Development and application of statistical seasonal forecasts for reservoir optimization in the Tekezé Basin, Ethiopia

By

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Abstract

The Tekezé Reservoir in northern Ethiopia is a crucial resource for hydropower generation regionally and nationally, with electricity demand expected to increase in the coming decades. However, achieving reliable power generation is complicated by significant spatial and temporal variability in precipitation within the basin. Additionally, seasonal hydrological forecasts must be developed at an appropriate spatial scale for successful water resources management and decision-making. Chapter 2 develops local-scale precipitation and inflow forecasts leveraging the asymmetric relationship between El Niño Southern Oscillation (ENSO) phase and local hydrological conditions, thereby unveiling additional teleconnections influencing atmospheric moisture transport to the basin. This work demonstrates that a locally tailored statistical forecast approach is skillful for our study site, with potential applications in other regions subject to highly variable hydrological patterns.

Chapter 3 couples the forecast developed in Chapter 2 with a reservoir optimization model to determine an optimal operation strategy for maximizing hydropower generation during the rainy season. Adopting a flexible reservoir operation strategy based on seasonal forecast information results in improved maximum hydropower generation and increased minimum firm energy generation compared to climatology-based static operational rule curves. This case study demonstrates the potential benefits of incorporating local-scale hydrological forecast information at the decision-making scale to mitigate the effects of a variable climate for sustainable power generation.
Chapter 1: Introduction

1.1 Motivation

Reservoirs are a critical component of infrastructure systems constructed to harness water resources for societal benefit, e.g., hydropower generation, irrigation, and drinking water. However, hydrologic variability threatens reservoir reliability and sustainability. Seasonal precipitation forecast models, whether dynamical or statistical, have demonstrated skill in predicting hydrological conditions globally and can improve water management strategies in areas subject to variability. Using predictive information to improve operations has been applied to reservoir systems globally, such as in central China (Yang et al. 2021), northern California (Jasperse et al. 2017), and western Ethiopia (Alexander et al. 2020). While research in this domain is gaining momentum, this prospect remains relatively unexplored, particularly in data-limited, yet rapidly developing, regions.

Dynamical approaches leverage global climate models (GCMs) to predict precipitation, with advantages of global coverage, forecasts out 9-12 months, high levels of support, and available publicly. Dynamical models, such as the GCMs contributing to the North American Multi-Model Ensemble (NMME), are comprised of several GCMs each with multiple ensemble members. This approach has widespread potential water resources application, such as reservoir operation (Block et al. 2009, Block and Goddard 2012) and irrigation management, particularly in data-limited regions (Kirtman et al. 2014, Shukla et al. 2016). For example, Kioutsioukis et al. (2017) downscale a Weather Research and Forecasting (WRF) regional climate model (RCM) ensemble to predict precipitation for irrigation management in Eastern Europe, while Faber and Stedinger (2001) use National Weather Service (NWS) ensemble streamflow predictions in combination
with stochastic dynamic programming to optimize reservoir operations. However, biases and other discrepancies may be exacerbated during downscaling, which may result in inaccurate representations of local-scale climate conditions (Block and Rajagopalan 2007; Lupo and Kininmonth 2013). Further, some dynamic prediction models failed to properly capture precipitation variability at smaller scales (Zhang et al. 2016). While post-processing may enhance forecast skill in some cases, predictability is generally better on a regional scale rather than local scale (Satti et al. 2017).

Statistical approaches have a potential advantage in addressing local scale prediction by utilizing direct connections with atmospheric and climate variables. While statistical prediction models may not capture complex climate interactions, adopting this approach can unveil relationships between small-scale regional factors and large-scale teleconnections such as the El Niño Southern Oscillation (ENSO), affect precipitation variability (Korecha and Sortenberg 2013, Zhang 2016). Water resource management decisions, such as flood control, irrigation management, and hydropower generation, benefit from prediction frameworks tailored to local climate conditions (Alexander et al. 2020b, Giuliani et al. 2019, Keating et al. 2021, Plotz et al. 2017, Zimmerman et al. 2016). For example, Keating et al. (2021) leverage the relationship between precipitation and ENSO to improve flood prediction at two sites in Peru, resulting in detection of flood conditions that were previously not identified by global-scale dynamic models. Giuliani et al. (2019) employ artificial intelligence techniques to improve seasonal forecasts for reservoir operations in Lake Como, Italy. Zimmerman et al. (2016) develop a statistical prediction model for the Lower Colorado Basin, Texas, through teleconnections between ENSO phase and local precipitation, demonstrating skill during extreme wet/dry conditions and
outperforming dynamic models for the region. Applying statistical models at the local scale not only can enhance forecast skill but may result in increased uptake by end users (Alexander et al. 2020, Gilles and Valdivia 2009).

Coupling seasonal forecasts with reservoir optimization models has been previously investigated to evaluate potential benefits of incorporating predictions into operational decision-making. Many studies utilize dynamic forecast models to guide optimal reservoir allocations due to their ability to capture large-scale climate dynamics (Block et al. 2009, Faber and Stedinger 2001). Some studies regarding seasonal statistical predictions for reservoir management have shown improved performance (Alexander et al. 2020, Georgakakos 1989, LaMontagne and Stedinger 2018, Yang et al. 2020). Doering et al. (2021) incorporate short term forecasts with a reservoir model of the Conowingo Dam to determine the value of perfect inflow information across various lead times and reservoir objectives, including maximizing hydropower generation revenue. While hydropower generation was found to be more sensitive to storage than inflow information on average, issuing forecasts in key seasons when inflows are historically high (e.g. late winter and spring) is shown to be valuable. Yang et al. (2020) compare Pareto fronts of forecast-informed and no-forecast-informed reservoir operating rules and evaluate forecast skill of various synthetic streamflow forecasts for the Hangjiang cascade multipurpose reservoirs in the Yangtze River Basin, China. Incorporating forecasts was found to improve reservoir operations primarily through increasing power generation by up to 100 million kWh/year in the reservoir system. Within the United States, there is significant interest by water resource managers for the development and implementation of such systems, perhaps most notably under the name Forecast Informed Reservoir Operations (FIRO; Army Corps of Engineers) applied at
Lake Mendocino in northern California (and elsewhere) to optimize water supply sustainability and to mitigate effects of climate variability (Jasperse et al. 2017).

1.2 Case Study

The Ethiopian Ministry of Finance and Economic Development, in conjunction with the United Nations, released the second National Growth and Development Plan in 2015 with the intent to bolster rapid economic growth while promoting sustainable development goals (Growth and Transformation Plan II 2015). A major part of this plan outlines pathways to expand reliable infrastructure and increase production of clean, modern energy (Transforming our World 2015). To meet these goals, it will be necessary to leverage existing energy infrastructure – particularly hydropower dams – to enhance efficiency and subsequently production while simultaneously ensuring reliable and sustainable releases for downstream needs. However, several challenges face the hydropower sector, particularly within the northern region of Ethiopia (Alexander et al., 2020, Conway 2000, 2005; Segele and Lamb 2005; Zhang et al. 2016). Precipitation and streamflow exhibit significant inter- and intra-annual variability, with potentially large impacts on reservoir storage and available water (Gizachew 2015), leading to unnecessary spills (Annys et al 2020) or insufficient levels to maximize power generation. Therefore, there is a role for development of local-scale precipitation and streamflow forecasts for hydrological decision-making in northern Ethiopia.

