RESEARCH BASE ASSESSMENT OF INTEGRATED APPROACHES TO NATURE-BASED SOLUTIONS (RAINSOLUTION)
Tailoring Seasonal Forecasts Towards Hydrological Applications for the Vaal Dam

Willem A. Landman, Emma Archer, Pearl Gosiame, Brian Nkala

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Tailoring Seasonal Forecasts Towards Hydrological Applications for the Vaal Dam

Report to the
Water Research Commission

by

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EXECUTIVE SUMMARY

BACKGROUND

The Vaal Dam is South Africa's second largest dam by area and a vital national resource. Since its levels are linked to summer rainfall in its catchment, summer inundation and drought have a significant impact on inflows and discharge. Due to the lack of operational real-time seasonal forecasting systems specific to the Vaal Dam, the project set out to develop and test statistical forecast systems for the Vaal dam on seasonal time scales, with the goal of eventually demonstrating operational forecasting capability using the developed models.

AIMS

In this project we test for seasonal predictability for Vaal Dam characteristics such as dam levels and downstream flows. We establish pragmatic and cost-effective ways that can also lead to real-time prediction and decision-making. In this project we use simplified statistical models to test for predictability and to establish real-time forecasting for the dam. The following are the aims of the project:

1. To develop statistical forecast systems for the Vaal Dam on seasonal time scales.
2. To test the models' performances for both deterministic and probabilistic forecasts.
3. To test operational forecasting capability using the developed models over various lead-times.

METHODOLOGY

Linear statistical models are developed for both dam levels and for downstream flows of the Vaal Dam. Catchment rainfall figures are used in a multiple linear regression model as predictors. Simple linear regression is used to see if dam levels can be linked to downstream flows. All the models are tested to determine if the models have potential use in a real-time operational forecast setting.

RESULTS AND DISCUSSION

A strong link is found between rainfall in the catchment and dam levels, as well as what happens downstream of the dam. This link is evident mostly during the summer rainfall season. There is also a link between dam levels and downstream flows. Although real-time prediction for both dam levels and downstream flows is possible, useful, including profitable, probabilistic forecasts are only found with short lead-times, and in particular for dam levels during the second half of summer. Notwithstanding these limitations, the real-time information that the forecast models can potentially provide is of interest and benefit to forecast users such as Rand Water. The latter is interested in water quality fluctuations caused by inundation and drought.

GENERAL

The robust statistical methods developed in this project show that seasonal predictability of the Vaal Dam is possible. This predictability is restricted to dam levels and downstream flows and are possible mainly during the summer rainfall season (Aim 1). Most of the predictability is found during the second half of the summer rainfall season, and the best predictor is antecedent rainfall in the catchment. These results are found using an approach where only the forecast models' deterministic capability is assessed. This is a necessary step to first establish if predictability exists (Aim 2). After this, since seasonal forecasts are of a probabilistic nature, the models probabilistic forecast capability is tested. However, forecasts need to be made at lead-times in order for them to be of potential use, and hence probabilistic forecast performance over lead-times shows that operational real-time forecasts are possible, albeit at short forecast lead-times (Aim 3).

CONCLUSIONS

The statistical models developed here show a strong link between seasonal rainfall in the catchment and dam levels and with downstream flows, mainly during summer. There is also a concurrent link between dam levels and downstream flows, but this link is strongest during the second half of summer and during autumn. A significant result from the work is that real-time prediction for both dam levels and downstream flows is possible, but that the predictability is mainly a result of using antecedent rainfall in the catchment as predictor, and that the models only really work at short lead-times. Usually, high forecast skill can be obtained in certain catchments where ENSO forcing is contributing strongly to seasonal variability. In the Vaal Dam catchment, however, where ENSO forcing is not that strong, antecedent rainfall is a critical component in the forecasts systems presented here and emphasises the importance of maintaining robust observational networks in the region. A significant conclusion to be drawn here is that predictability is restricted to the second half of summer, going into autumn. This result is to be expected for models where antecedent rainfall is the best predictor. In a catchment where no or very little rainfall is usually received during winter and spring, rainfall during these seasons is subsequently not a good indicator of what is to be expected later on in the season.

The main conclusions that can be drawn from probabilistic skill assessments are that only short lead-times are associated with usable skill, and that only high skill forecasts may be profitable to a forecast user. This result is potentially a caveat that may result in such forecasts not being used by a forecast user, especially if longer lead-time forecasts are required for optimal decision-making. Notwithstanding, the added information that the forecast models can potentially provide may be of interest and benefit to a user such as Rand Water. Through this project, Rand Water has become aware of the operational forecasts of the Vaal Dam being produced at the University of Pretoria. Follow up meetings with Rand Water and other invested parties should happen so that the predictability identified here can be further applied and forecasting systems further developed in a true co-development process.

RECOMMENDATIONS

The work has demonstrated a seasonal forecast capability for the Vaal Dam. Since forecasts for the second half of summer, going into autumn, have been shown to be skilful, the planning of water release downstream can benefit from such forecasts, albeit at a short lead-time. The observation that high rainfall totals may have been observed during summer over the catchment can help with such planning. However, the forecast models presented here are not able to provide guidance on hydro-climate variability during spring or during winter. Sophisticated hydrological models should be configured to see if they can assist with seasonal forecasts for the Vaal Dam during these seasons and also to see if such models can improve on the forecasts presented here. Until such time, simple linear models may be the only viable way to make skilful seasonal forecasts for the Vaal Dam.

Given these limitations, it is important that modellers (atmospheric and hydrologists) should more actively engage with the dam's managers in order to start a process of co-development of seasonal forecast products most suitable for improved decision-making in areas where climate variability affects dam fluctuations.

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ACRONYMS & ABBREVIATIONS

CPT	Climate Predictability Tool
GCM	General circulation model
SST	Sea-surface temperature

CHAPTER 1: INTRODUCTION AND BACKGROUND

1.1 INTRODUCTION

South Africa`s seasonal rainfall varies significantly in space and time. Roughly about 9% of rainfall eventually reaches river systems making an average annual runoff of 49 210 million m^3/year for the whole country (Van Vuuren, 2012). The Vaal Dam has a full capacity of around 2575 million cubic metres and according to Rand Water there is a growing demand placed upon it since its establishment (Dippenaar, 2013). It is the second largest dam in South Africa by area of around 323km^2 and fourth largest by volume of around 1.4 million cubic meters. South Africa usually faces severe and prolonged droughts affecting much of the country at once, adding on to this, South Africa is water scarce and because of its hot summers faces a high rate of evaporation (Van Vuuren, 2012)

Because the Vaal Dam is a key economic player, it has a requirement of 200% of its capacity to withstand a 1:50 year drought. Dam management and development is an expensive business, Eutrophication and or hypertrophic, i.e. enrichment of water with nutrients is another problem influenced by urbanisation, agriculture and industry facing South African Dams (Van Vuuren, 2012). This can lead to water quality deterioration. Salination is a problem too. Sectors such as agriculture, which rely heavily on water provided by the dams for irrigation face a potential challenge due to population increase thus increase in water demand (IPCC, Chapter 5).

Even without the influence of climate change, it is predicted that South Africa will utilise most of its surface water resources within a few decades. The most significant impacts of climate change on water resources are the potential changes in the intensity and seasonality of rainfall. While some regions may receive more surface water flow, water scarcity, increased demand for water and water quality deterioration are very likely to be problems in the future. (UNFCCC 2000).

Under a wetter future climate scenario, increased runoff would result in increased flooding, human health risks, ecosystem disturbance and aesthetic impacts. However, under drier future climate scenarios, there would be reduced surface water availability. Reduced water availability would most likely create significant trade-offs in terms of the allocation of water resources between agricultural and urban-industrial water use. Projections for national runoff range from a 20% decrease to a 60% increase based on an unmitigated emissions pathway, which reflects substantial uncertainty in rainfall projections.

Because of these challenges facing Vaal Dam management, one approach to address these challenges is to only rely on technological strategies. However, in this report we propose an alternative solution in order to holistically manage the Vaal Dam as a socio-ecological system so that the delivery of ecosystem services to human populations can be better maintained – a so-called nature-based solution. We consequently argue that the development of seasonal-to-interannual prediction systems to assist with Vaal Dam management can help with disaster risk reduction, consequently, reduce vulnerability of, for example, agricultural ecosystems to drought as well as extreme precipitation events that may lead to flooding. Moreover, the models developed in the project have the potential to improve the flood resilience of the Vaal Dam.

1.2 THE VAAL DAM

Vaal Dam has a height of 63m, volume 1.4 million m^3, storage capacity 2610 million m^3 and water surface area 323 km^2 (Van Vuuren, 2012). According to the South African Department of Water and Sanitation (DWS) "by mid-2019, 2.5% of water in South Africa is directed to mining, 3% to industrial use, 2% goes towards power generation and 61% is taken up by agriculture – leaving 27% for consumption for a population of over 60 million" (*www.gov.za*). The Vaal Dam is a water source and key economic player – it feeds an estimated 33% of South Africa's population and is a major water source for Gauteng. It supplies water to about 46% of the country's economy (*www.daily maverick.co.za).* Its catchment area spans around 60% in the Free State, Gauteng, Northwest and Mpumalanga Province (Marx et al., 2003). Rivers which supply the Vaal Dam include Vaal River, the Little Vaal, Klip River, Watervals River and Wilge River, "that used to meet the Vaal River before the Vaal Dam was built but now flows straight into the Vaal Dam" (Rand Water).

The Vaal River catchment, which is part of the Vaal Dam catchment, has a zonal gradient of ~ 1m/km, spanning from the Drakensberg Escarpment. There is a cool-east to warm-west temperature gradient mirrored by the rainfall, thus rainfall decreases as you move from east to west. Rainfall over the Vaal River catchment peaks around October to November, but because of high potential evaporation, discharge rises during December and peaks by February. There is a one-month delay in inflow, therefore a focus period in a previous study was the influence of Dec-Jan rainfall on Jan-Feb discharge (Jury, 2016)

1.3 HYDRO-CLIMATE MODELS

Hydroclimate is part of the climate pertaining to the hydrology of a region, (IPCC 5th Assessment Report) and models which express this relationship are called hydro-climate models. In this project we aim to develop hydro-climate models based on linear statistics for Vaal Dam characteristics (inflow, downstream flow, and dam levels) as well as models predicting seasonal rainfall over the Vaal Dam catchment area, all on seasonal time scales. The main reason for this prediction model development is to determine if Vaal Dam characteristics are predictable at a level that is high enough for dam managers to include seasonal forecasts in their planning and decision-making. Once predictability has been demonstrated, then a meeting with a potential user of the forecasts can be had to talk about the way forward.

Inflow forecasts are usually statistical regression analysis using inflow observations as the predictand and monthly rainfall observation as the predictor. Other statistical methods may include singular value decomposition and partial least-squares regression (Moradkhani and Meier, 2010). (Najafi et al., 2012)identified the Ensemble Streamflow Prediction (ESP) as a better way of forecasting streamflow but it requires sophisticated models, additional data analysis and the basin's initial conditions, for example soil moisture. Seasonal rainfall predictability is not always possible for all areas and times of the year (e.g. (Landman et al., 2012). However, rainfall predictability for South Africa is highest during El Niño and La Niña years as opposed to ENSO-neutral years (Landman and Beraki, 2012). In such cases where a linear relationship is not possible nonlinear equations may be used in which transformed streamflow values are predicted by a linear equation (Pagano and Garen, 2003)

Ways to verify a forecast is by using the relative operating characteristic (ROC) and the reliability diagram (Landman and Beraki, 2012), (Muchuru et al., 2016). And these features are present in the Climate Predictability Tool (CPT), the tool to be used in this work. "Much of statistical hydrologic and weather forecasting is based on linear least-squares regression." (Moradkhani and Meier, 2010).

1.4 CASES

A study by (Tootle et al., 2007)on using partial least square regression improved on a technique of streamflow prediction by “utilizing component scores of both sea surface temperatures and streamflow (i.e. SK LEPS score greater than 10%)” and this resulted in encouraging outcomes for certain areas of the United State. But this method did not work well for a particular ENSO affected area where cross-validation forecast skills were not so robust, possibly because of the nonlinearity of ENSO with streamflow response. This begs the question of how this analysis would work for the Vaal Dam catchment area since it is an ENSO affected area.(Kennedy et al., 2009)also used large-scale predictors “the Pacific North American Pattern, Southern Oscillation Index, Pacific Decadal Oscillation (PDO), Multivariate El Niño-Southern Oscillation Index, Niño3.4, and a revised Trans-Niño Index (TNI)” and found only TNI to have an influence of streamflow forecast. The area of study was Upper Klamath Lake (UKL-snow driven streamflow), Oregon, USA that has highly varying climatic conditions (Soukup et al., 2009) studied streamflow forecasts for North Platte River USA, also used SSTs (Niño 3.4 index, the PDO index and the AMO index.) as the predictor but included 500 hPa geopotential heights values as well. The latter yielded better results than SSTs. Geopotential heights predicted by climate models might be worth incorporating into this study.

The motivation for the paper by (Muchuru et al., 2016) was to prevent disasters, loss of property and life caused by flooding over the Lake Kariba catchment leading to high inflow into the dam and subsequently flooding downstream. Thus, the paper had as one of its aims to investigate whether or not the climate model-based prediction system could have been able to issue a warning of the observed flooding several months ahead of time. The more sophisticated modelling system presented superior levels of skill over the simple statistical model. The discrimination and reliability of the forecasts showed to be able to prove guidance to users. For the months of DJF higher model skill was observed and may be attributed to the fact that the austral mid-summer circulation is skilfully captured by most general circulation/climate models (Landman et al., 2012). For the peak months of rainfall and inflow a 1-month lead-time and a 3-month lead-time set of forecasts were shown as both probabilistic and deterministic outcomes, respectively. Thus, proving useful and reliable forecasts for the users.

To investigate the impacts of changing climate on water resources for the Alabama-Coosa-Tallapoosa River Basin in south-eastern United States, a 33-member ensemble of hydrologic projections was generated using 3 distributed hydrologic models of different complexity. The 8.5 emission scenario was dynamically downscaled and bias-corrected future climate simulations, with 40 years each in baseline (1966-2005) and future (2011-2050) periods. The uncertainty associated with the ensemble hydro-climate response, analysed through an analysis of variance technique, suggested that the choice of climate model is more critical than the choice of hydrologic model for the studied region. (Gangrade et al., 2020)

1.5 DATA AND MAKING FORECASTS

For statistical modelling to be successful as a means to predict seasonal climate and its derivatives (e.g. rainfall induced streamflow’s), certain criteria have to be met. First, phenomena to be predicted should contain a climate signal (e.g. ENSO) in the data. Second, the archived data to be used for statistical models must be over sufficiently long enough periods so that robust statistical relationships can be developed. Finally, some form of quality control of the data had taken place (Landman et al., 2012). From a southern African perspective, the reason why ENSO needs to be prevalent in the phenomena (e.g. High and low flows) is because global climate models are frequently used in the prediction process and these models do best during ENSO seasons as opposed to non-ENSO seasons (Landman and Beraki, 2012). Regarding sufficiently long period of data, not only do we need long periods to develop robust models, but for short testing periods, which is often the case in seasonal forecasting, e.g. (Landman et al., 2012), verification statistics are also more representative of true model skill if tested over longer as opposed to shorter periods (Landman et al., 2012). Data quality is of course important since the models to be developed rely on this, since poorly observed data will negatively impact on the development of prediction models.

