistical approach is considered—using the Kenya highlands daily rainfall, band filtered to retain periods in the range 30–60 days (red lines in Figs. 6b, 7b). Thirty percent of rainfall fluctuations (r^2) in the period 2008–18 fall into the 30–60-day range across all seasons, suggesting links with MJO

emerging from the Atlantic Ocean (Guo et al. 2018). Although local knowledge on synoptic weather forcing of floods is mature, new insights here suggest that tracking the 30–60-day MJO-filtered signals could improve Kenya’s preparedness for dry and wet spells.

Seasonal forecasts. The ability of long-range coupled ensemble models to forecast Kenya’s seasonal rainfall was evaluated. Correlation values achieve a paltry 35% between the ECMWF model and GPCC-interpolated observations (Figs. 8a,b), confirming an unpredictable nature. Adding the observed 30–60-day MJO influence in March–May season does not help; however, adding the observed IOD influence in September–November season does segregate flood and drought. The scatterplots highlight that the ECMWF model is wetter over the highlands than

Fig. 8. (a) Scatterplots of ECMWF 2-month lead forecast vs GPCC highlands rainfall: (a) March–May and (b) September–November seasons, 1981–2015; dots are sized by (a) MJO and (b) IOD. (c) The 15-yr running correlation of Indian Ocean dipole SST with Pacific Niño-3.4 SST, after filtering to remove cycles below 18 months, with a quintile envelop.

gauge averages (of similar elevation).

The link between the Pacific Niño-3.4 SST and IOD (west–east gradient) was analyzed (Fig. 8c) and found to be weak from 1950 to 1965 and again from 2005 to the present, but strong from 1975 to 2000. This unsteady behavior explains why long-range forecasts are poor, e.g., variable response of IOD to Pacific ENSO.

Given the weakness of long-range predictions by numerical models, an analysis of statistical predictability was made using the all-Kenya net OLR time series (Fig. 9a). We correlated with SST fields over the period 1980–2018 (Fig. 9b) and found an alternating warm–cool–warm–cool pattern in the tropics: linking Pacific La Niña and local drought. Similar correlations with the 200-hPa zonal wind field found a strong signal over the east Indian Ocean (Fig. 9c). The ENSO signal carried by the Niño-3.4 SST index has a weaker influence on Kenya rainfall (Fig. 9d) than upper zonal wind (Fig. 9e). The 200-hPa *U* wind is a reliable predictor that may overcome the unsteady connection between ENSO and IOD.

To summarize, this part of the evaluation confirmed limitations in operational long-term numerical rainfall forecasts, and uncovered a statistical tool to improve seasonal predictions, e.g., upper easterlies over the east Indian Ocean anticipate Kenya drought.

Climate trends. We quantify trends in Kenya's climate to understand the local impact of global change and help monitoring and forecast services prioritize their interventions for adaptation and mitigation. Mean annual temperatures have increased by 1.0°C since 1950, at a rate of 0.21°C decade⁻¹ (McSweeney et al. 2009). Hence, glaciers on Mount Kenya have retreated to higher elevation. However, rainfall since the 1950s has not shown a statistically significant trend, except for a marginal increase of October–December rainfall. Meanwhile, the hot months

Fig. 9. (a) Correlations of the filtered all-Kenya net OLR time series compared with $P - E$. Correlation maps of (b) SST and (c) upper zonal winds during 1979–2018. Lag correlations of net OLR time series with (d) tropical east Pacific SST and (e) east Indian upper zonal wind. Tercile envelopes (green lines) show SST is variable but wind is steady (dashed). Cool Pacific and easterly upper winds precede drought [+OLR, arrow in (c)].

of January–February show increasing potential evaporation and coastal rains have intensified (MENR 2002).

The western half of Kenya experiences higher concentrations of short-lived heat-trapping gases (CO , CH_4) as reflected in Figs. 10a and 10b. Spatial trend maps for rainfall and

Fig. 10. Mean air chemistry 2005–18: (a) carbon monoxide and (b) methane concentration (ppb). Trend maps of linear regression slope during 1980–2018: (c) CHIRPS2 rainfall ($\text{mm month}^{-1} \text{yr}^{-1}$), (d) vegetation color (fraction yr^{-1}), (e) surface wind (vectors; $\text{m s}^{-1} \text{yr}^{-1}$), and (f) ECMWF5 maximum air temperature ($^{\circ}\text{C yr}^{-1}$).

vegetation since 1980 (Figs. 10c,d) show increases in the western highlands and decreases in the eastern lowlands (dividing on 37°E). Over the Tana valley there is a trend of divergent winds that favor sinking motions (Fig. 10e). ECMWF temperatures show weak upward trends on the east coast and in the highlands (35°E), and stronger upward trends in the Tana valley (39°E, Fig. 10f).

Temporal trend analyses compare past observed and future CMIP5 ensemble projections. Highlands runoff anomalies exhibit a weak linear rising trend (Fig. 11a) that is projected to continue (trend $r^2 = 30\%$). The all-Kenya maximum air temperature (Fig. 11b) exhibits global warming and a second-order slope from past to future ($r^2 = 96\%$). Projected year-to-year temperature fluctuations are below observed due to ensemble averaging, but accelerating climate change will require strategic plans for land and water management, and measurement of potential evaporation in arid zones.

This section has shown divergent responses to climate change: Kenya's lowlands are drying while the highlands are moistening. Evidence of overlap between past and future trends (cf. Figs. 11a,b) builds confidence in model projections that inform mitigation strategies.