The Tekezé basin is located in the state of Tigray in northwestern Ethiopia, covering approximately 86,000 km² of mountainous regions (~4500 masl) in the southeast and lowlands (~800 masl) near the Sudan border in Ethiopia (Figure 1). The Tekezé dam blocks the Tekezé in
the upper part of the basin, draining approximately 29,000 km² (Abera et al. 2018). It was constructed in 2009, has a generating capacity of 300 MW, a total storage capacity of 9200 million cubic meters (MCM; 5300 MCM live storage), and a surface area 147 km² when full (Abera et al. 2018). The Tekezé River flows into the Atbara River in Sudan, which is a tributary to the Nile River.

Figure 1. Map of Tekezé basin, Ethiopia, with the Tekezé dam watershed shown in red (via SimpleMappr/ Natural Earth).

Precipitation in the basin is largely seasonal, with the majority of rainfall occurring during the primary rainy, or Kiremt, season, extending from July-September (JAS; Figure 2) (Block and Rajagopalan 2007). Rainfall during these months accounts for 60-70% of the average annual precipitation (Conway 2000) and is responsible for the vast majority of annual reservoir inflow, which is crucial for sustaining hydropower generation for the duration of the year. Interannual variability in precipitation is stark, ranging from 300-700mm during JAS across the past 40 years (Figure 2), resulting in a coefficient of variation equal to 18%. Low amounts of precipitation
during these months can lead to reduced hydropower generation and food insecurity. This was particularly notable in 2015 when approximately 10 million people were classified as food insecure and reservoir volumes were notably low (Alem 2018).

Minimal attention has been devoted to linking reservoir operations and climate information for the Tekezé dam. Optimization strategies under long-term climate change scenarios have been explored (Abera et al. 2018), however predicting streamflow over seasonal time scales to inform short-term operations has not been addressed. Short-term streamflow predictions present a useful strategy for better managing operations and maximizing hydropower generation to meet increasing demand.

Figure 2. Annual precipitation within the Tekezé river basin. JAS precipitation shown in blue, cumulative annual precipitation shown in gray.
Dynamical precipitation and streamflow forecast models for East Africa exist, such as through the Global Flood Awareness System (GloFAS), Water Global Assessment and Prognosis (WaterGap), and Seasonal Water Resources Management for Semi-Arid Areas (SaWaM). GloFAS Seasonal issues monthly global seasonal streamflow predictions for flood risk derived from the SEAS5 forecast product at 36km resolution. SEAS5 is the ensemble seasonal forecast of the European Centre for Medium-Range Weather Forecasts (ECMWF) and of a seasonal ensemble product from the Copernicus Climate Change Service (Alfieri 2013). WaterGap, a global freshwater model developed at the Universities of Kassel and Frankfurt, calculates human consumption of groundwater and surface water and is used to improve the understanding of global water flows (Müller et al. 2021). However, downscaling of the GloFAS and WaterGap models is necessary for direct application to northern Ethiopia. Recently, SaWaM improved upon the SEAS5 forecast product by downscaling the spatial resolution to 0.1°, resulting in bias-corrected, disaggregated seasonal precipitation and temperature forecasts for the Tekeze-Atbara and Blue Nile Basins within Eritrea, Ethiopia, and Sudan (Lorenz et al. 2020), though this product is currently in a prototype stage and further work is needed to derive categorical (probabilistic) regional forecasts. Beyond these examples, there is evidence to suggest RCM and GCM downscaling offers little additional value for application in East Africa (Cheneka et al. 2016; Diro et al. 2012; Nikulin et al. 2017; Ogutu et al. 2017; Shukla et al. 2014a). For example, Gleixner et al. (2017) found that dynamical predictions from 11 GCMs were outperformed by simple linear regression between observed precipitation across Ethiopia and ENSO indices in the tropical Pacific. Zhang et al. 2017 adopted a k-means cluster approach to compare dynamical and statistical precipitation predictions clustered regions in Ethiopia. Although dynamic predictions
were skillful at the cluster level, applying predictions at higher resolution results in skill deterioration (Zhang et al. 2017).

Typically, statistical approaches utilize direct relationships between precipitation and streamflow observations and atmospheric climate variables, but most models within Ethiopia represent regional, national, or sub-national zone scales (Funk et al. 2014, Diro et al. 2011a, Korecha and Barnston 2007). National-scale statistical predictions are issued by the Ethiopian National Meteorological Agency (NMA), although evaluation by Korecha and Sorteberg (2013) suggest the operational forecast underpredicts dry events and has modest skill. Local-scale statistical prediction models in central Ethiopia have shown to be skillful when both global atmospheric teleconnections and local climate variables are considered and could be more useful for decision-making in energy or environmental sectors (Alexander et al., 2020). Within the northern region, dynamical models are used to develop short term (7-12 day) streamflow predictions (currently in experimental phase) by adopting a multi-model approach comprised of satellite precipitation products and near-term precipitation forecasts (G-WADI 2021) to guide site-specific decision-making. Decadal streamflow predictions using downscaled regional climate models (RCMs) have also been developed to evaluate potential climate change impacts on water availability in the basin and reservoir (Abera et al. 2018, Haile and Kassa 2015, Gebremeskel and Kebede 2018), but there is a lack of statistically-based seasonal forecast development for water resource management application in the basin. Evidence suggests that predictability in regions subject to high spatial and temporal precipitation variability can be achieved using local-scale statistical models. Chapter two describes the development and evaluation of a statistical seasonal prediction model for local-scale precipitation and streamflow
to address the question: *Can a skillful local-scale forecast model be developed to predict seasonal inflow in the Tekezé basin?*

While few studies have applied hydrological predictions to reservoir operations within Ethiopia, available research suggests coupling reservoir operations with predictive information can improve reservoir performance (Abera et al. 2018, Alexander et al. 2020, Block 2011). Alexander et al. (2020) compare statistically downscaled GCMs with a local-scale statistical model to explore benefits to hydropower generation and agriculture allocation within the Blue Nile Basin, demonstrating the value of statistical prediction models at the decision-making scale. Block (2011) combines tailored seasonal forecasts with dynamic rainfall-runoff and reservoir models to improve hydropower reliability in the Blue Nile Basin. Within the Tekezé Basin, Abera et al. (2018) use a dynamic model to optimize Tekezé dam performance under climate change scenarios, utilizing downscaled climate data from the Coordinated Regional climate Downscaling Experiment over African domain (CORDEX-Africa) RCM. However, the optimization period is at the decadal scale and does not address short-term reservoir management decisions. While the success of this previous work indicates the potential for incorporating prediction methods into reservoir operations in Ethiopia, a statistical prediction – reservoir optimization approach has yet to be applied to the Northern Ethiopian region and the Tekezé Basin. Chapter three thus poses the question: *how does inclusion of a skillful streamflow prediction model in reservoir operation decisions influence the prospects for hydropower generation at the Tekezé dam?*
Chapter 2: Precipitation and Streamflow Prediction