Three types of observed data are usually used for this type of statistical seasonal forecast model development and prediction. The first type used for making seasonal forecasts is sea-surface temperature (SST) data. SST has been used successfully for making seasonal forecasts, especially during the early stages of seasonal forecasting in southern Africa, e.g. (Landman and Mason, 1999). The second is the use of antecedent rainfall totals (e.g. Muchuru et al., 2014), and the third involves the use of output from global climate models that have in the past been successfully used as predictors in statistical streamflow models, e.g. (Malherbe et al., 2014).

Historical rainfall data often used in climate work is from the CRU (Climate Research Unit; Harris et al., 2020) or CHIRPS (*Rainfall Estimates from Rain Gauge and Satellite Observations*) (Funk et al., 2014) sets, to name but two. The choice of rainfall data is significant since the data serve the dual purpose of predicting Vaal Dam data, as well as a verification set for modelling seasonal rainfall in the catchment. We also need good quality Vaal Dam data, for example flows in cumecs into the dam. For this purpose, we contacted the National Department of Sanitation who has provided daily data of inflow, downstream flow, dam levels, etc. values from 1980 to present. The provision of such data is paramount to the success of a project of this nature, as has been demonstrated for the case of Lake Kariba (Muchuru et al., 2016).

Global climate model (GCM) output is also considered in the development of the statistical models for the dam. The *ECHAM4.5-MOM3* (DeWitt, 2005) coupled ocean-atmosphere model data was successfully applied to test the predictability of inflows into Lake Kariba (Muchuru et al., 2016), as well as the predictability of seasonal rainfall in the catchment of the Lake (Muchuru et al., 2014). Here, we will use archived as well as real-time forecast fields from the North American Multi-Model Ensemble (NMME; Kirtman et al., 2014) that has recently been used for predictability studies over southern Africa (Landman et al., 2019). One of the NMME models has been used over the past few seasons to provide forecasts that form part of a prediction system for inflows into the Lake. Figure 1.1 shows a forecast produced in October 2019 for the Dec-Jan-Feb 2019/20 season. Similar products do not yet exist for the Vaal Dam and the project attempts to develop such products with the assistance from those managers involved with operations.

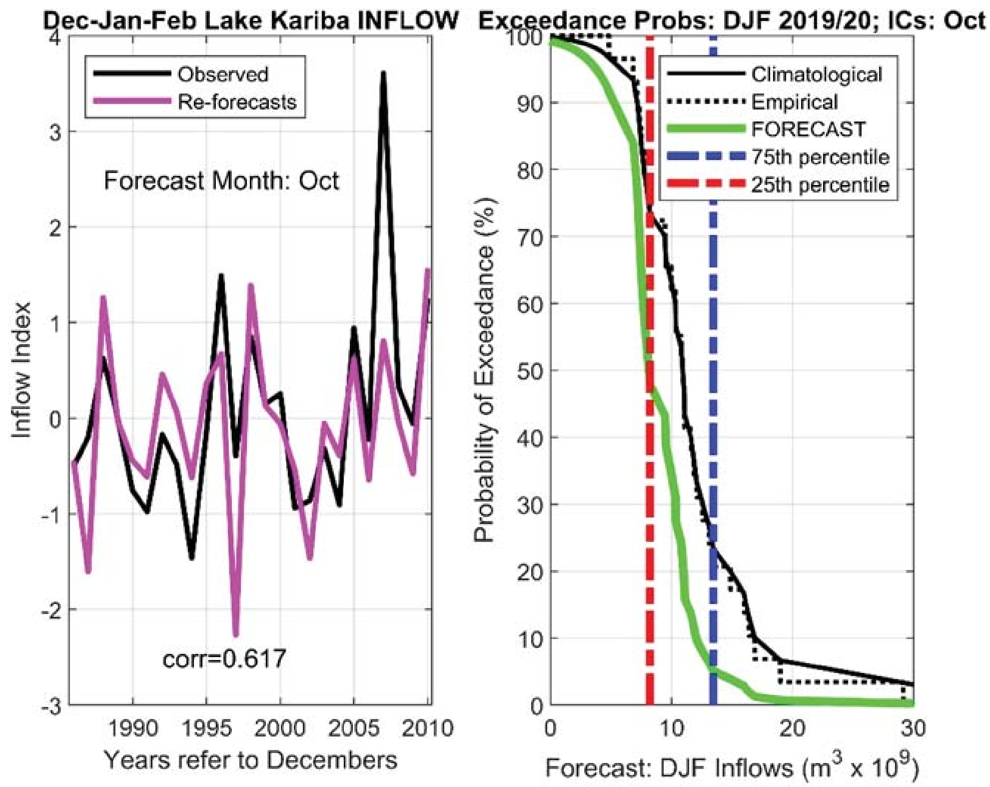


Figure 1.1: Hindcasts (or re-forecasts) (left) and probability real-time forecast (right) of inflows into Lake Kariba for the DJF season. The forecast on the right shows the probabilities of certain inflow thresholds being exceeded.

SST may also be used for Lake Kariba inflows but has not been tested for that dam specifically. However, since SSTs have been used for other hydro-climate modelling, e.g. (Tootle et al., 2007) (Kennedy et al., 2009)) forecast skill in predicting Vaal Dam characteristics need to be used too, at least to establish a baseline model that needs to be outscored by more complicated forecast systems that include the use of GCM output in the statistical models.

An important consideration that needs to be discussed between forecast producers and forecast users is the format of the forecast. In *Figure 1.1* the Lake Kariba inflows forecast for the DJF season is presented as a probability of exceedance graph as explained *here* . The main advantage of presenting a seasonal forecast in this manner is to present forecasts within the full probability range and not only for the chance of a predetermined category threshold to be exceeded or not. The latter is usually done for operational seasonal categorised forecasts and may or may not be ideal for dam management that considers operating dam levels (water level to which the reservoir or storage lake is operated under normal operating conditions at a given time of the year). One of the most commonly used tools to aid reservoir operation is the rule curve. This rule gives a priori pattern of the desired storage values in every month of the year. According to such a curve the storage should gradually drop down between July and January, to provide sufficient storage for annual floods, which is expected to fill the reservoir in the following summer months. *Figure 1.2* shows the reservoir levels of Lake Kariba for a number of years as well as the rule curve. The levels for one El Niño and two La Niña seasons are presented in the figure, which may have been predicted with the use of probability of exceedance graphs as presented in *Figure 1.3.* There is still a mismatch, however, since the forecasts are for inflows while the data presented in *Figure 1.3* are for dam levels. This example shows the importance of what a climate modeller may deem as a useful forecast and what a user of that forecast may consider important. This discrepancy is probably the biggest gap there currently exists between the forecasts and what may be required. We will show in this project how this caveat can be addressed through a process of co-production between the modellers and the managers of the Vaal Dam.

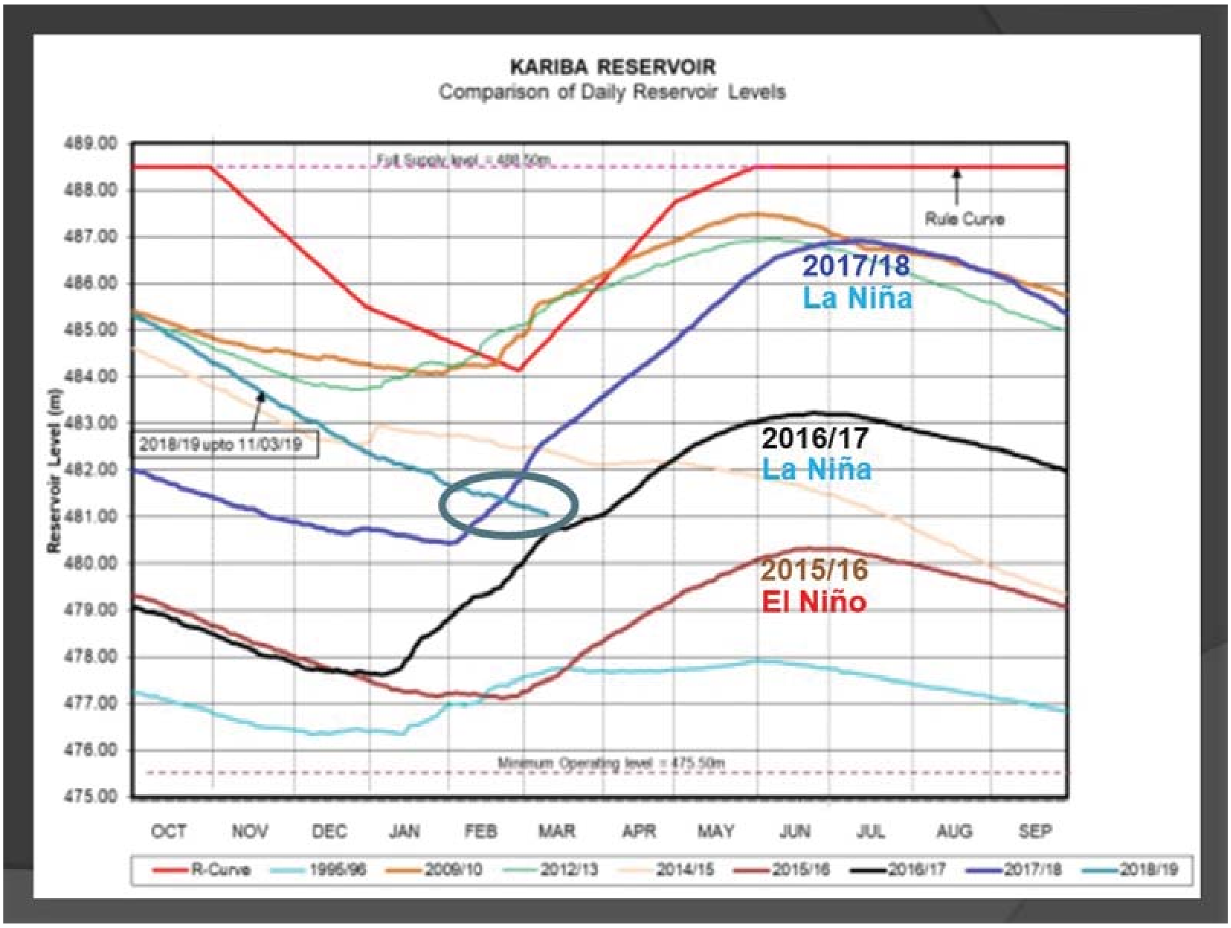


Figure 1.2: Rule curve and levels at Lake Kariba during certain years.

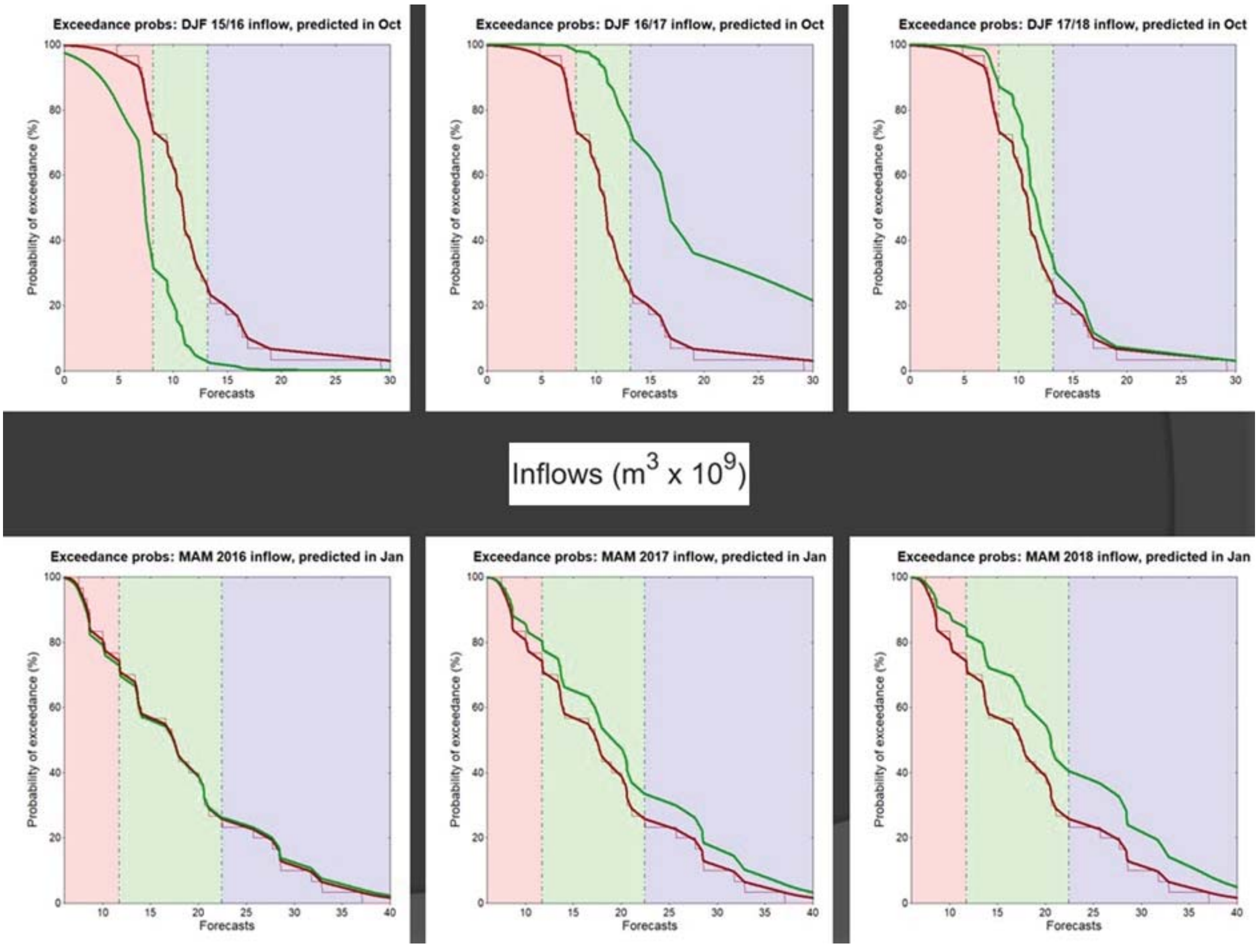


Figure 1.3: Probability of exceedance forecasts for DJF and MAM seasonal inflows into Lake Kariba during the one El Niño and two La Niña seasons presented in Figure 2. The green curves represent forecasts and the red curves the climatology of the respective seasons based on observations.

Other important considerations include the length of the seasons for which forecasts need to be made and the forecast lead-times. For the former consideration, users may want to get monthly as opposed to or in addition to 3-month seasonal forecasts. However, forecast skill may not be high enough for monthly forecasts as a result of a low signal-to-noise ratio for such forecasts and thus more risky than seasonal forecasts. Regarding lead-times, dam managers may need to make decisions several months ahead of the main rainfall season or may only need forecasts made at short lead-times when decisions need to be made in the middle of the main rainfall season. Another consideration is that the main inflow season may be several months after the main rainfall season. This discrepancy is found for Lake Kariba where it was found that the main inflow season is 2 to 3 months after the main rainfall season and that the inflow during the main season is less predictable than inflows during the start of the maximum inflow period. Therefore, there are different temporal scales to consider, and before detailed modelling is embarked on there is a clear need for forecast producers and users to meet to discuss the way ahead for modelling Vaal Dam characteristics.

1.6 PROJECT AIMS

The general objective was to test for seasonal predictability for Vaal Dam characteristics in a pragmatic and cost-effective way that can also lead to real-time prediction and decision-making. The use of statistical models is far less computationally demanding than using more sophisticated models such as hydrological models, and so in this project we used simplified statistical models to test for predictability. Once predictability is established and the conditions under which Vaal Dam characteristics can be predicted, operational utility of the developed models needs to be ascertained. For this purpose, we effectively pursued three aims, namely:

1. To develop statistical forecast systems for the Vaal Dam on seasonal time scales by considering a number of statistical models that have in the past been shown to successfully predict hydrological variables such as inflows into Lake Kariba.