Discussion and recommendations

The above review and evaluation indicate that useful short-term forecasting resources are in hand, but that accuracy may be compromised by the declining density and timeliness of operational reports received by global centers for data assimilation (cf. Fig. 4b). Statistical correlations determined that daily rainfall from satellite versus model hindcasts achieved 75%, while model forecasts at 2–6-day lead achieved 55%–58%. The daily satellite versus model soil moisture had a significant correlation (84%), and model runoff versus gauge streamflow reached 61%. The 2-day delay between rainfall and streamflow response supports the use of GPM in flash-flood warnings; however, long-range forecast performance was weak (35%). Seasonal lead-time mitigation strategies for Kenya are constrained by an unpredictable climate (cf. Figs. 8a,b) which is not easily overcome. Flowing from these outcomes, what improvements can be made?

Considering the declining hydrology network (Fig. 12),

Fig. 11. (a) Temporal analysis of highlands annual runoff anomalies, comparing past observed (GRUN) and future trends projected by CMIP5 models with RCP8 scenario. **(b)** As in (a), but for all-Kenya annual maximum air temperature using the past (CRU4) and future CMIP5 RCP8 ensemble.

it is advisable to limit the gauge network to a manageable level and focus on telemetric stations reporting to global centers for satellite–model calibration. Spatial maps of the rainfall and temperature network (cf. Figs. 4a–c) indicate adequate coverage, but time series show dwindling reports that are often late, and few streamflow gauges (Fig. 12).

The existing network of automatic weather stations may be sufficient with addition of instrumentation for surface heat flux and soil moisture. Weather equipment needs to be low maintenance, integrated, no-moving-parts type, and gradually replace the existing network. These should be collocated with ~20 real-time streamflow gauges distributed across Kenya, naturally more concentrated in the highlands (Fig. A2). This “minimal” monitoring network is less than recommended in Aurecon (2019b), and excludes manual offline measurements for water demand. Real-time communications are essential to the minimal network, so needs for infrastructure, security, and weather exposure will need to be optimized on a site-by-site basis. Due to a lack of reporting in adjacent countries, weather monitoring around the perimeter of Kenya is just as important as the center, since long-term projections of a warming lowlands may impact the highlands climate.

During a workshop with KMD and WRA at Nairobi in December 2019, many tools for monitoring and forecasting were presented (Table 3) to create awareness of global data assimilation products for Kenya. Initially there was resistance among local delegates that satellite–model interpolations could be trusted to fill gaps between gauges, but that view was overturned by the end of workshop. We visited KMD forecast and communication centers, and discussed hydrology network improvements that stressed quality over quantity and the need for real-time reporting to ensure satellite–model calibration for interpolation between gauges.

Fig. 12. Streamflow gauges (rows) operating in the Tana River catchment during 1941–2018, with color referring to percent available per year (columns) from 100% (green) to 0% (red). It is evident that the gauge network has declined to zero in recent years. The arrow points to the gauge used in Fig. 5c. The appendix shows an aerial photo of the Tana River (Fig. A1).

Table 3. Websites used during the Nairobi workshop. Note that maps generated via external websites use standard GIS packages to show country boundaries, which exclude the Ilelmi triangle (Figs. 1a,b, 2a,b, 4a,c, 6d, 10e,f). These figures were sourced from the following websites.

URL	Description
apdrc.soest.hawaii.edu/las86/Ul.vm	Visualization and extraction of hydromet and ocean data: GPM, CFSr2, ECWMF5, HYCOM
telemetry.wra.go.ke	Kenya WRA online streamflow network for monitoring data
climexp.knmi.nl	Sophisticated statistical analysis and extraction of hydromet and ocean data
flood.umd.edu	Monitoring of high-resolution streamflows and flood inundations
iridl.ldeo.columbia.edu/SOURCES/	Sophisticated analysis and extraction of high-resolution hydromet and ocean data
giovanni.gsfc.nasa.gov/giovanni/	Visualization and extraction of air chemistry and hydrology data
www.ecmwf.int/en/forecasts/quality-our-forecasts/monitoring-observing-system#Availability	Visualization of data received by the ECMWF coupled assimilation system
www.cpc.ncep.noaa.gov/products/international/africa/africa.shtml	Africa Desk: Centralized source of real-time monitoring and prediction data
www.aviationweather.gov/metar	Visualization of surface weather reports
ipad.fas.usda.gov/cropexplorer/...global_reservoir/	Visualization of satellite vegetation, soil moisture, drought monitoring, ..., lake levels
www.wmo-sat.info/oscar/gapanalyses?variable=148.../oscar/satellites/view/156	WMO information on satellite monitoring of soil moisture, ..., GPM rainfall
wxmaps.org/pix/soil10	CFSr2 soil moisture forecasts via UMD-COLA
sharaku.eorc.jaxa.jp/GSMaP_NOW/index.htm	Real-time monitoring of high-resolution multisatellite GPM rainfall
www.ospo.noaa.gov/Products/land/smops/	Real-time monitoring of global soil moisture

KMD and WRA delegates considered ways to share logistics to enable operational reporting of streamflows, in support of global coupled data assimilation. Supplementary monitoring by the agriculture service and industrial farmers (soil moisture, potential evaporation) could be included in the real-time system.

The workshop revealed that the WRA is tasked with managing both water supply and demand, and suggested that some of those services might be decentralized and outsourced to the larger municipalities. Agencies involved in cost recovery have fewer resources to track water supplies. Limiting WRA responsibility to bulk distribution would enable more effort on monitoring and prediction, together with KMD. The workshop concluded that Kenya’s preparedness for weather and climate stress could be improved in a realistic and sustainable manner through optimized use of the global tools identified here.

Appendix: Aerial photo of Tana River (A1) and layout of Kenya monitoring network (A2).

Fig. A1. Aerial photo of the Tana River in central Kenya.

Fig. A2. Kenya WRA telemetry streamflow monitoring network.
 Note that only three gauges were operational at the time of writing (2020).

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