2.1 Moisture Sources and Large-Scale Climate Dynamics

Precipitation in northern Ethiopia during the Kiremt (JAS) season exhibits significant interannual variability in onset (Lala et al. 2020) and total amount (Block and Rajagopalan 2007) influenced by large-scale climate phenomena such as the shifting of the intertropical convergence zone (ITCZ), ENSO phase, and the Indian Ocean Monsoon. The ITCZ forms when moisture-laden winds from the southeast meet dry northeasterly winds, forcing the moist air to rise and condense. The shifting of the ITCZ is directed by a low-pressure system brought about by surface warming, dictated by the seasonal migration of the sun. This shifting has been shown to impact seasonal total precipitation and duration, as well as surface air temperature, affecting evapotranspiration in the region (Block and Rajagopalan 2007, Conway 2000, Viste and Sorteberg 2013). ENSO is a coupled atmosphere-ocean oscillation that has warm (El Niño) and cool (La Niña) phases across the tropical Pacific Ocean (Bjerknes 1969, Neelin et al. 1998, Philander 1990, Timmermann 2018, Yeh et al. 2005); El Niño events have been shown to disrupt regional pressure and wind patterns, resulting in drought conditions across Ethiopia (Camberlin 1995). Independent of ENSO, monsoon conditions in India are linked to a heightened equatorial pressure gradient, influencing strong westerly winds and moisture advection from the Congo Basin to Ethiopia (Camberlin 1997). Understanding the influence of these large-scale climate drivers aids in developing skillful seasonal precipitation forecasts.

Generally, above average sea surface temperatures (SST) during the El Niño phase correspond to warmer air temperatures and lower precipitation across northern Ethiopia, while below average SST during the La Niña phase typically result in cooler air temperatures and higher precipitation amounts (Beltrando and Camberlin 1993, Block and Rajagopalan 2007, Segele et al. 2009). This
relationship is evident in Figure 3. Several dry years, such as 1982, 1987, and 1997, occur during strong (greater than 0.5 Niño 3.4 anomaly), well-known El Niño years, while high precipitation years, including 1988, 1998, and 1999, occur during strong La Niña conditions (less than -0.5) (Figure 3). The relationship between ENSO and precipitation is not necessarily symmetric across ENSO phases, however (Figure 3). Furthermore, years with neutral conditions (Niño 3.4 anomaly between +/- 0.5, denoted by dashed lines in Figure 3) have no distinct correlation between ENSO phase and precipitation amounts, e.g., 1984 had the lowest JAS precipitation during the 40 year period and occurred under weak La Niña conditions, while 2003 had relatively high JAS precipitation under weak El Niño conditions. This can be further illustrated by observing SST regions (pre-season or concurrent) that are highly correlated with JAS precipitation and streamflow (Figure 4). Regions highlighted as statistically significant are consistent with previous literature describing global teleconnections to East Africa. SSTs in the Pacific Ocean are consistent with the influence of preseason ENSO on seasonal precipitation in northern Ethiopia (Diro et al. 2011, Funk et al. 2014, Segele and Lamb 2005) while SSTs in Indian and Atlantic Oceans have been linked to regional precipitation (Goddard and Graham 1999, Funk et al. 2014).
Moisture transport in the Ethiopian highlands is influenced by advection over the Congo Basin, Mediterranean and Red Seas, and Indian Ocean (Beltrando and Camberlin 1993; Block and Rajagopalan 2007, Dubache et al. 2019, Gimeno et al. 2010, Segele et al. 2009, Viste 2012, Viste and Sortenberg 2013). Increased evaporation over the Mediterranean and Red Seas has been linked to summer precipitation in Ethiopia (Viste and Sortenberg 2013, Gimeno et al. 2010). Dubache et al. (2019) utilize singular mode decomposition to examine the relationship between the Indian Ocean and Ethiopian rainfall, concluding that positive SST loading in the Central Indian Ocean results in below (above) normal precipitation in western (eastern) Ethiopia. Camberlin (1997) observed a strong link between increased (reduced) summer precipitation with below (above) normal sea level pressure (SLP) along the western coast of India. Viste (2012)
similarly concludes that the largest contribution to moisture transport in the Ethiopian highlands is from the Indian Ocean due to the high humidity and quantity of air flow traveling to the region. Other indicators of summer circulation, such as an increase in cross-equatorial flow across Central Africa and a strengthening in the Somali and Tropical Easterly Jets have been found to have positive correlation with summer rainfall in Ethiopia (Diro et al. 2010, Segele and Lamb 2005, Segele et al. 2009). While previous studies stress the significance of these mechanisms for moisture transport to the region, ongoing analysis suggests that the relative importance of these moisture sources and associated teleconnections may be changing. Preliminary evaluation from Wu and Block (2021) finds a drop in correlation between precipitation and post-2000 predictors, such as variables describing ENSO, the Tropical Easterly Jet, and Indian Ocean SSTs, compared to pre-2000 predictors; This analysis poses a necessity for the development of new regional forecast models based on post-2000 predictor relationship trends.
(a) Precipitation

![Correlation map of JAS seasonal precipitation](image)

(b) Streamflow

![Correlation map of JAS seasonal streamflow](image)

Figure 4. Correlation maps of JAS seasonal a) precipitation and b) streamflow with preseason (AM) SSTs by ENSO phase. Regions statistically significantly correlated at \( p < 0.05 \) are included.

2.2 Data

The basin upstream of the Tekezé dam, (Figure 1) extends from 36.5°-39.7°E and 11.5°-15°N (Abera et al. 2018). Precipitation data was sourced from the Climate Hazards Group Infrared Precipitation with Stations (CHIRPS) dataset developed by the Climate Hazards Center at the University of California at Santa Barbara (Funk et al. 2015). The dataset is monthly (1981-present) at a 0.5° x 0.5° resolution globally. Inflow data for the Tekezé reservoir is monthly (1951-2000) as measured at upstream gauges, and provided by the Ethiopian Ministry of Water, Irrigation, and Electricity. Gridded atmospheric variable datasets, such as SST, SLP, GPH, and
SAT, were provided through NOAA National Center for Environmental Prediction (NCEP) at 2.5° x 2.5° resolution. Soil moisture was provided by the NMME NCEP dataset. Atmospheric and hydrologic datasets were accessed through the International Research Institute for Climate and Society Data Library (IRI; http://iridl.ldeo.columbia.edu).

Due to the absence of historical streamflow data in the last two decades, pseudo-observations of JAS streamflow are created by regressing CHIRPS precipitation data onto historical streamflow for 1981-2000 (Pearson coefficient = 0.83; Figure 5) and then extending for 2001-2020 (Figure 6).

Figure 5. JAS precipitation and streamflow scatterplot.
Figure 6. JAS streamflow pseudo-observations 2001-2020 with climatological (1981-2000) mean shown as a dashed line.

2.3 Predictor Selection and Model Development

Given the apparent asymmetric relationship between the mean state of the atmospheric-oceanic climate system and associated teleconnections with precipitation and streamflow in northern Ethiopia, the Niño Index Phase Analysis (NIPA) approach (Zimmerman et al. 2016) is selected to distinguish between phases of ENSO. Predictor identification and model development based on ENSO phase, as opposed to lumping all years together, has been shown to improve forecast skill in Texas (Zimmerman et al. 2016), Italy (Giuliani et al. 2019), and Peru (Keating et al. 2021). NIPA utilizes the Multivariate ENSO Index (MEI), the leading Empirical Orthogonal Function (EOF) of tropical Pacific SST and sea-level pressures (SLP), to bin years into phases. Here, a two-phase model is adopted, with the positive phase defined as an MEI value greater
than zero and the negative phase with an MEI value less than or equal to zero. A three-phase model (including a neutral category) is not investigated given the relative scarcity of data. Effectively, a unique set of predictors and a unique, independent, model is constructed for each phase. Thus, for operational forecasts, the state of ENSO is first observed and then the associated model is selected. Although different models may be used to predict historic years based on phase, these years can be reassembled in chronological order to form a hindcast.