2. To test the models' performances using recognised forecast verification systems. Here we need to test for both deterministic and probabilistic forecasts. The former is to first find out if there are statistical links between predictors such as rainfall in the catchment and Vaal Dam characteristics, and the latter to see if the models demonstrate probabilistic forecast skill since seasonal forecasts need to be issued probabilistically.

3. To demonstrate operational forecasting capability using the developed models. Forecasts need to be made at lead-times that are sufficiently long for effective decision-making. Here we test forecast skill over various lead-times and determine at which lead-times forecasts can be considered useful.

1.7 SCOPE AND LIMITATIONS

The methods tested here are based on linear statistics. No nonlinear methods are employed here and so more sophisticated techniques involving, for example, neural networks, may have to be developed to see if these techniques can outperform the linear models presented here. The focus is also on 3-month calendar months, and it may be worth it to test predictability on single-month periods.

CHAPTER 2: PRELIMINARY PREDICTION MODELS TO TEST PREDICTABILITY OF DAM INFLOWS AND LEVELS

2.1 INTRODUCTION

The Vaal Dam in South Africa lies on the Vaal River, one of South Africa's strongest-flowing rivers. Other rivers flowing into the dam include the Wilge, Klip, Molspruit and Grootspruit Rivers. Vaal River discharge in the Vaal River is strongly influenced by climate variations caused by ocean-atmosphere interactions (Jury, 2016)and may thus be predictable on seasonal climate time scales, owing to the climate “signal” in flow or related hydrological data (Muchuru et al., 2016). It has been demonstrated that river flows are sensitive to climatic variability – flows have, as a result, been successfully modelled on seasonal time scales (Coelho et al., 2006). In this deliverable, we will demonstrate predictability of Vaal Dam levels and of downstream flows by using linear statistical models developed in the project.

2.2 DATA

Vaal Dam data used here for statistical hydro-climate modelling includes dam levels (meters) and downstream flow (cumecs), obtained from the National Department of Water and Sanitation in South Africa. Daily data are averaged into 3-month seasonal means and are considered from the early 1980s to 2016. In order to ensure that all of the level and flow values are from normal distributions for optimal statistical modelling to be performed, the natural logarithms of the level and flow values for each season are calculated prior to developing the statistical models.

Seasonal predictability is assessed first by investigating how seasonal rainfall in the catchment (*Figure 2.1*) may influence both dam levels and downstream flows. The rainfall data used for this part of the modelling are obtained from the CHIRPS set *Rainfall Estimates from Rain Gauge and Satellite Observations*; (Frank et al 2014). The CHIRPS data are used to determine if antecedent as well as concurrent 3-month seasonal rainfall totals are linked to dam levels, and to downstream flows. The CHIRPS data are at a 0.05° x 0.05° resolution and are used over an area representing the Vaal Dam catchment of 23°S to 30°S, and 25°E to 31°E (*Figure 2.2*).

Sea-surface temperature (SST) anomalies are often used in statistical seasonal forecast models (e.g. Landman and Mason, 1999). Here, we use tropical and sub-tropical SST over the Indian and Pacific Ocean basins *Figure 2.3* as predictors of dam levels and downstream flows. The SSTs are from the extended reconstructed sea-surface temperature data set (Huang et al., 2017) at a 2° x 2° resolution, and calculated as 3-month averages.

Finally, we use rainfall fields as forecast by a global climate model as predictors of dam levels and flows. The hindcasts (or re-forecasts) are from the fully coupled ocean-atmosphere model (*GFDL-CM2p5-FLOR-B01,* hereafter referred to as “GFDL”) of the North American Multi-Model Ensemble (Kirtman et al., 2014). Monthly global hindcast data from the early 1980s to the present are available at a 1° x 1° latitude-longitude resolution for 12 ensemble members and for several months lead-time. For simplicity, we are using only 1-month lead-time hindcasts (e.g. a forecast for the December-February season made from observations through the end of October), and the ensemble mean. This GFDL model has recently been used successfully for southern African predictability studies (Landman et al., 2019, Landman et al., 2020). The area from which the model’s rainfall data is extracted is shown in *Figure 2.2.*

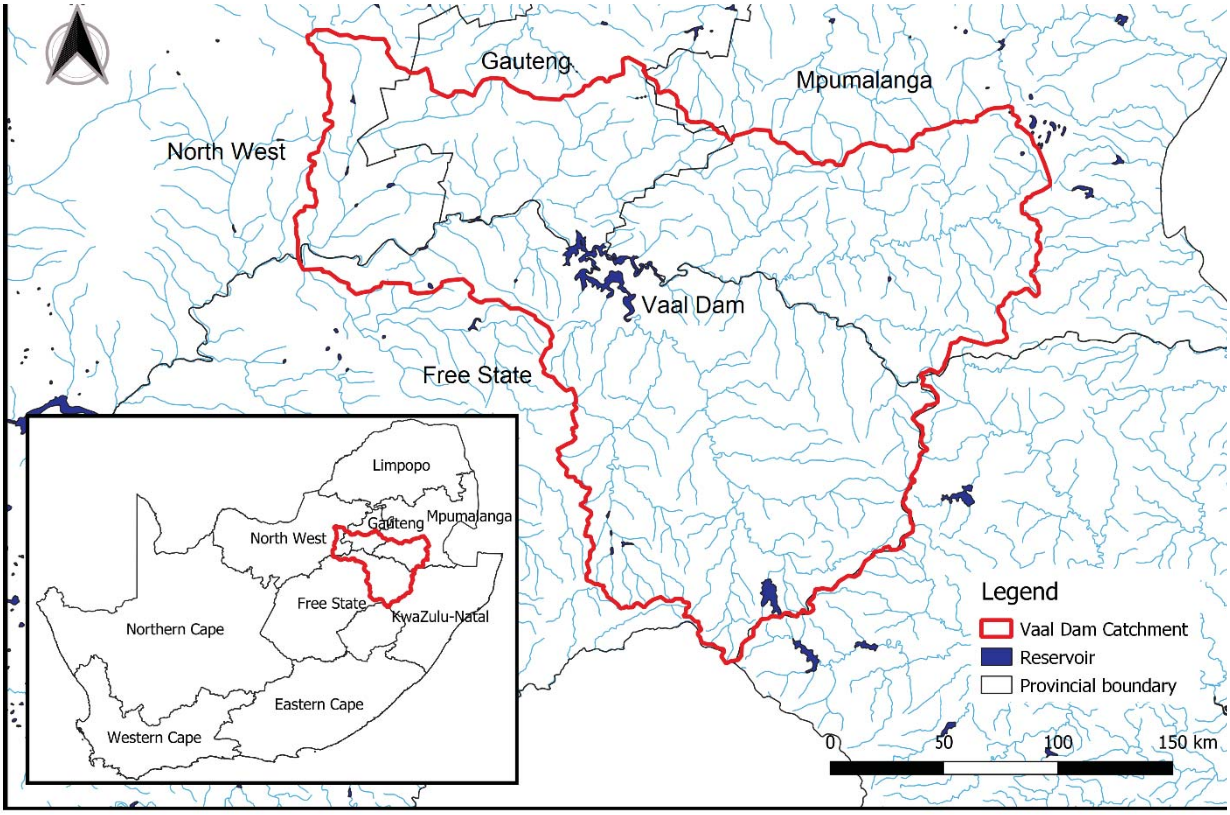


Figure 2.1: Vaal Dam catchment.

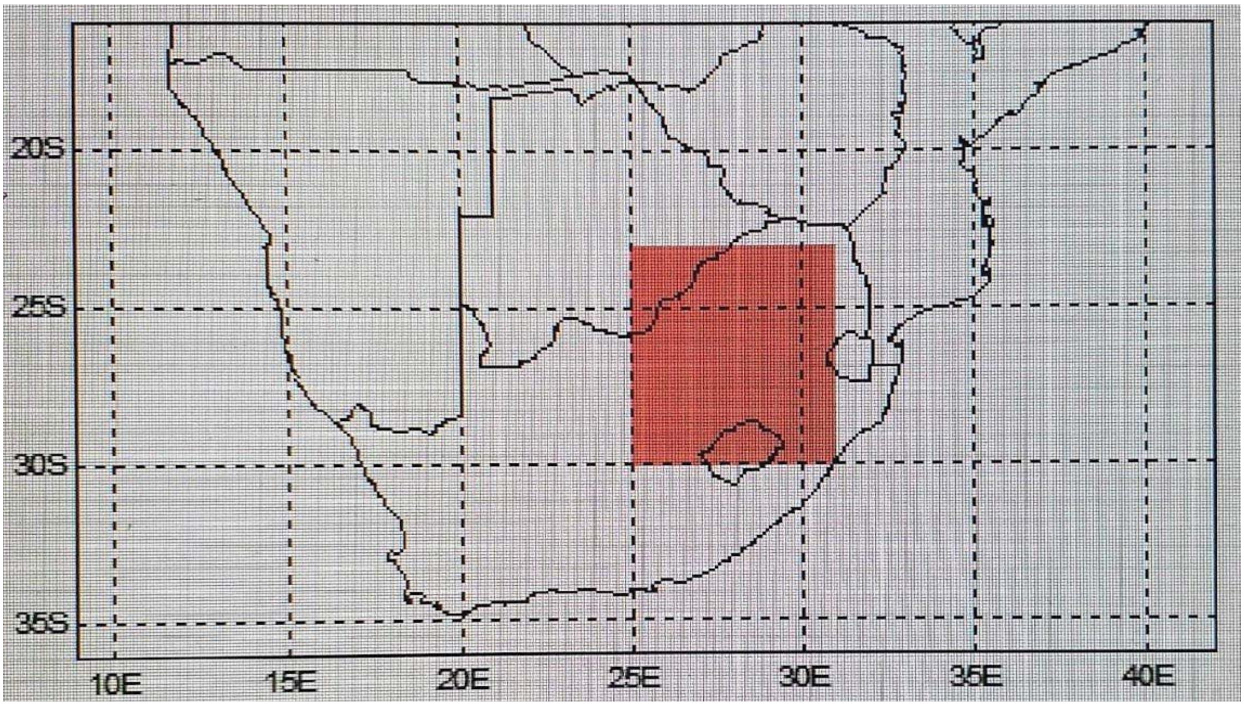


Figure 2.2: The domain is used to extract seasonal rainfall data from the CHIRPS set as well as from the GFDL hindcasts.

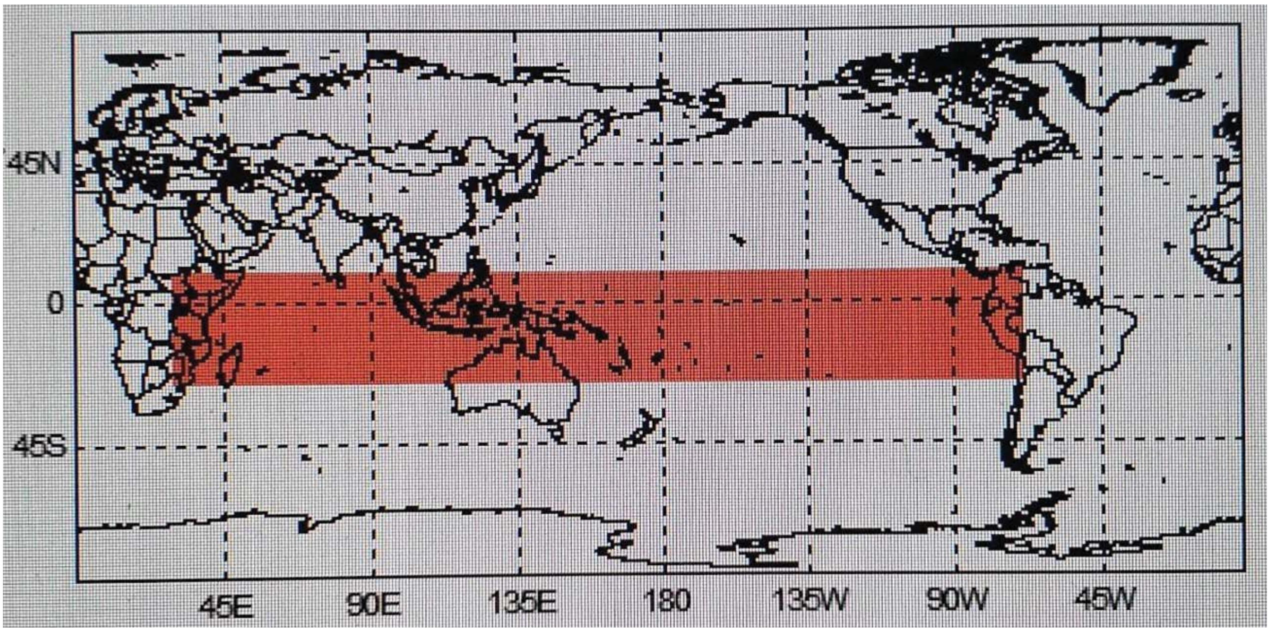


Figure 2.3: The domain from which the SSTs are extracted for the SST-based statistical prediction models. Land points are masked out.

2.3 METHODS

Linear statistical models are developed for both dam levels and for downstream flows. The software used for the statistical modelling is the IRI's Climate Predictability Tool (CPT; (Mason and Tippett, 2016). First, concurrent seasonal rainfall data are used for simulating dam levels and downstream flows – for example, December to February (DJF) rainfall totals over the catchment are used to simulate DJF levels and flows. The reason for testing concurrent seasons is to determine to which extent rainfall in the catchment directly affects levels and flows. Canonical modes of the rainfall as calculated by the CPT are used in a multiple linear regression model as predictors (Landman et al., 2020). The models are tested in a 5-year-out cross-validation design (Efron and Gong, 1983). Second, antecedent seasonal rainfall is also used in the same modelling configuration, but for this part of the modelling, prediction skill instead of simulation skill is estimated. For example, September to November (SON) rainfall totals are used to predict DJF levels and flows. Thirdly, for those seasons for which the most skilful simulations and predictions are obtained, SST fields and GFDL rainfall fields are also used as predictors. For SST, for example, the SON temperatures are used to predict DJF levels and flows. For GFDL, DJF rainfall forecasts initialized in November (Landman et al., 2019) are used to predict DJF levels and flows. Therefore, as with antecedent rainfall as predictor, using SST and GFDL forecasts as predictors, a 1-month forecast lead-time is tested. Finally, simple linear regression is used to see if dam levels can be linked to downstream flows.

All the models are tested over a common period from 1995/96 to 2015/16, a 21-year period for each statistical model. Each statistical model uses a stringent 5-year-out cross-validation design in order to minimize skill inflation. Simulation and forecast skill over the 21-year period are estimated in this deliverable by calculating the Spearman rank correlation between predicted and observed levels and flows. This preliminary approach is sufficient for demonstrating levels of predictability.

2.4 RESULTS

The results (Spearman correlations) for the various statistical models across all 3-month seasons are presented in *Figures 2.4* and *Figure 2.5. Figure 2.4* shows the correlation when 3-month seasonal rainfall, concurrent with the dam levels and downstream flow seasons, is used to simulate the levels and flow. A general conclusion is that downstream flows have the potential to be more predictable than dam levels, owing to the mostly higher correlations for flows in the figure. The flow season with the highest correlation (skill) is found for DJF, and we thus test for true forecast skill by first using a climate model to predict DJF rainfall that can subsequently be used as a predictor of flows at a 1-month lead-time. In addition, we also used SST of the SON season to predict DJF flows. The prediction's verification results are shown in *Figure 2.4,* but with correlations considerably lower than the DJF simulation case. Notwithstanding, at least for the case of using SST as DJF flow predictions, downstream flows are predictable at a level (Spearman correlation of 0.4442) that may be useful for dam management.