NIPA-based prediction models are developed for:

a) JAS total precipitation averaged across the Tekezé basin and

b) JAS average streamflow inflow to the Tekezé reservoir

Predictors for each model and each phase are restricted to season-ahead observations from April-May (AM) and predictions of expected JAS conditions issued prior to July. The suite of potential predictors includes large-scale and local scale climate and hydrologic variables, specifically SST, SLP, geopotential height (GPH) at 500 hPa, air temperature at 850 hPa (AT), and soil moisture. Soil moisture was evaluated by averaging gridded data across a subset of the basin upstream of the reservoir (approximately 38°-39.5°E and 12.5°-14°N). SLP, GPH, and AT were selected from regions that were identified to have significant correlation to precipitation (streamflow) using the NOAA Physical Sciences Laboratory (PSL) NCEP/NCAR Reanalysis Plotting Tool (https://psl.noaa.gov). Regions with atmospheric teleconnections to the Tekezé Basin (previously described in section 2.1) with a Pearson correlation coefficient value greater (less) than or equal to 0.4 (-0.4), based on the 99th significance level for a 40-year sample size, assuming no autocorrelation, are averaged across the subsection of grids and retained as a
potential predictor. Figure 7 demonstrates this selection process for preseason (May) air temperature where significant regions are approximately outlined in red.

Predicted precipitation from selected NOAA NMME models (accessed via IRI Data Library) is also evaluated as a potential streamflow predictor. The NMME is comprised of hindcast and real-time ensemble forecasts derived from Coupled Global Climate Models (CGCMs) at monthly, 1.0 degree resolution (Kirtman et al. 2014) and has previously demonstrated greater precipitation prediction skill in East Africa compared to climatology (Shukla et al. 2016). The NCEP-CFSv1 and NCEP-CFSv2 models are used in this analysis based on previous literature demonstrating skillful precipitation forecasts for this region (Block and Goddard 2012). The model datasets are comprised of 15 and 24 ensemble members, respectively, and are averaged.
across the JAS season for all ensembles and grids across the basin, resulting in a single seasonal precipitation prediction value. The dynamical model precipitation prediction is evaluated as a potential streamflow predictor alongside the statistical precipitation forecast (Table 2).

Large-scale global ocean-atmospheric observations (SST, SLP, GPH at 850 hPa) from AM were evaluated independently by correlating the global gridded datasets with seasonal precipitation and streamflow. Various combinations of pre-JAS observations were evaluated, including average AM season and single month ahead values (e.g. May only). This process was repeated 100 times, and only those grids that were statistically significantly correlated at the 95th percentile 80% of the time were retained (e.g. Figure 7). A principal component analysis (PCA) was applied to the remaining grids, a statistical technique based on factor analysis to minimize multicollinearity and maximize variance (signals) from a dataset (Delorit et al. 2017, Zhang et al. 2016, Zimmerman et al. 2016). PCA transforms gridded data or variables into orthogonal principal components (PCs) which are then ordered by the amount of variance explained in the dataset. The first PC is retained as a potential predictor. The full suite of potential predictors is listed in Tables 1 and 2.

The NIPA prediction model approach uses principal component regression, essentially performing a PCA on all significantly correlated predictors (variables and PCs), then using those new PCs in a multiple linear regression framework. All PCs explaining more than 10% of the variance are retained as predictors (n total predictors). The equation is as follows:

$$ y = \beta_0 + \beta_1 PC_{1,t} + \beta_2 x PC_{2,t} + \cdots + \beta_n PC_{n,t} + \epsilon_t $$

(1)
Where, \( y \) represents the predictand (total precipitation or average streamflow) for year \( t \), \( PC_{n,t} \) represents the PC value in year \( t \), \( \beta_n \) represents the fitted coefficients, and \( \epsilon_t \) is the residual error.

A “leave-one-out” cross validated hindcast is performed to fit the model and produce a deterministic JAS prediction for each year (1981-2020), issued early June. The leave-one-out cross validation approximates a prediction for a given year by training the model on all data except for the current year; this process is repeated for each data point. As in previous similar studies (Alexander et al. 2020, Delorit et al. 2017, Zhang et al. 2016,17), a probabilistic prediction ensemble is formed by fitting model error residuals from all hindcast years, \( \epsilon_t \), to a normal distribution (mean of zero) and adding to the deterministic prediction values, resulting in a distribution of yearly precipitation/streamflow predictions.

Table 1. Suite of potential season-ahead climate and hydrologic precipitation predictors. Months listed in parentheses. Statistically significant predictors (\( p < 0.05 \)) designated with *; predictors retained in final model are in **bold**. Predictors represent May values unless otherwise specified in parentheses.

<table>
<thead>
<tr>
<th>Predictor</th>
<th>Spatial Region</th>
<th>Statistic Correlation with Precipitation</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Negative Phase</td>
</tr>
<tr>
<td>Preseason Precipitation</td>
<td>Tekezé Basin</td>
<td>-0.16</td>
</tr>
<tr>
<td>Sea Surface Temperature (AM)</td>
<td>1st PC of NIPA-identified region</td>
<td>-0.73*</td>
</tr>
<tr>
<td>Sea Level Pressure</td>
<td>Red Sea</td>
<td>-0.23</td>
</tr>
<tr>
<td></td>
<td>Equatorial Pacific</td>
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<tr>
<td>Geopotential Height (850 hPa)</td>
<td>Red Sea</td>
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<tr>
<td></td>
<td>Equatorial Pacific</td>
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</tr>
<tr>
<td>Air Temperature (850 hPA)</td>
<td>Tekezé Basin</td>
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<tr>
<td></td>
<td>Equatorial Pacific</td>
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</table>
Table 2. Suite of potential season-ahead climate and hydrologic streamflow predictors. Months listed in parentheses. Statistically significant predictors (p < 0.05) designated with *. Predictors retained in final model are in bold. Predictors represent May values unless otherwise specified in parentheses.

<table>
<thead>
<tr>
<th>Predictor</th>
<th>Spatial Region</th>
<th>Statistic Correlation with Streamflow</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Negative Phase</td>
</tr>
<tr>
<td>NMME Precipitation Forecast (JAS)</td>
<td>Tekezé Basin Average</td>
<td>0.55 *</td>
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<tr>
<td>Statistical Precipitation Forecast (JAS)</td>
<td>Tekezé Basin Average</td>
<td>**0.71 ***</td>
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<td>Sea Surface Temperature (AM)</td>
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<td>Soil Moisture</td>
<td>Tekezé Basin Average</td>
<td>**-0.80 ***</td>
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</table>

2.4 Performance Metrics

Several metrics are considered to evaluate the hindcast performance of the prediction models: Statistic (ordinary) correlation, Hit Score (HS), and Rank Probability Skill Score (RPSS) (Barnston 1992, Wilks 2011). Both HS and RPSS are categorical measures; HS is based on deterministic predictions whereas RPSS accounts for the full prediction distribution. Due to the relatively short observational record, only two categories are evaluated: low (L) and high (H) precipitation/streamflow. Precipitation and streamflow are categorized as H (L) if observations are above (below) the 50th percentile of the respective time series for both HS and RPSS evaluation. While performing well across both categories is preferred, skill in the low category is of particular interest considering impacts during drought conditions can be severe, specifically for hydropower generation.
HS (Barnston 1992) is defined as:

\[
\text{Hit Score (HS)} = \frac{\sum \text{Hit}_L \text{Hit}_H}{n}
\]  

(2)

where, \(\sum \text{Hit}_L, \text{Hit}_H\) represents the sum of occurrences when the predicted and observed value fall within the same category (value of 1), summed over the \(n\) years. Years where the predicted category is different from the observed is considered a miss (value of 0). HS values range from 0-1, where an average HS would be 0.5.

RPSS determines forecast skill (Wilks 2011) in relation to a reference forecast, in this case, climatology, and is represented as:

\[
\text{RPSS} = 1 - \frac{\text{RPS}_{\text{forecast}}}{\text{RPS}_{\text{climatology}}}
\]

(3)

where RPS represents the Rank Probability Score of the forecast or climatology and is the average of the squared difference between the forecast and historical observations. The RPS is defined by:

\[
\text{RPS} = \sum_{i=1}^{n} (\text{CP}_{\text{forecast}}_i - \text{CP}_{\text{observations}}_i)^2
\]

(4)

where \(\text{CP}_{\text{forecast}}\) and \(\text{CP}_{\text{observations}}\) represents the cumulative probability of the forecast or observations within category \(i\), through \(n\) categories (here \(n=2\)). RPSS values range from \(-\infty\) to 1, with 1 representing perfect forecast skill and any positive value an improvement over climatology. RPSS is computed for every year, however, as is commonly practiced, only the median value across the hindcast is presented here.

### 2.5 Model Results and Discussion

Dividing the historical record (1981-2020) into phases by MEI results in 24 years in the negative phase and 16 years in the positive phase. Overall, the model predictions track observations, although hindcast years falling into the negative phase demonstrate a relatively strong
relationship between observations and predictions, whereas this relationship is less robust in the positive phase (Table 3). Considering categorical skill scores, RPSS illustrates that the model is a strong improvement over using climatology. Similarly with HS, the model correctly categorizes high precipitation events in 75% of instances and low precipitation events in 80% of instances. Unfortunately, this drops off, however, for the streamflow predictions (75% and 70%, respectively).

Table 3. Performance metrics for precipitation and streamflow predictions.

<table>
<thead>
<tr>
<th>Forecast</th>
<th>RPSS</th>
<th>Pearson Correlation</th>
<th>HS (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>A</td>
<td>N</td>
<td>P</td>
</tr>
<tr>
<td>Precipitation</td>
<td>0.41</td>
<td>0.55</td>
<td>0.38</td>
</tr>
<tr>
<td>Streamflow</td>
<td>0.24</td>
<td>0.28</td>
<td>0.21</td>
</tr>
</tbody>
</table>

Note: A- all years, N-negative phase years, P – positive phase years, H – high precipitation (streamflow) years, L – low precipitation (streamflow) years.

The asymmetric skill may be due to the distribution of years within each phase (24 years negative, 16 years positive) or due to the inflow categorization within those years. The negative phase is comprised of nine (36%) observed high precipitation/inflow years while the positive phase has only three (20%) high precipitation/inflow years. However, approximately half of both phases (52% negative, 53% positive) are above the climatological average JAS precipitation value of 1780 mm/season. For inflow, 52% of the negative phase years are above the climatological JAS inflow average of 1605 Mm³, while only four positive phase years (26%) are considered above average JAS inflow. Adopting a three-phase approach consisting of negative, neutral, and positive ENSO phase conditions may improve the forecast skill yet would require a longer observational dataset to avoid any model overfitting.
Most encouraging, the statistical models capture several well-known historical droughts, indicating skill in predicting climate extremes. Both the precipitation and streamflow forecasts correctly predict some historical drought years, such as in 1982, 1993, and 2016 (Figures 8 and 9). While the inflow forecast misses the drought of 1989-91, the forecast does correctly characterize the inflow conditions as below-average. Ability to characterize categorical drought conditions, in addition to predicting the deterministic inflow value, may provide useful information to water resource managers. In the event of a predicted dry JAS season, managers can conserve reservoir storage to endure the drought, thereby avoiding any catastrophic water supply or turbine failure (“EEP revives two turbines,” 2019).

Figure 8. Probabilistic JAS precipitation predictions (boxplots). Negative phase years indicated in blue; positive in red. Observations represented by the solid line. Horizontal dashed line represents the 50th percentile of observations.
Figure 9. Probabilistic JAS average streamflow predictions (boxplots). Negative phase years indicated in blue; positive in red. Observations represented by the solid line. Horizontal dashed line represents 50th percentile of observations.

Model uncertainty, represented by boxplot size in figures 8 and 9, is asymmetric across ENSO phases and forecasts. While both phases for the precipitation forecast appear relatively similar, the positive phase model for streamflow has significantly more uncertainty than negative phase years. This asymmetric skill across phases may be due in part to the strength of teleconnections with streamflow during each phase; for instance, the negative phase model demonstrates a strong relationship with preseason soil moisture (Table 2). Statistical forecast methods are limited by short observational data time series (40 years for precipitation, 20 years for streamflow, in this
case) and are sensitive to anomalies. With 16 years, the positive phase precipitation and streamflow forecast models are only calibrated on a randomly sampled eight-year period and validated with the remaining eight years (performed 100 times to generate a distribution of of probabilistic forecast values). Limited data records, combined with weaker teleconnections, likely contributes to greater uncertainty for the streamflow model, particularly in the positive phase.

Final retained predictors (Tables 1 and 2) are consistent with literature describing climate teleconnections influencing moisture in the region. The first PC of NIPA preseason SST highlights a correlation in the Indian Ocean for precipitation across all observed years (Figure 4a), a relationship previously described by Dubache et al. (2019) and Block and Rajagopalan (2007). SST in the Mediterranean Sea is also found to have a positive correlation with negative phase precipitation (Figure 4a), consistent with studies postulating the link between evaporation in this region and summer rainfall (Viste and Sortenberg 2013, Gimeno et al. 2010). Correlation between negative phase precipitation and streamflow with Atlantic Ocean SSTs (Figure 4a and b) is supported by Mohamed et al. (2005) and Segele et al. (2009). A positive relationship between SST in the equatorial Pacific and streamflow in positive phase years is also observed, consistent with findings by Beltrando and Camberlin (1993), Block and Rajagopalan (2007), Segele et al. (2009). While correlation between the first PC of NIPA global SST and precipitation/streamflow is relatively strong (Table 2), further investigation comparing preseason SST (AM) versus predicted SST (JAS) and the associated teleconnections for precipitation and streamflow (JAS) prediction is warranted. Other relevant SST regions and associated teleconnection patterns also require further investigation. For example, the NIPA approach
develops two unique forecast models based on ENSO phase, but the influence of SST patterns in
the Atlantic Ocean suggests that developing a similar approach using the Atlantic Multi-decadal
Oscillation (AMO) may be beneficial.