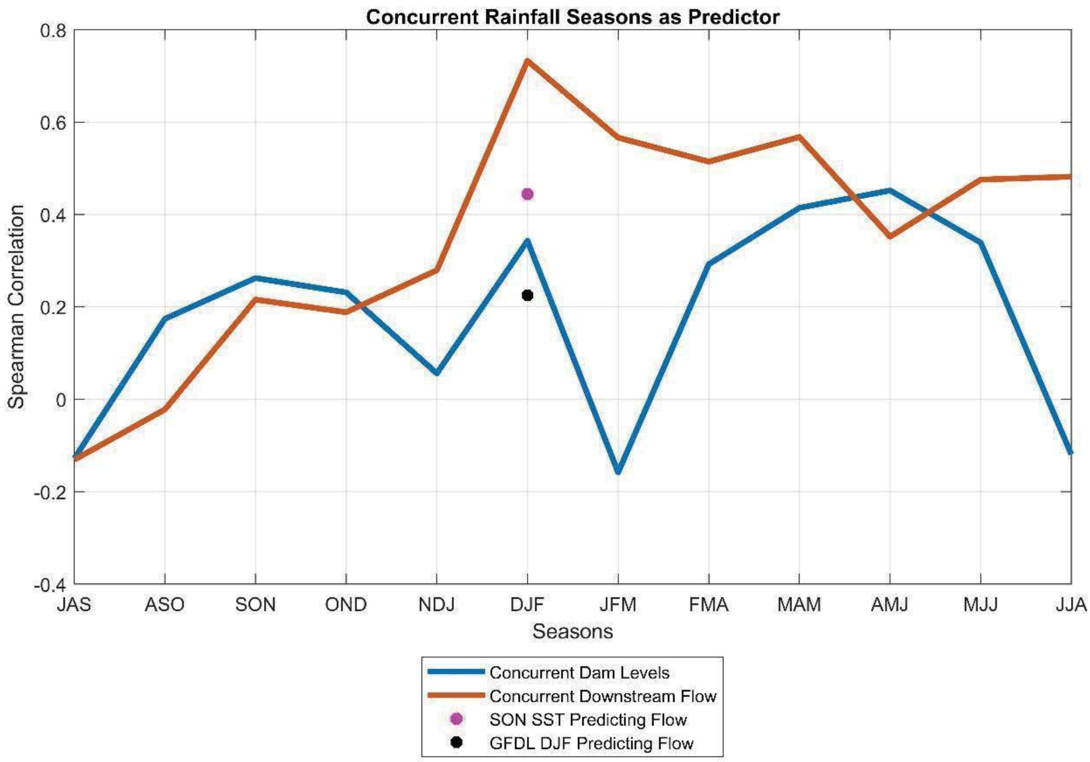


Figure 2.4: Spearman correlations between simulated and observed dam levels and downstream flows. Also shown on the figure are correlations obtained by predicting DJF downstream flows with a) SON SST and b) GFDL rainfall predicted in November

Figure 2.5 shows the correlation results obtained by verifying 1-month lead predictions of flows and levels, and results from experiments using concurrent dam levels to simulate downstream flows. The season of highest dam level predictability (highest Spearman correlation) is JFM when observed OND rainfall is used as a predictor. The best predictions of downstream flows occur during FMA, when NDJ rainfall is used as predictors. Those models using antecedent observed conditions as predictor outscore those forecasts from both the climate model and from using SST as predictor. Moreover, the skill levels for downstream flows from antecedent conditions compare favourably with the simulation results when concurrent dam levels are used to simulate flows. Take note that antecedent dams' levels (i.e. SON) predicting downstream flows (i.e. DJF) produces low or negative Spearman correlations, which means dam levels cannot be used to predict downstream flows at a forecast lead-time.

We have demonstrated how statistical models using antecedent observed rainfall conditions can serve as skilful estimates of future dam level and downstream flow conditions, albeit at the short lead-times considered here. Next, we will look at the cross-validated time series of the skilful models in more detail.

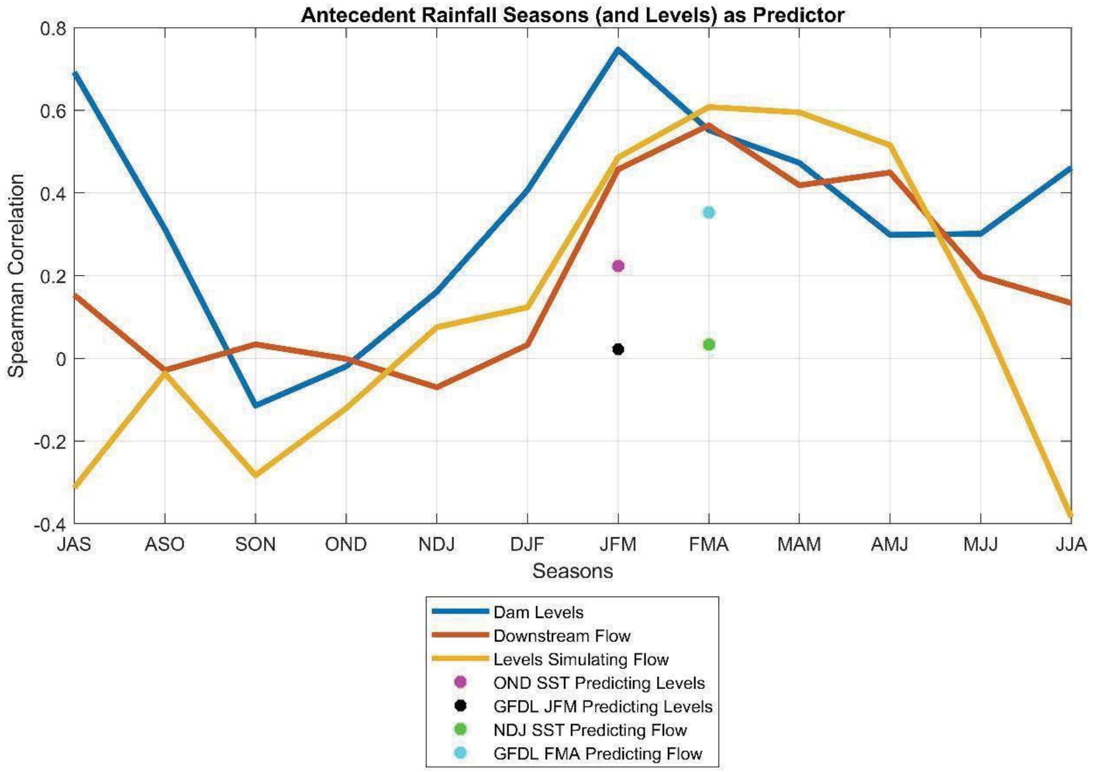


Figure 2.5: Spearman correlations between predicted and observed dam levels and downstream flows using antecedent rainfall conditions. Simulations using concurrent dam levels to simulate flows are also presented. Also shown on the figure are correlations obtained by predicting JFM dam levels and FMA downstream flows with a) SST and b) GFDL rainfall predicted by climate models.

The correlation analysis above does not provide insight into the ability of the statistical models to predict for specific seasons of interest – for example seasons of extremely high or low downstream flows. *Figure 2.6* to *Figure 2.9* present cross-validated predictions and simulations over 21 years for several selected seasons during which the statistical models performed well. The DJF downstream flow model simulations and predictions are presented in *Figure 2.6.* A highly significant correlation is found when simulating downstream flows concurrent to the DJF rainfall season. The result shows that seasonal rainfall strongly influences how much of the dam water is allowed to flow downstream of the dam. *Figure 2.6* moreover provides further evidence of skill in predicting such flows at a short lead-time of one month.

As shown above, predicting for dam levels is not as skilful as predicting for downstream flows. However, *Figure 2.7* shows results from forecasts for dam levels and demonstrates that antecedent rainfall in the catchment can provide skilful forecasts of dam levels during JFM. Notwithstanding, neither SST nor the climate model could contribute to skilful dam level forecast models (statistical level of significance below 90%). *Figure 2.8* shows forecast performances for FMA downstream flows, and both antecedent (NDJ) rainfall in the catchment as well as predicting NDJ rainfall with a climate model, produce statistical downstream flow models with statistically significant results.

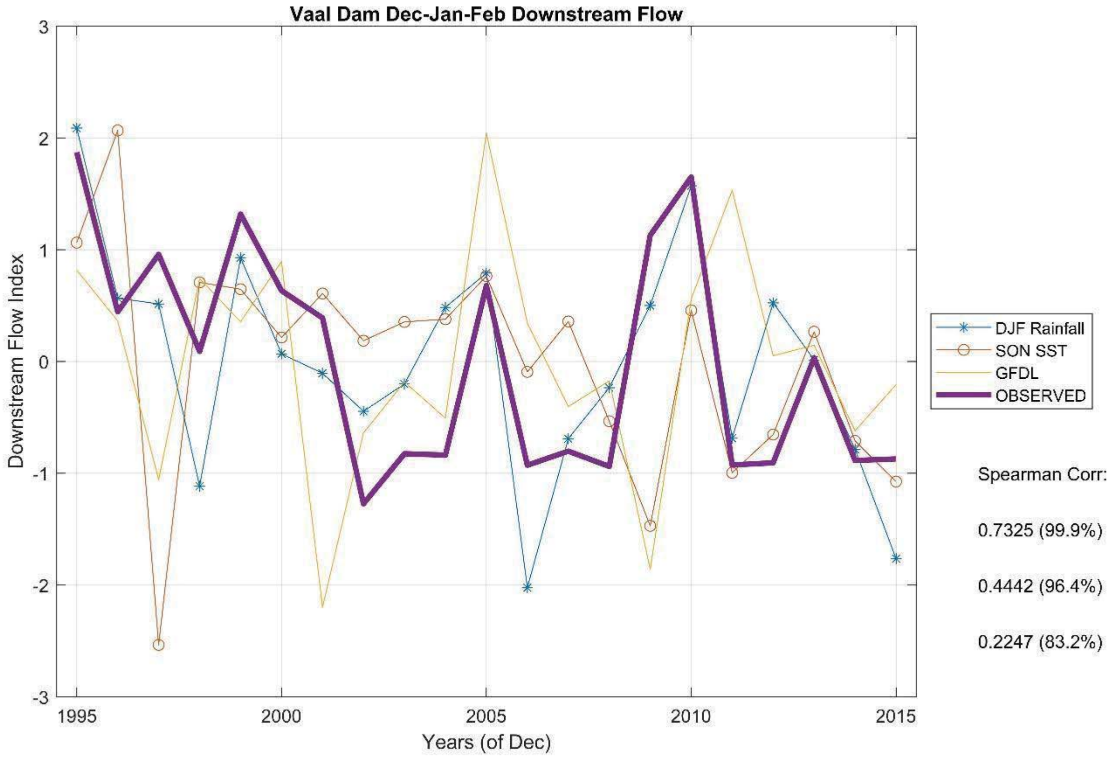


Figure 2.6: DJF downstream simulations and predictions, using concurrent (DJF) rainfall conditions for simulations, and SON SST and DJF rainfall forecasts from the GFDL climate model for predictions.

The correlations and their level of statistical significance are listed in the same order from top to bottom as shown in the key.

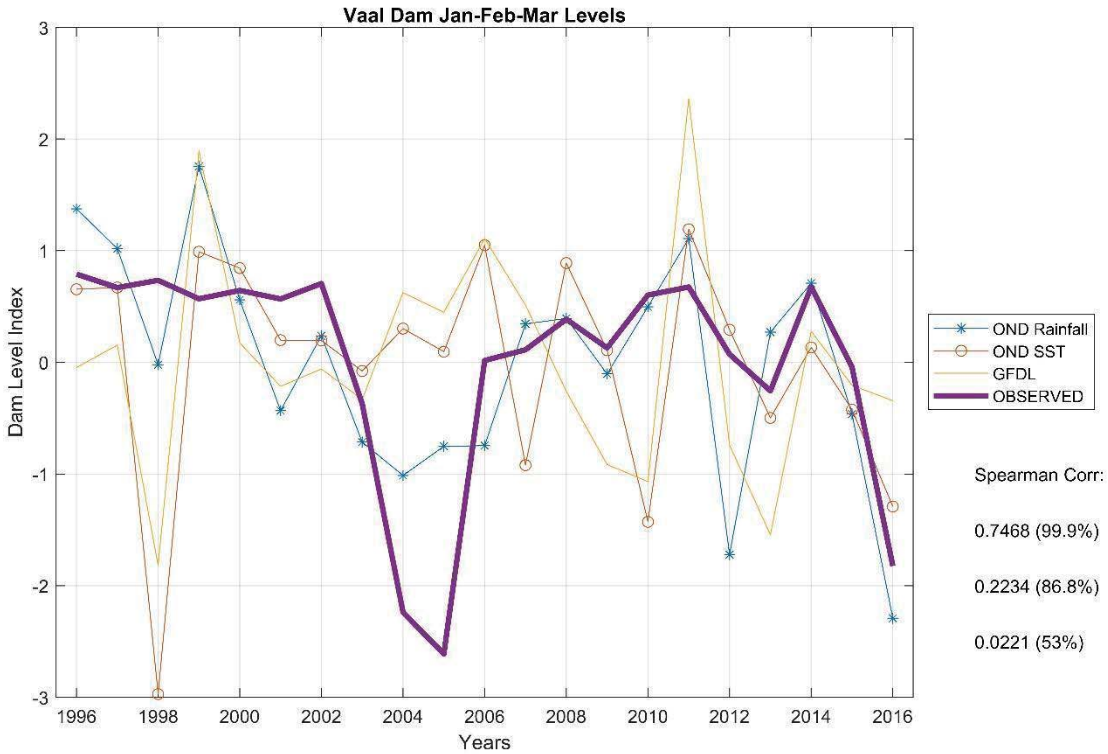


Figure 2.7: JFM dam level predictions, using antecedent (OND) rainfall conditions, OND SST and JFM rainfall forecasts from the GFDL climate model. The correlations and their level of statistical significance are listed in the same order from top to bottom as shown in the key.