2.6 Conclusion

The Tekezé Basin in Northern Ethiopia experiences significant spatial and temporal precipitation
and inflow variability, affecting water resource management strategies in the region. Dynamical
forecasts for Ethiopia have been skillful on large spatial scales yet struggle to capture small-scale
hydrological factors contributing to local-scale climate variability. Through the development of
local-scale statistical seasonal precipitation and streamflow forecasts, this work demonstrates
hydrological predictability at the decision-making scale for water resources management.

Chapter two focuses on the development of statistical forecast models for local precipitation and
streamflow in the Tekezé Basin conditioned on local climate variables and global phenomena.
Both statistical forecasts capture modulating factors of local-scale variability, resulting in skillful
predictions compared to climatology. The statistical precipitation forecast was evaluated as a
predictor for the inflow model in addition to dynamical predictions, namely the NMME CFSv1
and CFSv2 models. While these models have demonstrated skill across Ethiopia, downscaling
the dynamical forecast showed moderate correlation with inflow compared to the statistical
precipitation forecast (Table 2). Further analysis to evaluate the inclusion of both the statistical
and dynamical precipitation predictions as inflow predictors could yield additional skill.
However, this result confirms statistical forecast models, which capture small-scale interannual
factors, such as local air temperature and soil moisture, in addition to teleconnections with global phenomena, such as ENSO state and the Indian Monsoon, can play an important role in prediction evaluation and potentially enhance predictability in local regions with significant variability.

While statistical forecast models may serve as a more skillful tool for local-scale decision making, this method is limited by length of observational records. Given the number of years with near-neutral ENSO conditions (± 0.5 MEI) (Figure 3) adopting a three-phase approach to bin years into an additional “neutral” category may improve forecast skill (Keating et al. 2021). However, the available observational data set for streamflow (20 years observed, 20 years derived pseudo-observations) is too limited for three-phase evaluation. Additionally, model uncertainty for each phase is difficult to characterize given the length of the calibration and validation periods for each model. Additional prospects for better characterizing these uncertainties and evaluating forecast skill may be to derive pseudo-observations from the Community Earth System Model (CESM; Kay et al. 2014), with its wealth of representative years.

Model value can be dependent on the scale at which predictions are applied. While dynamical models may have reduced skill for local predictions, they are able to capture complex climate interactions applicable for regional and global scales. Seasonal statistical forecasts, conversely, are conditioned on small-scale climate variables which modulate moisture transport to the region and exhibit skill in predicting local-scale precipitation and inflow. While few operational statistical forecasts exist, leveraging relationships between climate and local hydrological
conditions has shown predictive skill in various climate regimes (Alexander et al. 2020, Keating et al. 2021, Yang et al. 2020). This suggests statistical forecast methods, such as those outlined here, may be widely applicable to innumerable local regions.
Chapter 3. Forecast-informed Reservoir Optimization

Coupling streamflow prediction models with reservoir operations may benefit local-scale electrification efforts, by either maximizing overall hydropower generation or increasing minimum firm energy production. Currently, the Tekezé reservoir generates the majority of annual hydropower generation during high inflow months (JAS) but interannual variability in precipitation and streamflow can lead to inconsistent reservoir volumes. Poorly timed reservoir releases can result in periods when no power is generated, affecting electrical stability across the region (Sleet 2019). Electricity rationing is often employed in response to low energy production, which deprives residential areas and businesses of consistent power access and hinders economic growth (Kigura 2019). Optimizing reservoir releases for hydropower generation during key inflow months (JAS) may reduce the occurrence of these power failures. To maximize potential benefits, a skillful seasonal forecast issued with adequate lead time to adapt operational strategies based on predicted inflow conditions before the key inflow season is required. Therefore, a June 1st forecast (one-month lead) is issued to guide JAS reservoir operations.

3.1 Reservoir Optimization Model

A model of the Tekezé reservoir and dam is developed to simulate operational storage and release decisions for managing hydropower generation. Reservoir and dam characteristics were sourced from the Tekezé Medium Hydropower Project Feasibility Report (1997), including reservoir and dam sizes, reservoir stage-storage curves, evaporation rates, and a release schedule.

The reservoir storage of the Tekezé dam was evaluated based on three preliminary maximum storage scenarios: 4354, 6499, and 9293 Mm³. Various live storage combinations were modeled
for each scenario. The final combination of maximum and live storage was selected based on the balance between maximizing firm power and minimizing turbine operating head range (Tekezé Feasibility Report, 1997). The final preliminary design was a maximum storage of 9293 Mm³ with 5293 Mm³ of live storage intended to produce 112 MW of firm power for a turbine head variation between 126 to 154 m. However, current reports suggest the dam often struggles to meet firm power requirements (“EEP revives two turbines,” 2019, Sleet 2019).

The Tekezé reservoir was designed for 97% duration-based reliability, meaning firm hydropower generation will not be achieved for 3% of the historical simulation period (Tekezé Feasibility Report, 1997). For the 40-year historical period (1957-1997) simulated in the Feasibility Report, there are 14 months in which firm power is not achieved. However, recent reports show low reservoir levels and suboptimal operation strategies have resulted in sustained periods without power generation (Abera et al. 2018, “EEP revives two turbines,” 2019, Sleet 2019).

Due to limited information regarding reservoir seepage and groundwater fluxes, these are disregarded as in other work (Alexander et al. 2020); however, their expected influence is likely very small compared to reservoir inflow and release volumes. Therefore, the reservoir water balance equation reduces to:

\[ S_t = S_{t-1} - R_t + I_t - E_t \]  \hspace{1cm} (5)

where \( S \) is the reservoir storage volume (Mm³) for each monthly time step, \( t \), \( R \) is monthly release (Mm³), \( I \) is monthly inflow (Mm³), and \( E \) is monthly evaporation (Mm).
In this study, three inflow scenarios are explored:

1. **Perfect Forecast (observation-based predictions):** expected monthly inflow is the historical inflow observational record;

2. **Climatological Forecast (climatology-based predictions):** expected monthly inflow is based on climatological streamflow averages (1981-2020) and does not vary from year-to-year;

3. **Statistical Forecast (forecast for JAS developed in Chapter 2):** expected monthly inflow is based on climatological streamflow averages for October-June and predicted inflow for JAS. The time-series is constructed such that the JAS predictions do not become available to the model until the prior June, to represent realistic conditions.

The JAS streamflow forecast is disaggregated into monthly streamflow predictions utilizing the climatological distribution of cumulative JAS streamflow. Based on monthly climatological averages from observed streamflow (1981-2000), approximately 32.5% of JAS streamflow occurs in June, 45% occurs in July, and 22.5% in September. Monthly forecast prediction values are divided based on these proportions. Inflow during October-June is obtained from monthly climatological averages (e.g., the October inflow value is the average of all October inflows 1981-2000), resulting in a JAS seasonal prediction and a monthly inflow prediction across the time series.