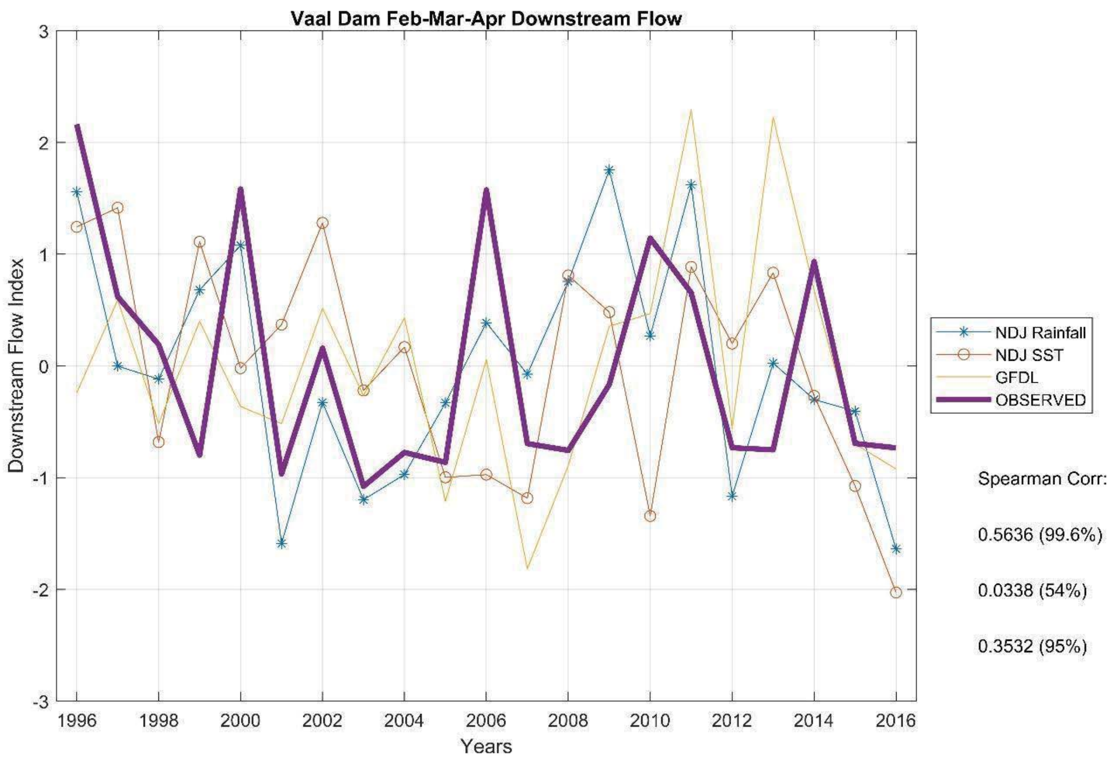


Figure 2.8: FMA downstream flow predictions, using antecedent (NDJ) rainfall conditions, NDK SST and FMA rainfall forecasts from the GFDL climate model. The correlations and their level of statistical significance are listed in the same order from top to bottom as shown in the key.

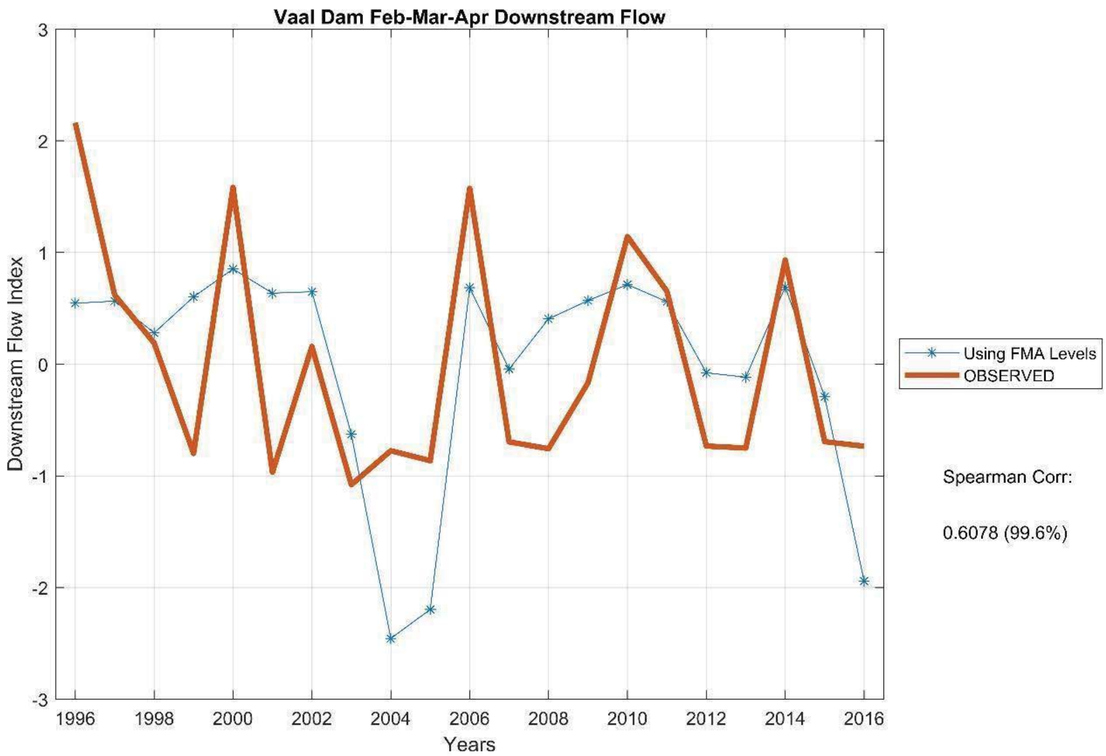


Figure 2.9: FMA downstream flow simulations using concurrent (FMA) dam levels in a statistical model. The correlation and its level of statistical significance are shown on the right of the figure.

Figure 2.9 shows the strong link between dam levels and downstream flows for the FMA season. In addition, *Figure 2.5* demonstrates how simulating downstream flows using concurrent dam levels as predictors can provide insight into the characteristics (high or low) of the downstream flows – but that the usefulness is restricted to the second half of summer through autumn. It is important to note that, as mentioned above, there is no evidence of antecedent dam levels being linked linearly to downstream flows. Although there is, thus, no prediction utility found with these flow simulations, the results certainly show the strong link between dam levels and what happens further downstream.

2.5 CONCLUSIONS AND DISCUSSION

The main objective of this chapter is to develop prototype models in order to demonstrate that a subset of the hydrological characteristics of the Vaal Dam is predictable on a seasonal time scale. In this study, we used a number of predictors in linear statistical models for predicting dam levels and downstream flows, including concurrent and antecedent seasonal rainfall totals in the catchment, SSTs and seasonal rainfall forecasts from a climate model.

From verifying the statistical models over a recent 21-year period, the following main conclusions may be drawn:

1. As may be expected, there is a strong link between rainfall in the catchment and dam levels; as well as what happens downstream of the dam. This link is less pronounced during winter.
2. There is also a concurrent link between dam levels and downstream flows, but this link is strongest during the second half of summer and autumn.
3. Real-time prediction for both dam levels and downstream flows is possible, but the predictability demonstrated here is mainly a result of using antecedent rainfall in the catchment as predictor in a statistical model, as opposed to using a climate model's forecasts or SSTs as predictors. This result does not mean that climate model output has been found to be redundant, but rather that one should be considering a range of possible predictors that may or may not include climate model forecasts.

It is important to note that this chapter did not undertake an in-depth verification of Vaal Dam forecast models, nor did it verify a set of probabilistic seasonal forecasts of dam levels and flows, e.g. (Landman et al., 2020). Since seasonal forecasts are required to be expressed probabilistically (or at the very least be provided with an indication of uncertainty) the following chapters aim to provide a thorough assessment of the attributes of interest for probabilistic forecasts, such as discrimination and reliability.

We have provided evidence of predictability that has the potential to be of benefit to managers of the Vaal Dam. In the next chapter we engage with Rand Water representatives in order to discuss the way ahead for more advanced modelling through a process called co-production, in which forecast users are part of the forecast system development.

CHAPTER 3: SOCIAL INCLUSION FOR USER-ORIENTED FORECAST SYSTEMS

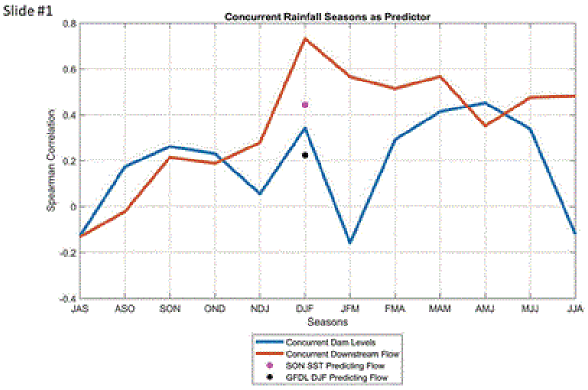
3.1 INTRODUCTION

The focus of this project is the predictability of Vaal Dam characteristics such as levels, inflows and downstream flows on a multi-month seasonal time scale. Predictability is made possible since the Vaal River discharge is strongly influenced by climate variations caused by ocean-atmosphere interactions. Moreover, it was shown in Deliverable #2 that flows associated with the Vaal Dam are in fact predictable with lead-time and skill. Notwithstanding, even with perfect predictability of these hydrological variables, the modelling research will be insufficient if it does not benefit some of the sectors affected by the dam. Therefore, in this deliverable, we report on the meeting we had with representatives from *Rand Water* in order to discuss with them the modelling results of Deliverable #2 and to find out how forecast systems may be able to benefit from their decision-making.

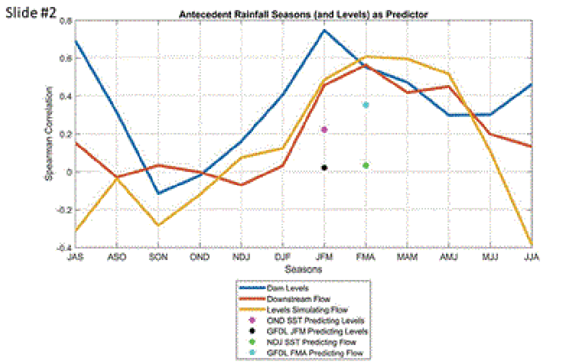
3.2 THE PRESENTATION TO RAND WATER

The background and motivation for the study was presented first, including the objectives of the project and how the historical dam levels, inflows and downstream flows were obtained. Testing for the predictability of these three variables using statistical models is the primary modelling objective of the project. However, we do not only want to test models, but we made it clear in our presentation that we also wanted to find out from Rand Water whether or not our presented forecasts may be of any value to them.

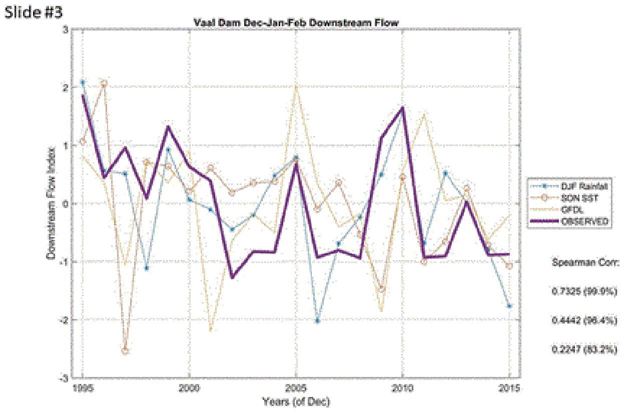
Five slides were presented in the meeting. The first slide (marked “Slide #1” on *Figure 3.1*) represents a preliminary estimate of our forecast capabilities since 3-month seasonal rainfall totals concurrent with 3-month dam levels and downstream flows are used to “simulate” levels and flows. The term simulate is used in this context because there is no forecast lead-time involved so that the models can only test if there may be potential predictability to be tapped from. Here it is evident that for the most part, the potential predictability of downstream flows is higher than that of dam levels. However, also presented on the figure are results from making 1-month lead-time forecasts by using as predictors in statistical models both equatorial sea-surface temperature (SST) fields for the September-October-November (SON) season and the December-January-February (DJF) rainfall predicted in early December using a global climate model (GCM). With the statistical model using SST as predictor, the Rand Water representatives were introduced to the skill levels of operational forecasts associated with this type of modelling approach. Moreover, the figure also shows that mid-summer (DJF) rainfall over the catchment is strongly linked to dam levels and downstream flows. One of the Rand Water representatives was concerned where exactly the downstream measuring was taking place. Unfortunately, we do not know exactly where but assume that it is downstream close to the dam. A comment was also made on the use of physical hydrological models in the flow predictions. However, the modelling approaches presented in the project are much simpler than hydrological models and serve the purpose of first testing for predictability on a seasonal time scale and also to set a baseline skill level against which much more complicated systems (like hydrological models) can be tested at a later stage. Moreover, neither we nor the Rand Water representatives were aware of any hydrological model forecasts currently being used to produce operational flow forecasts on seasonal time scales for the dam.



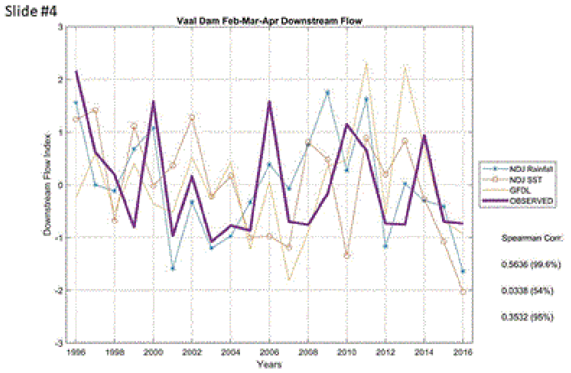
Spearman correlations between simulated and observed dam levels and downstream flows. Also shown on the figure are correlations obtained by predicting DJF downstream flows with a) SON SST and b) GFDL rainfall predicted in November.



Spearman correlations between predicted and observed dam levels and downstream flows using antecedent rainfall conditions. Simulation using concurrent dam levels to simulate flows are also presented. Also shown on the figure are correlations obtained by predicting JFM dam levels and FMA downstream flows with a) SST and b) GFDL rainfall predicted by climate model.



DJF downstream simulations and predictions, using concurrent (DJF) rainfall conditions for simulations, and SON SST and DJF rainfall forecasts from the GFDL climate model for predictions. The correlations and their level of statistical significance are listed in the same order from top to bottom as shown in the key.



FMA downstream flow predictions, using antecedent (NDJ) rainfall conditions, NDK SST and FMA rainfall forecasts from the GFDL climate model. The correlations and their level of statistical significance are listed in the same order from top to bottom as shown in the key.

Figure 3.1: Four of the five slides presented to the Rand Water representatives. The slides are some of the figures presented in Chapter 2.

One of the Rand Water representatives was concerned where exactly the downstream measuring was taking place. Unfortunately, we do not know exactly where but assume that it is downstream close to the dam. A comment was also made on the use of physical hydrological models in the flow predictions. However, the modelling approaches presented in the project are much simpler than hydrological models and serve the purpose of first testing for predictability on a seasonal time scale and also to set a baseline skill level against which much more complicated systems (like hydrological models) can be tested at a later stage. Moreover, neither we nor the Rand Water representatives were aware of any hydrological model forecasts currently being used to produce *operational* flow forecasts on seasonal time scales for the dam.

Next, results obtained by developing statistical models with a 1-month lead-time were discussed. From the second slide (marked "Slide #2" in *Figure 3.1)* it is evident that most of the predictability occurs during the second half of the summer rainfall season. This result is expected because most of the predictability arises from using antecedent rainfall totals in the catchment. In other words, since measured rainfall in the catchment provides the best estimate of both future levels and downstream flows, low rainfall totals usually occurring during winter and spring contribute little to predictability. Once again, using equatorial SST or climate model forecasts as predictors did not perform as well as when using rainfall totals over the catchment as predictor.

"Slide #3" and "Slide #4 of *Figure 3.1* shows the time series of the best modelling results presented above in order to present a visual representation of how well the simulations and predictions compare with observed data. Owing to the uncertain nature of seasonal forecasts, some of the seasons for particular years are missed by the models, and the variance of the forecasts is not a perfect match with the observed. A much more detailed verification exercise is required in order to obtain a more complete understanding of the attributes of the forecast systems. Here we only wanted to introduce our statistical models and to demonstrate that some of these models have forecast skill. We believe we have successfully demonstrated this notion. However, we need to more comprehensively demonstrate that our skilful models can produce useful forecasts to a user such as Rand Water. Since seasonal forecasts are inherently probabilistic, they need to be expressed probabilistically, especially in a real-time operational forecast environment. Such a probabilistic forecast is shown in *Figure 3.2* ("Slide #5).

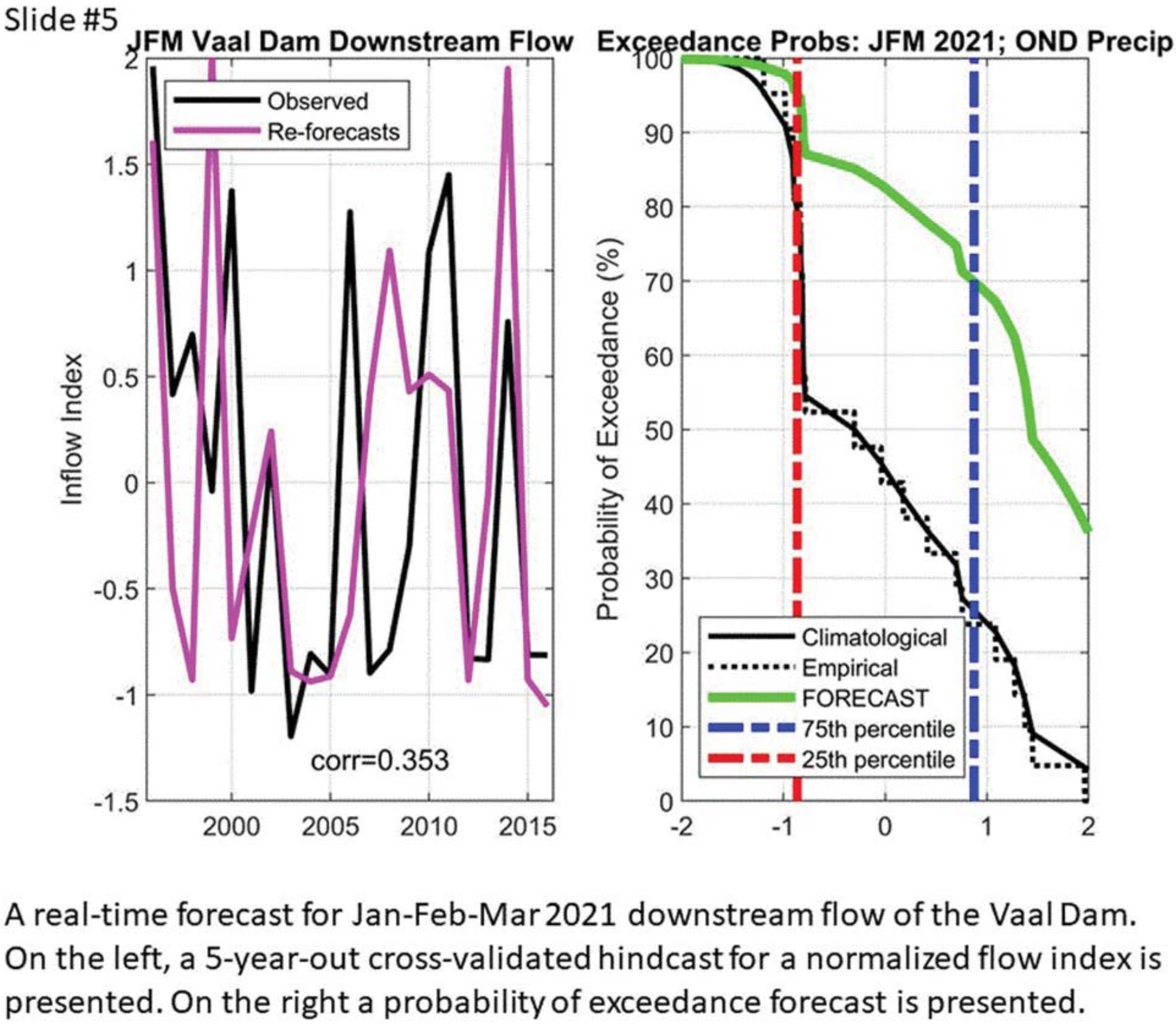


Figure 3.2: "Slide #5" presented during the meeting with Rand Water

Exceedance probability is referred to as the probability that a certain value (e.g. downstream flow) will be exceeded during a predefined future 3-month season. The exceedance probability can be used to predict extreme events such as downstream floods. *Figure 3.2* is an example of a real-time forecast for the Vaal Dam's downstream flow for the January-February-March season. The predictor used here is the October-November-December (OND) observed rainfall in the catchment, thus constituting a 1-month lead-time forecast. Two graphs are shown on *Figure 3.2.* On the left a cross-validated hindcast (or re-forecast) set is presented against observations in order to show to a user the skill of the forecast system. On the right is the actual forecast represented as an excess of probabilities. We believe that a probability of exceedance forecast may be more useful to the water sector since one is not restricted to the usual three-category forecasts approach normally associated with seasonal forecasts – probabilities of certain extreme thresholds being exceeded, as specified by the user, can be determined using such a forecast. When we raised the question to Rand Water, based on what we presented in terms of model skill and the probability of exceedance forecast, whether or not our forecasts may be useful they replied that as Rand Water they do not manage the Vaal Dam. That is the function of the Department of Water and Sanitation. However, any information additional to what they currently obtain, is deemed useful. For instance, they have a big focus on water quality, and flows affect water quality. Water with poor quality needs treatment. During a season of inundation, lots of sediment and silt are deposited – all organic matter goes under water. This scenario requires treatment of the water and presents a big challenge to Rand Water. Therefore, a forecast of enhanced probabilities of large flow volumes associated with the coming summer season will assist Rand Water in their planning. Take note, however, that below-normal flow volumes also present water quality implications.

3.3 CURRENT OPERATIONAL FORECAST CAPABILITY

Seasonal downstream flow forecasts have been produced operationally by the University of Pretoria since November 2020 as part of the project. *Figure 3.3* is from the forecast bulletin issued on the 10th of November 2020 and shows downstream flow forecasts for January-February-March, February-March-April and March-April-May. These forecasts are all predicting enhanced probabilities of high downstream flow volumes. Archived forecasts of the University can be found *here*: and for real-time seasonal forecasts are updated at this link Click *here* and then click on the (*Seasonal Forecast Worx logo*).

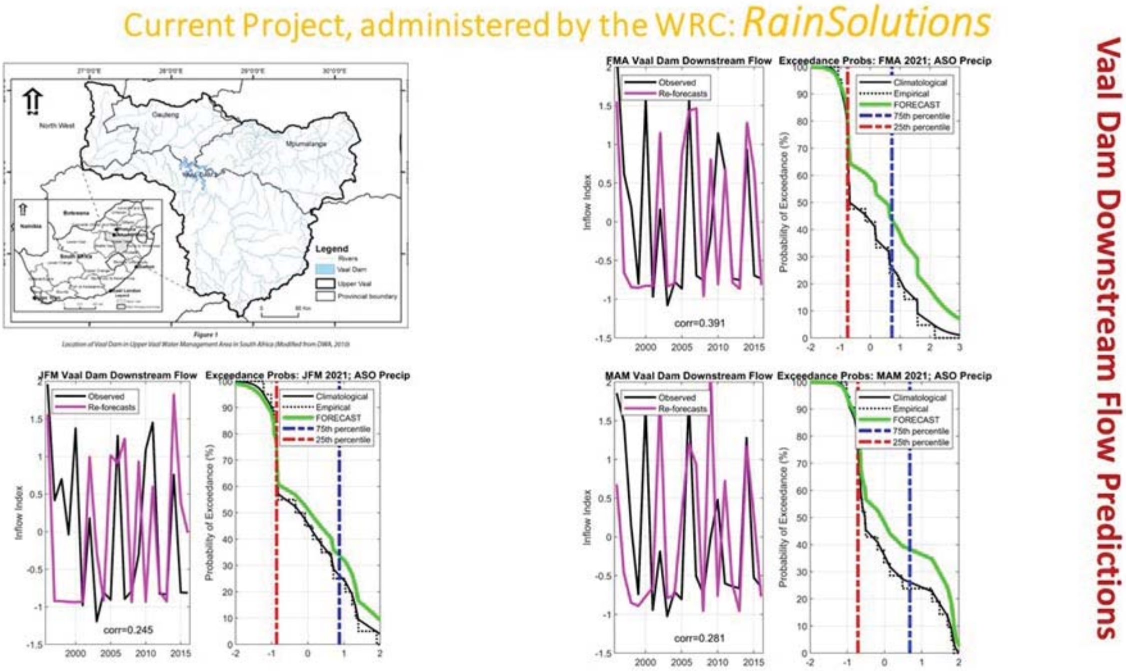


Figure 3.3: The first Vaal Dam seasonal forecasts of the University of Pretoria, November 2020.

3.4 WAY FORWARD

The next chapter deals with case studies of tailored predictions for recent extreme flow years. We therefore made use of the meeting to ask Rand Water in which seasonal case studies they would be most interested in. They replied that any extreme season of high or low flows would be of interest to them, especially during recent events. We also enquired about the data they would be willing to share with us. Although all flow and dam level data are available from the Department of Water and Sanitation, Rand Water can share their water quality data recorded over several years. They will prepare the data and make it available to us. They advised that we should be cognizant of the fact that the dam is quite stable, and hence water quality measurements are only made once or twice a month. They further advised that, regarding the dam's water quality, the rainfall-runoff relationship is not the only determining factor. We therefore need to explore other possible predictors than just the rainfall over the catchment if we want to develop water quality statistical models.

3.5 CONCLUSIONS

The previous chapter demonstrated our ability to use statistical models to predict dam levels and downstream flows, with greater forecast skill associated with the latter as opposed to the former. In this chapter we wanted to find out how our forecast models may be of benefit to a user, and in particular Rand Water. After our meeting, the following main conclusions may be drawn:

1. Although Rand Water does not manage the operations at the Vaal Dam, the added information that the forecast models can potentially provide will be of interest and benefit to them.
2. The meeting has resulted in Rand Water becoming aware of the forecasts that we produce on a monthly scale; we have learned from them that they are interested in water quality fluctuations caused by inundation and drought. This gaining of knowledge by both parties is a positive consequence of the co-production process we have embarked on during this deliverable.

CHAPTER 4: CASE STUDY TESTING

4.1 INTRODUCTION

The previous chapters have shown that there is a strong link between rainfall in the Vaal Dam catchment and dam levels, as well as what happens downstream of the dam. Real-time prediction for both dam levels and downstream flows has been shown to be feasible, but the predictability demonstrated has mainly been a result of using antecedent rainfall in the catchment as predictor in a statistical model, as opposed to using a climate model's forecasts or sea-surface temperatures (SSTs) as predictors. Take note that the demonstrated forecast skill levels are estimated by calculating the Spearman rank correlation between predicted and observed levels and flows in order to demonstrate levels of deterministic predictability. However, since seasonal forecasts are required to be expressed probabilistically (or at the very least be provided with an indication of uncertainty), this chapter will provide an assessment of the attributes of interest for probabilistic forecasts, such as discrimination and reliability. Also, it will demonstrate typical tailored probabilistic forecasts over a recent 6-year period that includes two El Niño, two La Niña and two ENSO-neutral summer seasons.

4.2 THE MODELLING SETUP

Since antecedent observed rainfall totals in the Vaal Dam catchment have been demonstrated in this project to be the best predictors for seasonal dam levels and downstream flows, we will use the same statistical model set up as discussed in the previous chapters. There is, however, a difference in the climate periods used for model training. First, we will set up the statistical model to perform an evaluation of the models' probabilistic forecast skill. For this purpose, the statistical models are initially trained over an 11-year period from 1996 to 2006 to make a probabilistic forecast for 2007. The models are then retrained over a 12-year period in order to make a forecast for 2008. This process is repeated until 10 years of probabilistic forecasts (2007 to 2016) have been produced. Forecast verification is subsequently performed over these 10 years. In addition to the verification work, we also produce probability of exceedance graphs for the 6-year period of 2011 to 2016 as examples of a set of tailored forecasts.

4.3 ASSESSMENT OF PROBABILISTIC FORECAST SKILL

We are assessing the probabilistic skill levels of the seasons and variables associated with the highest skill levels as presented in the previous chapters. Two seasons are considered, and they are the 3-month seasons of January-February-March (JFM) and February-March-April (FMA). The two dam variables are downstream flows for the JFM and FMA seasons, and dam levels for the JFM season. Forecast skill is determined for three near equi-probable categories of below-normal, near-normal, and above-normal. The forecast attribute of discrimination is determined by the calculation of relative operating characteristic (ROC) scores. The ROC score is able to indicate whether or not the probabilistic forecasts are discernibly different given different outcomes. ROC score needs to be above 0.5 for the forecasts to be considered skilful. We will also present verification results in terms of a graphical representation of forecast reliability using attributes diagrams. Such an assessment will provide insight if the forecast confidence communicated in the forecast is appropriate. For an explanation on the use of these two forecast attributes in a South African context, please consult: Landman, W.A., DeWitt, D. Lee, D.-E Beraki, A. and Lötter, D. 2012 by clicking *here*

The three models that we are evaluating are those with the highest correlation between forecast and observed and they are:

1. October-November-December (OND) catchment rainfall predicting JFM dam levels,
2. OND catchment rainfall predicting JFM downstream flows,
3. November-December-January (NDJ) catchment rainfall predicting FMA downstream flows.

The table below shows the ROC scores for the above – (A) and below-normal (B) categories for each of the three models.

Table 4.1: ROC scores for the three models considered.

	JFM levels	**JFM downstream**	**FMA downstream**
ROC Above	0.813	0.810	0.833
ROC Below	0.900	0.660	0.722

All of the *Table 4.1* ROC scores are higher than the cut-off value of 0.5 for skilful forecasts, indicating that all of the model forecasts possess the attribute of discrimination. Thus, model forecasts in general have high hit rates and low false alarm rates. However, ROC scores do not indicate if the probability forecasts are communicated with the correct confidence. For example, are the probability forecasts for above-normal in agreement with the frequency with which above-normal conditions are observed? Here we use the attributes or reliability diagram to test for this. *Figure 4.1* shows the reliability estimates across all three categories of above-, near- and below-normal.

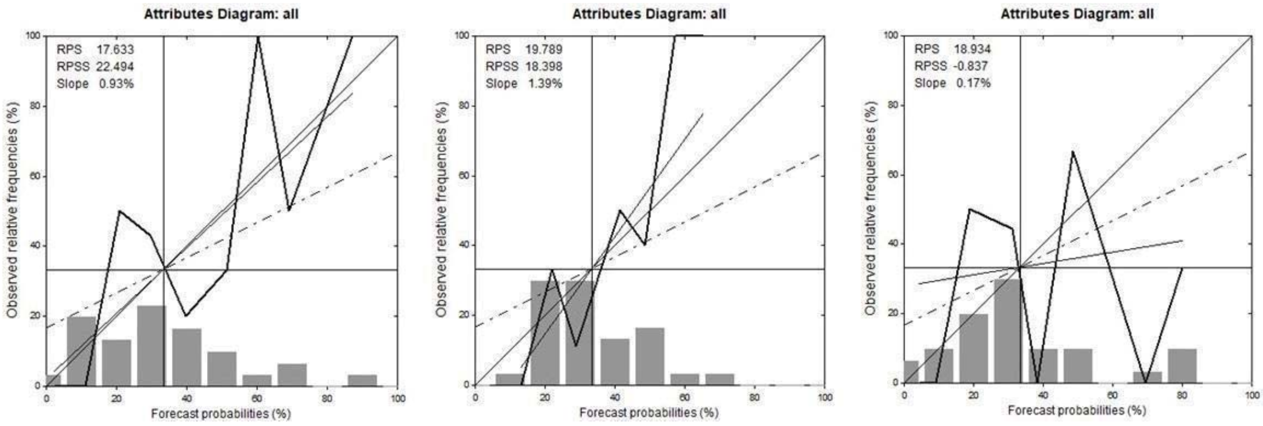


Figure 4.1: Reliability diagrams for the three models across all three categories. Panel on the left: JFM levels; middle panel: JFM downstream flow; panel on the right: FMA downstream flow.