The reservoir model (run separately for each inflow scenario) takes a stochastic dynamic programming (SDP) approach to optimize reservoir operations with an objective function to maximize hydropower generation. The objective function for maximizing hydropower generation is as follows (Yang 2021):

\[
\text{Max}(E) = \sum_{t=1}^{T} P_t \cdot \Delta t, \quad \text{where} \quad P_t = \eta \cdot g \cdot \rho \cdot Q_t^p \cdot H_t^p
\]  

(6)
where $E$ is electricity generation (kWh) over periods $T$, $P_t$ is power generation (kW) over time $t$, $\eta$ is unitless power generation efficiency of the turbines (0.85; Tekezé Feasibility Report, 1997), $g$ is gravitational acceleration (9.81 m/s\(^2\)), and $\rho$ is water density (1000 kg/m\(^3\)). $Q_t^P$ and $H_t^P$ are the reservoir release volume for power generation (m\(^3\)/s) and average head (m) during period $t$, respectively.

Power generation is subject to reservoir capacity and turbine power constraints, described as:

$$S_{min} \leq S_t \leq S_{max} ; \quad P_{t\min} \leq P_t \leq P_{t\max}$$

where $S_{min}$ and $S_{max}$ represents the range of allowable live reservoir storage (5300 to 9200 Mm\(^3\)) and is subject to variable monthly inflow gains and evaporation losses (Equation 5) and $P_{t\min}$ and $P_{t\max}$ are the minimum and maximum turbine power generation capacity limits (0 to 300 MW) for time $t$ (Yang et al. 2021).

Stochastic dynamic programming is a commonly adopted strategy for reservoir optimization (Cancelliere et al. 2002, Kelman et al. 1990, Kim et al. 2021, Lee and Labadie 2007, Loucks et al. 1981, Reznicek and Cheng 1991, Trezos and Yeh 1987, Wu et al. 2018, Yang et al. 2021, Zhao et al. 2012, Zhao et al. 2017) which incorporates multiple reservoir storage states, rather than a single value, within each month when calculating operational release decisions (Kelman et al. 1990). SDP is based on the concept of the Markov chain, which determines a series of possible events (optimization period) where the probability of such events depends on the previous event state (Butcher 1971), e.g., the future sequence of yearly reservoir operations could be determined by the state of the previous year’s reservoir storage. A continuation of SDP, called Sampling Stochastic Dynamic Programming (SSDP), uses individual streamflow scenarios in lieu of a Markov chain and may better utilize hydrologic information to optimize
reservoir operations (Faber and Stedinger 2001, Stedinger et al. 2013), but is not investigated here. Dynamic programming (DP) is an additional alternative to SDP but is governed by deterministic inflow sequence with a discrete set of storage volumes (Karamouz and Houck 1987) and may be a less preferable option for reservoir optimization strategies in regions with high inflow variability.

In standard SDP approaches, reservoir releases (the decision variable) for each time-step will be optimized considering the full time-series simultaneously. However, in this study, future inflow values are clearly not known a priori (i.e. predictions not issued until June in the forecast scenario), thus an iterative approach is required. Instead of simultaneously considering the full-time series, for a given month only the next 24 months are simultaneously evaluated to determine optimal release decisions, reservoir storage, and hydropower generation across those 24 months. Only the values (final storage, releases, and hydropower generation) characterizing the state of the current month are retained and used to establish initial storage for the following month. However, for the climatological and statistical forecast scenarios, an additional storage correction step is required. This is necessary because the inflow assumed (climatology or forecast) differs from observed (actual) inflows. Thus:

\[ S_{t,\text{corrected}} = S_{t,\text{computed}} + [O_t - I_t] \]

where \( S_{t,\text{corrected}} \) is the sum of \( S_{t,\text{computed}} \), the first storage value from the optimization at time step \( t \), and \([O_t - I_t]\), the difference between observed \((O_t)\) and expected \((I_t)\) inflow at \( t \).

This iterative process is represented in the following flowchart (Figure 10).
3.2 Monte Carlo Sampling

Monte Carlo sampling techniques are used to understand the influence of sequencing on the coupled prediction-reservoir model. Annual streamflow observations are first evaluated for lag-1 autocorrelation to check for year-to-year persistence, however all lags have values less than +/- 0.3, indicating that annual persistence is negligible (Figure 11). The approach assumes stationarity and randomly resamples (with replacement) the historical record to assemble varying sequences of wet and dry years not observed. In reservoirs with large storage capacity, there may be a carry-over effect, and varying sequences of inflows will result in unique hydropower generation outcomes. One hundred randomly assembled 40-year time-series are created to understand the degree of this effect.
Figure 11. ACF plot of annual streamflow, 1981-2020.

3.3 Coupled Prediction-Reservoir Model Results and Discussion

Hydropower generation based on the perfect forecast optimization (Figure 12) results in an average annual hydropower generation of 3223 MW (117.8 GW cumulative) and outperforms climatology (2761 MW annual average; 102.2 GW cumulative) and the statistical forecast optimizations (2990 MW annual average, 110.0 GW cumulative). However, it’s possible for climatology or the statistical forecast to outperform the perfect forecast approach in any given year based on an individual season’s prediction, e.g. if the climatological forecast predicts more rainfall to occur than the perfect forecast, the reservoir model will release more water to maximize hydropower generation for that season. However, the climatological forecast has imperfect predictive information and will not efficiently rebound, resulting in lower hydropower generation in subsequent years. This is seen in years 1992-1994 where the reservoir in the climatology-based optimization stores water (Figure 13) before a large release in 1995, whereas the reservoir in the perfect forecast optimization shows decreasing reservoir levels from 1993-1995, resulting in a lower power generation than climatology in 1995. However, the
climatological model suffers from this large release through significantly decreased hydropower generation in the following two years, whereas the perfect forecast model maintains relatively stable power generation (Figure 12).

While it is expected that the perfect forecast approach will generate more cumulative hydropower over the time series (Table 3), the statistical approach generates as much or more hydropower than the perfect forecast in 13 of the 40-year time series. The statistical model performs particularly well in years preceding predicted high inflow years. For instance, the statistical approach releases less water than the perfect forecast approach during the relatively dry years of 1984-1985. This storage conservation benefits the statistical approach in 1987 when the model maximizes releases in anticipation of the predicted high inflow of 1988 (Figure 13). Hydropower generation in the following years (1990-1992) suffers due to the previous large releases and a sequence of poor predictions in those years. With storage depleted, the reservoir refills during years 1991-1993 before another large release in 1993 ahead of the predicted-high inflow in 1994. This pattern does not apply in all cases; releases from 1993-1996 depletes reservoir levels ahead of the predicted-high inflow of 1998-1999, causing a drop in hydropower generation in 1997.

The statistical forecast predicts less than observed streamflow in years 1992 and 2014 (Figure 12), but hydropower generation is only significantly affected in 1992. This is likely due to the statistical forecast predicting higher inflow than the observed drought conditions in 1989-1991 before the low-inflow prediction of 1992. Because of the sustained duration of the drought and missed predictions, hydropower generation under the statistical forecast approach suffers. An
incorrect low-inflow prediction in 2014 does not yield the same results and produces almost as much hydropower as the perfect forecast. In this case, however, the observed inflow for years 2011-2013 are high-to-average conditions and are correctly predicted by the statistical forecast. These illustrations demonstrate the many nuanced conditions that can dictate variable hydropower generation outcomes.