Forecasts are reliable when the forecast probabilities match the observed frequencies. When this is the case, the thin straight line on each of the diagrams, which is a weighted linear regression line that represents the respective reliability curves, will fall on top of the diagonal line of perfect reliability. The forecast models for JFM dam levels and JFM downstream flow are therefore more reliable than the forecasts for FMA downstream flows. In fact, perfect reliability is nearly obtained for JFM dam level forecasts, while under-confidence in the forecasts is found for high forecast probabilities for the JFM downstream flow model.

In general, all three of the models have the attributes of discrimination and of reliability. Next, we will show examples of probability forecasts for 6 years for each of the three models.

4.4 TAILORED PROBABILITY FORECASTS

The most recent 6 years of the available dam data include two La Niña seasons (2010/11 and 2011/12), two ENSO-neutral seasons (2012/13 and 2013/14) and two El Niño seasons (2014/15 and 2015/16). The 2010/11 was observed to have been a strong La Niña event, and 2015/16 a strong El Niño event. Usually, drought conditions over the austral summer rainfall regions occur during El Niño seasons, and wet conditions during La Niña seasons. These scenarios also tend to happen over the Vaal Dam catchment. Next, we discuss the probability of exceedance forecasts using the three models for the 6 years mentioned above. *Figure 4.2* shows forecasts for JFM dam levels. The easiest way to interpret the forecast curves of *Figure 4.2* would be to consider those curves below the red line (the line that represents the climatological distribution curve) to be probabilistic forecasts for anomalously low JFM levels. Forecast curves above the climatological distribution curve are probabilistic forecasts for anomalously high JFM levels. Take note that the years for which the forecasts may have turned out to be the most useful are 2011 (strong La Niña season), 2014 (ENSO-neutral season) and 2016 (strong El Niño season). The forecast for 2015 may also have been useful since the probability forecast curve is in fact to the left of the climatological distribution as is also found for 2016.

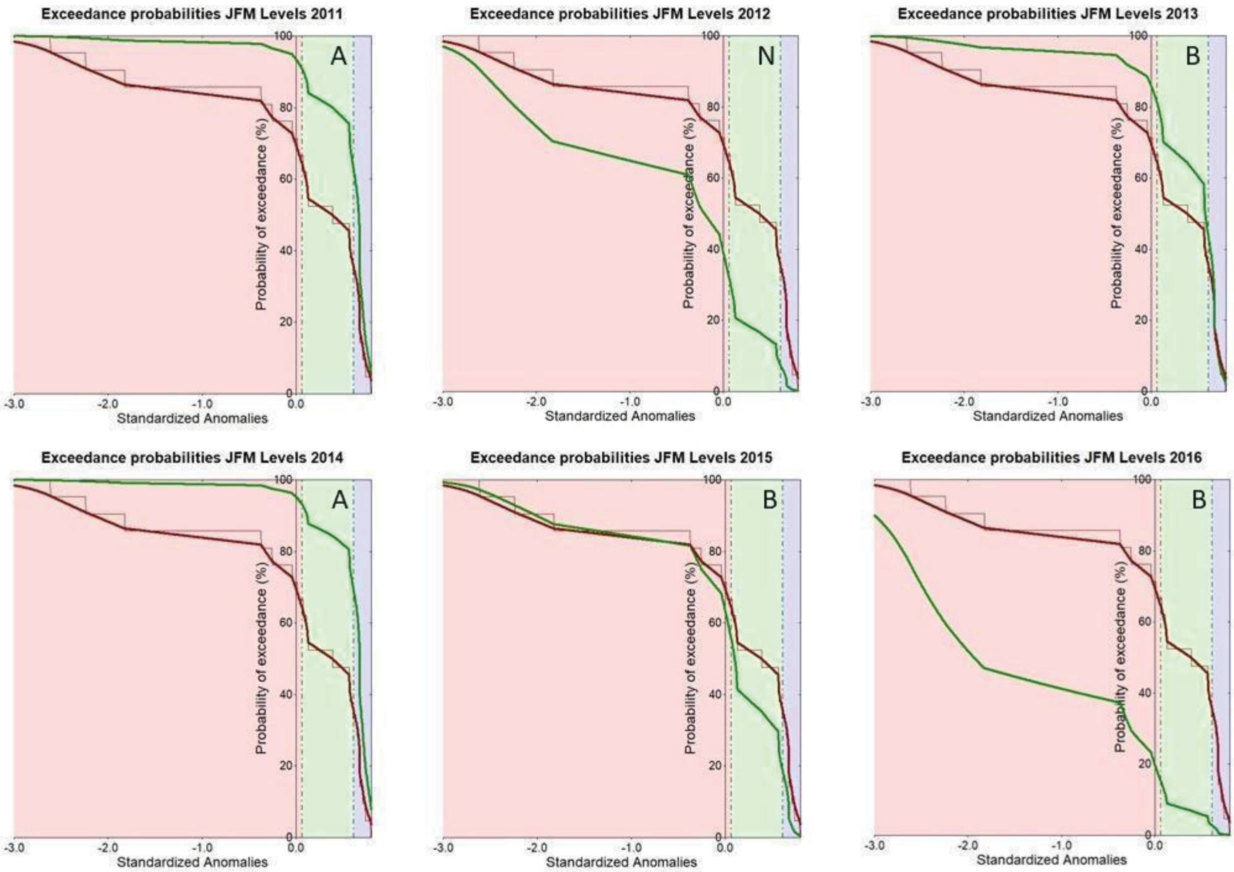


Figure 4.2: Probability of exceedance forecasts for 6 years, for JFM dam levels. The red curves represent the climatological probability distribution of JFM dam levels, and the green curves the predicted probability distributions for each year. The vertical dashed lines represent the category thresholds. The letters A, B and N in the top left-hand corner of each panel represent the observed categories per year.

Probability of exceedance forecasts for JFM downstream flow are shown in *Figure 4.3*. Here it seems that all of the probability forecast curves are in agreement with the observed outcome, except for 2013 when the forecast curve favoured above-normal downstream flow outcomes when it was found to have been below-normal. As with the dam levels, there is a good agreement between the probability forecast curve and the observed outcome for the strong La Niña event of 2011 and the strong El Niño event of 2016. *Figure 4.4* shows the downstream flow forecasts for the JFM season. Very similar outcomes are found between the forecasts and outcomes for JFM (*Figure 4.3*) and the outcomes for FMA (*Figure 4.4*).

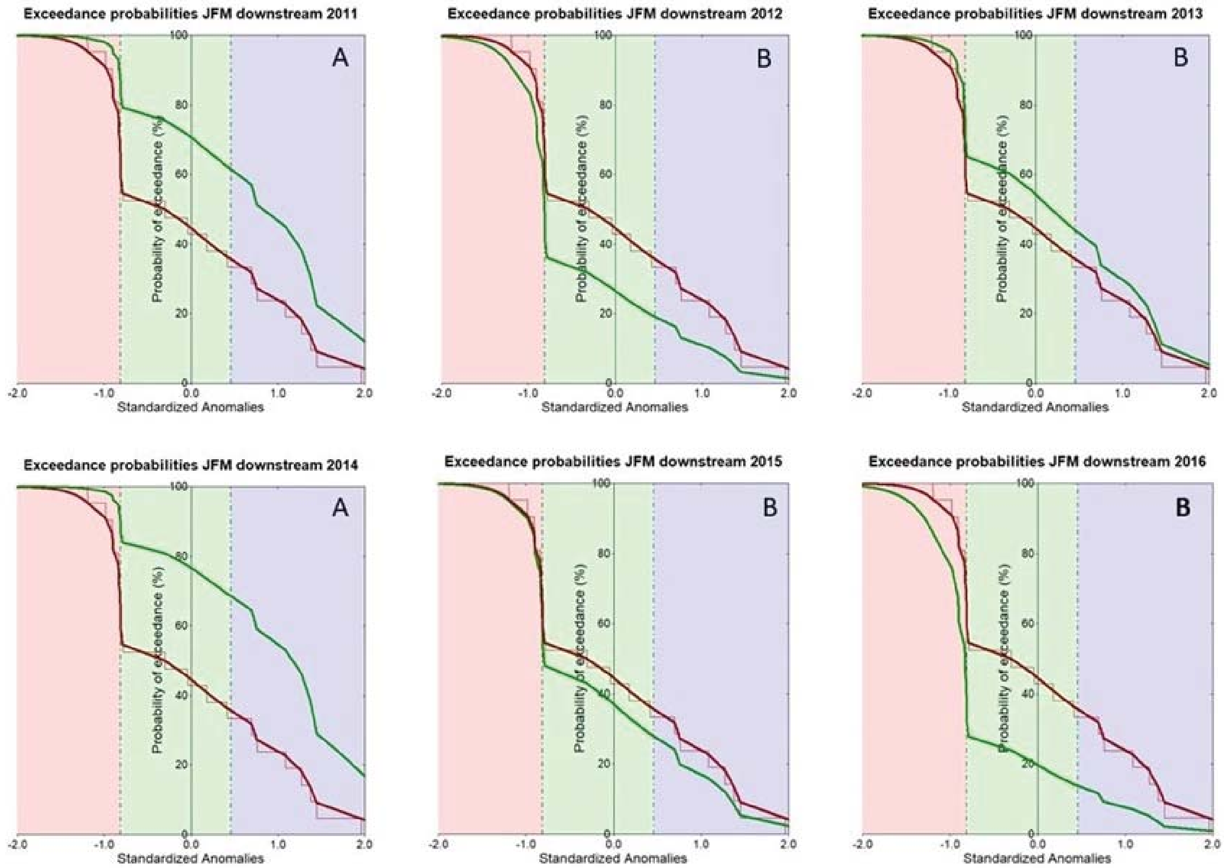


Figure 4.3: As for Figure 4.2, bur for JFM downstream flow.

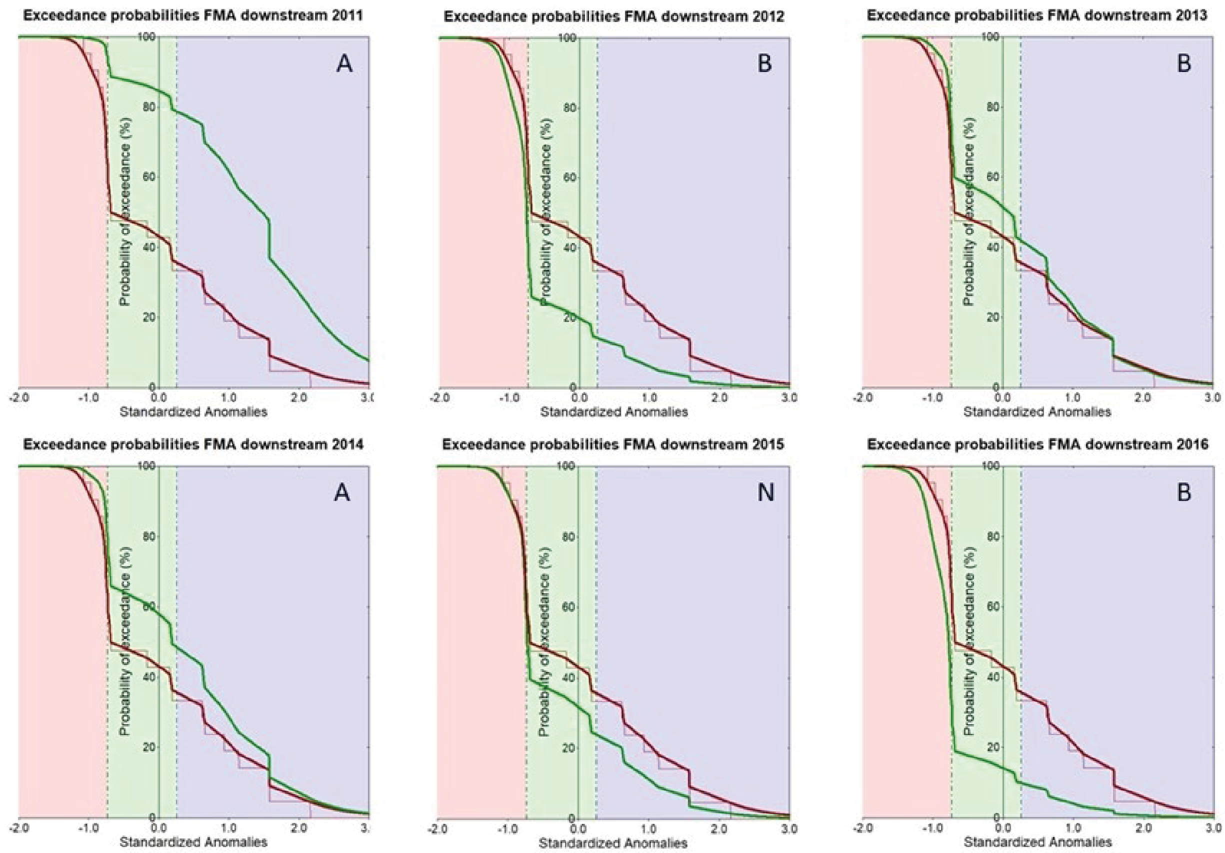


Figure 4.4: As for Figure 2, but for FMA downstream flow.

4.5 CONCLUSIONS

We have used the skilful models identified earlier to produce probabilistic forecasts over a 10-year test period, and then produced tailored forecasts for a 6-year period that contains two El Niño and two La Niña seasons. The main conclusions that can be drawn from this chapter are

1. The probability forecasts for JFM dam levels and downstream flows, and the forecasts for FMA downstream flows display the attributes of forecast discrimination and reliability.
2. We have developed a set of tailored forecasts of the most likely outcome of a coming season that can provide guidance to a user of the forecasts.
3. There is some variation among the forecasts, but above-normal (below-normal) levels and flows are skilfully predicted during the strong La Niña (El Niño) event of 2011 (2016).

Overall, the skilful models presented in this project should be suitable for operational use. In fact, forecasts for Vaal Dam downstream flows have been issued since November 2020.

CHAPTER 5: REPORT ON CASE STUDY APPLICATIONS

5.1 INTRODUCTION

Chapter 4 presented tailored forecasts for a 6-year period that contains two El Niño and two La Niña seasons. The main conclusions drawn from that chapter are that the probability forecasts for JFM dam levels and downstream flows, and the forecasts for FMA downstream flows display the attributes of forecast discrimination and reliability. Moreover, there is some variation among the forecasts, but above-normal (below-normal) levels and flows are especially skilfully predicted during the strong La Niña (El Niño) event of 2011 (2016). For this deliverable, on case study application, we first expand on the models presented thus far by increasing on the forecast lead-times from one to three months, and then test these expanded models over a 10-year independent period in terms of their ability to discriminate high (low) dam levels from medium and low (high) levels, and high (low) downstream flows from medium and low (high) downstream flows. Finally, we investigate which of these models can be used to benefit the users of such forecasts financially.

5.2 THE MODELLING SET-UP

As before, antecedent observed rainfall totals in the Vaal Dam catchment are used as predictors for seasonal dam levels and downstream flows. We use the same statistical model set up as discussed in the previous deliverables in order to generate 10 years of probabilistic forecasts from 2007 to 2016. In addition, in this deliverable we introduce forecast lead-times of up to three months ahead. For the JFM downstream and dam levels forecasts, the 1-month lead-time forecasts use OND catchment rainfall, SON rainfall for 2-month lead-times, and ASO rainfall for 3-month lead-time forecasts. The FMA downstream flow forecasts use NDJ catchment rainfall for 1-month lead-time forecasts, OND rainfall for 2-month lead-times, and SON rainfall for 3-month lead-times.