The statistical approach consistently produces higher hydropower than the climatology-based approach regardless of predicted wet/dry inflow conditions except for 1991-1992. This occurs for two reasons; firstly, the climatology approach produces significantly less hydropower in the preceding years 1987-1989, allowing reservoir levels to remain stable (Figure 13). Secondly, the missed prediction of 1992 by the statistical approach significantly impacts hydropower generation. However, the statistical approach rapidly rebounds and can generate over 3500 MW in 1993, whereas the climatological approach does not fully recover from the effects of the drought until 1995. The statistical forecast continues to outproduce climatology in the majority of years 1994-2020. Despite a missed prediction, the statistical approach is able to leverage future skillful predictions to recover from storage losses, resulting in higher annual average and cumulative hydropower generation.
Figure 12. Annual hydropower generation utilizing perfect (black), climatological (blue), and statistical (red) forecasts.
Figure 13. Annual average reservoir storage utilizing perfect (black), climatological (blue), and statistical (red) forecasts.

Table 3. Assessment metrics for reservoir optimization model under various forecasts.

<table>
<thead>
<tr>
<th>Forecast</th>
<th>Average Annual Hydropower Generation (MW)</th>
<th>Average Cumulative Hydropower Generation, 1981-2020 (GW)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Perfect Forecast</td>
<td>3223</td>
<td>117.8</td>
</tr>
<tr>
<td>Climatological Forecast</td>
<td>2761</td>
<td>102.2</td>
</tr>
<tr>
<td>Statistical Forecast</td>
<td>2990</td>
<td>110.0</td>
</tr>
</tbody>
</table>

Monte Carlo sampling of annual hydropower generation shows a moderate improvement in the median and upper bound of hydropower generation comparing the statistical forecast and climatology forecast optimization schemes (Table 4). The perfect forecast approach produces the most power generation, as expected, as it applies ideal predictive information to reservoir
operations, resulting in a median average annual hydropower generation of over 3500 MW. The statistical forecast approach, while generating less power, still produces over 3000 MW annually. Average cumulative hydropower generation represents the aggregate of power generation for each randomly sampled 40-year run. The statistical approach generates considerably more power than the climatology approach; the 95th percentile is marginally higher than the median for the climatology optimization scheme. Model uncertainty, signified by boxplot size, further establishes the benefit of adopting a seasonal forecast conditioned on global and local climate variables in lieu of a rigid climatology-based forecast. The lower quartile from the statistical approach is almost equal with the median from the climatology approach (approximately 2800 MW); the same lower quartile for the climatology approach is approximately 2200 MW (Figure 14a). Granted, some outliers for average annual hydropower generation from the perfect and statistical approaches, represented by open circles, are sufficiently low (Figure 14a), however, they are representative of individual years, which when aggregated across a 40-year run (Figure 14b) becomes muted. Nonetheless, it is important to recognize that years with low generation – particularly in the statistical and climatology approaches – are possible based on a hydropower maximizing approach.

Reservoir optimization for maximizing firm energy was not explicitly investigated in this study; however, the Monte Carlo sampling demonstrates the benefit of adopting seasonal forecasts to improve firm energy. The 95th percentile confidence interval for the statistical forecast approach shows a substantial improvement over adopting a climatology-based framework (Table 4) both for annual hydropower generation and cumulative hydropower generation. The statistical approach, excluding one anomalous 40-year run (Figure 14) generates over 1900 MW annually
at the 95% confidence level, while the climatology approach produces only 760 MW annually at this level. This increased level of firm energy suggests that improving energy production reliably is possible even in regions with high spatial and temporal variability by applying skillful predictive information to reservoir operations.

Figure 14. Boxplot of a) average annual hydropower generation (left) and b) average cumulative hydropower generation (right) for coupled perfect (P), climatological (C), and statistical (S) prediction-reservoir models. Outliers are denoted by open circles.
Table 4. Assessment metrics for Monte Carlo reservoir optimization under various forecasts.

<table>
<thead>
<tr>
<th>Forecast</th>
<th>Average Annual Hydropower Generation (MW)</th>
<th>Average Cumulative Hydropower Generation (GW)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Median 5th Percentile 95th</td>
<td>Median 5th Percentile 95th</td>
</tr>
<tr>
<td>Perfect Forecast</td>
<td>3596 3900 3072</td>
<td>113.2 116.8 108.5</td>
</tr>
<tr>
<td>Climatological Forecast</td>
<td>2935 3758 764</td>
<td>87.9 97.5 79.5</td>
</tr>
<tr>
<td>Statistical Forecast</td>
<td>3180 3851 1936</td>
<td>95.6 104.6 88.0</td>
</tr>
</tbody>
</table>

The primary purpose of the Tekezé dam is for hydropower generation and is not explicitly used for flood control. While analysis did not show evidence of significant reservoir spills, indicating flooding conditions, the reservoir optimization model is performed over the monthly scale, which may hide short-duration weather events such as high precipitation. Adopting a forecast optimization framework at the sub-monthly scale may uncover previously undetected flooding events.

This study evaluates the benefits of applying predictive information to reservoir optimization assuming stationary climate patterns, yet climate change may drive permanent changes to seasonal precipitation and inflow. Specifically, additional sensitivity studies may be warranted to investigate model performance for sequences of predominantly dry or wet inflow conditions to gain insight into how current seasonal forecasts may perform given potential future changes, e.g., if seasonal precipitation and inflow volumes are consistently high or low. However, statistical forecast skill in both wet and dry inflow years – based on the hindcast – suggests that integrating inflow predictions is beneficial across all conditions compared to relying simply on climatology.
Climate change may also alter well-known global climate phenomena (Fecht 2020), warranting reanalysis of relevant teleconnections and model configuration.

3.4 Conclusion

The Tekezé Reservoir is a crucial resource to the Ethiopian energy grid, supporting sustainable economic growth and improving residential electrification efforts, yet variable seasonal precipitation and inflow often limits hydropower generation. Reservoir operations are often guided by static rule curves, which can be challenged by significant temporal and spatial hydrological variability. Integrating local-scale precipitation and streamflow forecasts into reservoir management practices has been found to improve reservoir operations in regions demonstrating predictability. This work evaluates the effect of coupling a local-scale statistical streamflow prediction with a reservoir optimization model to maximize hydropower generation.

The coupled-prediction reservoir model of the Tekezé Dam exhibits skill in maximizing power generation and improving minimum firm energy. The value of integrating predictive information into operational strategies is clearly demonstrated in the improvement of annual hydropower generation between the statistical approach and climatological approach. The climatology-based approach relies on static predictive information to inform operational strategies, which does not facilitate reservoir operation to fully utilize high inflow years, nor is particularly conservative regarding severe drought years. Furthermore, the effects of a drought may be longer sustained with the climatology approach (Figure 13). While the statistical approach depleted storage in the drought years of 1990-1992, hydropower generation was able to recover more quickly than with
the static climatological approach. Thus, even though the statistical approach may occasionally issue poor predictions, this approach can still produce favorable hydropower generation if the forecast is overall skillful.

Bridging the gap between skillful forecasts and the end user is critical to facilitate transfer of valuable information to communities in support of water resources management decisions and to generally support mitigation of community vulnerability, particularly related to energy and agriculture. The benefit of incorporating seasonal forecasts with water resources planning and management have been demonstrated in various studies, yet few reservoir systems have adopted this practice. Studies suggest, however, that tailoring predictive information and actionable strategies to local regions supports increased understanding and utilization (Alexander et al. 2020b). Therefore, developing local-scale skillful forecasts and coupling with operational models, with appropriate training, may increase uptake by water resource managers and present opportunities to mitigate the effects of climate variability for community benefit.
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