5.3 ASSESSMENT OF PROBABILISTIC FORECAST SKILL

Forecast skill is determined for three near equi-probable categories of below-normal, near-normal, and above-normal, as determined over the 10-year independent test period (2007-2016). For this chapter we will focus only on the calculation of relative operating characteristic (ROC) scores in order to test for the attribute of discrimination (see an explanation in the previous chapter), and for generalized ROC (GROC) scores. The latter is also known as the 2AFC score (Mason and Weigel, 2009), and provides an indication of the forecast quality to the general public as well as communicating or transferring changes in forecast quality to officials. Therefore, this is a very useful and informative score not only to atmospheric scientists but also to a variety of stakeholders, such as Rand Water. Any value above 0.5 (or 50%) for this score indicates a skilful forecast, as it is better than purely guessing (Lazenby et al., 2014)

Figures 5.1 and 5.2 respectively represent the ROC scores for the three models (predicting for JFM downstream flows and dam levels, and FMA downstream flows) and for the two outer categories of above-normal levels and flows, and for below-normal levels and flows. ROC scores for the three lead-times are presented in these figures, but it is only the ROC scores for 1-month lead-time forecasts that are consistently above the threshold of 0.5 for skilful forecasts. This result means that for JFM flows and levels forecasts, one can expect skilful forecasts to be produced in early January as soon as the measured OND rainfall figures in the catchment have been obtained. Similarly, for FMA flows – skilful forecasts are possible only in early February. The GROC scores of *Figure 5.3* show a similar verification result, since the scores for all three models for the two longer lead-times are all below 0.5. Only 1-month lead-time forecasts have skill.

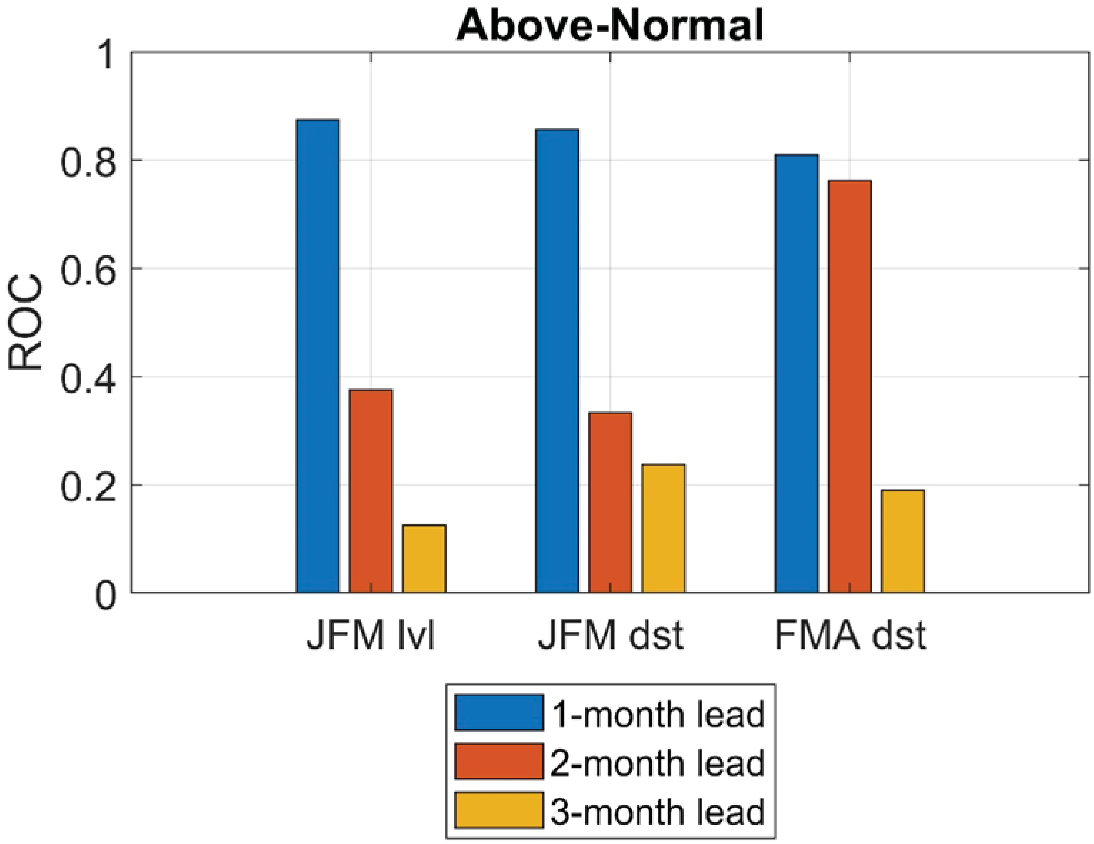


Figure 5.1: ROC scores for the three models predicting above-normal dam levels and downstream flows for JFM and for FMA. Scores for all three forecast lead-times considered are shown.

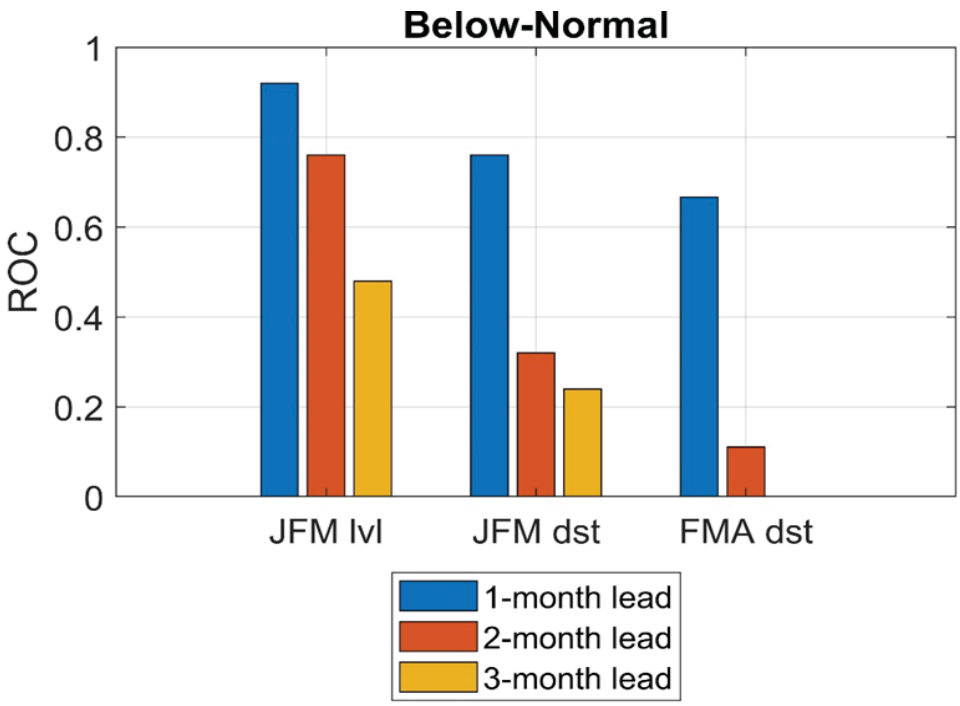


Figure 5.2: As for Figure 5.1, bur for below-normal values.

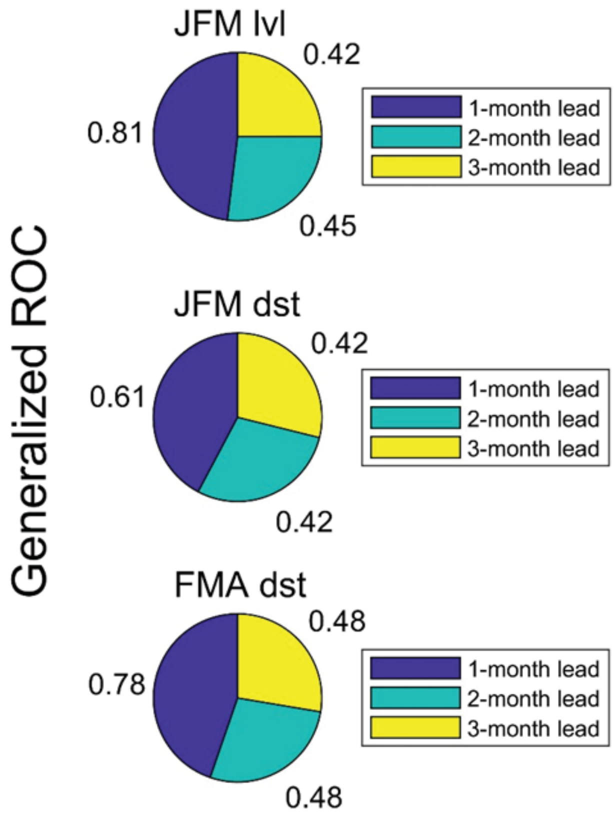


Figure 5.3: Generalized ROC scores for the three models and for the three forecast lead-times.

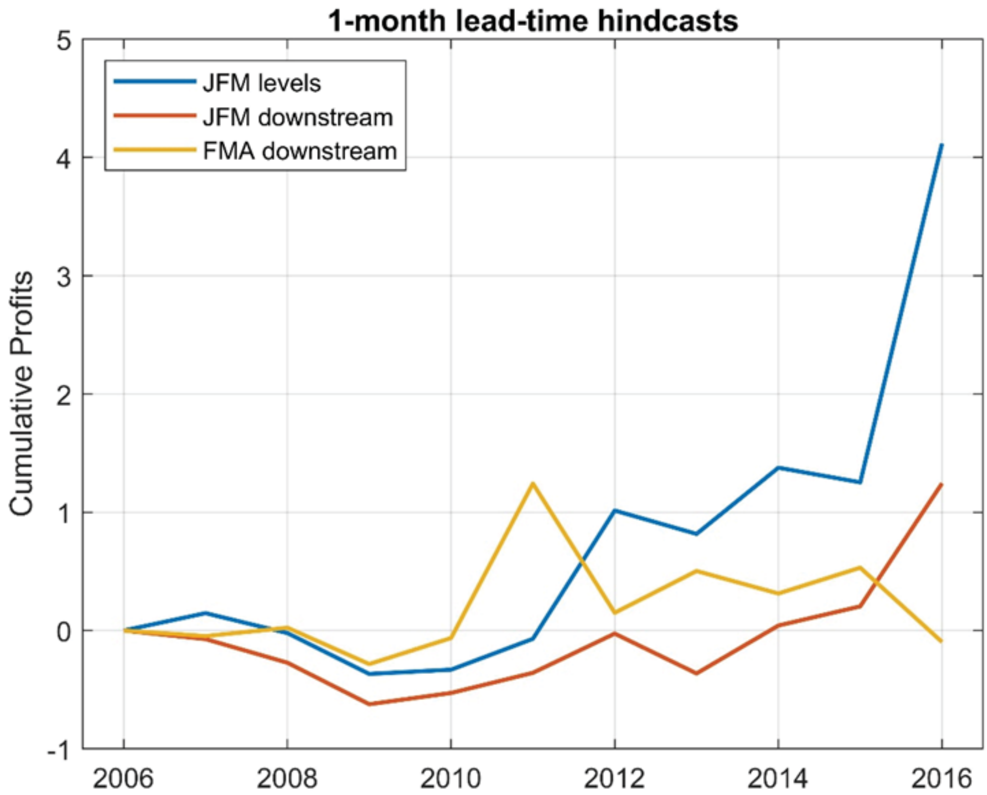


Figure 5.4: Cumulative profits graphs for the three models at 1-month lead-times.

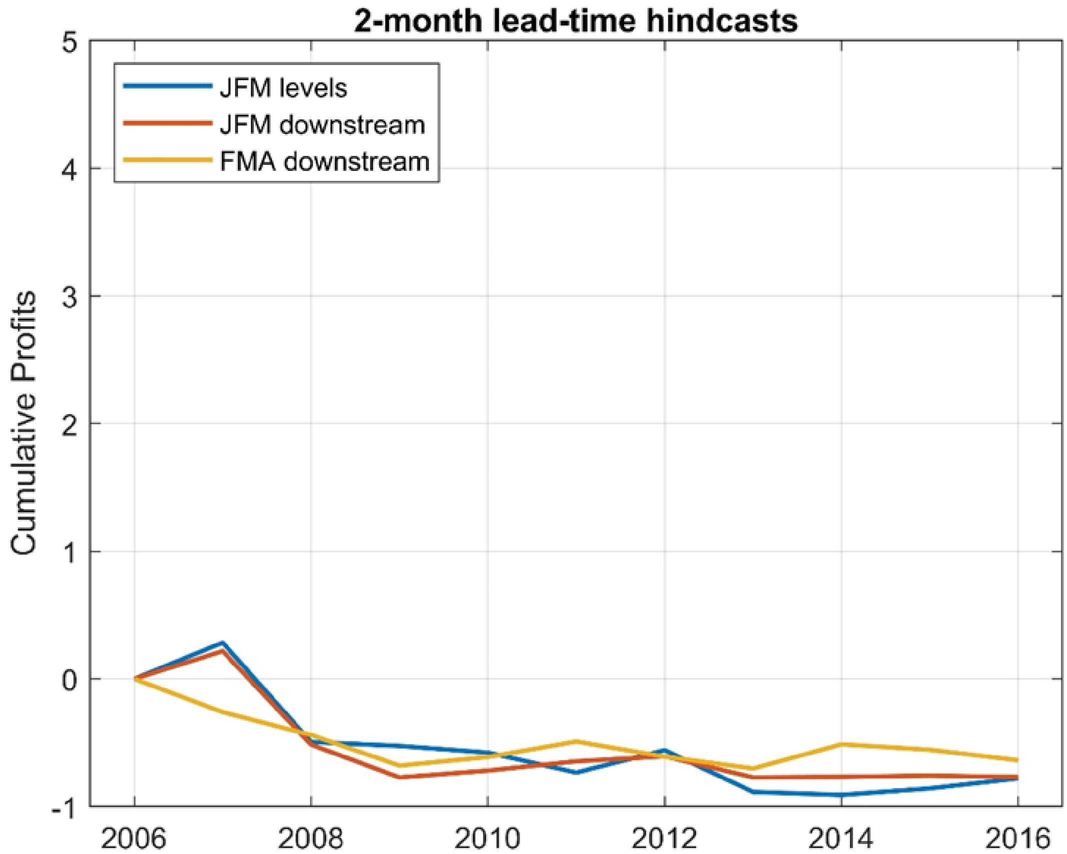


Figure 5.5: As for Figure 5.4, but for 2-month forecast lead-times

5.4 CONCLUSIONS

As with the previous chapter, we have used the skilful models identified earlier to produce probabilistic forecasts over a 10-year test period, but this time for 1-, 2- and 3-month lead-times. We then compared the ROC and GROC scores of the models and their lead-times. Then we introduced additional forecast performance evaluation in terms of its quality to the general public and its monetary value. The main conclusions that can be drawn from this deliverable are

1. Forecast skill in terms of the models' discrimination attributes, show that only short lead-times are associated with usable skill (i.e. ROC scores are only consistently above 0.5 for 1-month lead-times).
2. Analysing the GROC scores again show forecasts to only be useful at short lead-times.
3. Only high skill forecasts may be profitable to a user such as Rand Water, and in this case 1-month lead-time forecasts for JFM dam levels.

CHAPTER 6: CONCLUSIONS AND RECOMMENDATIONS

6.1 CONCLUSION

The project focussed on seasonal predictability of the hydroclimate of the Vaal Dam. The techniques used are based on linear theory to test for seasonal predictability by using a range of possible predictors. The predictors include tropical SST, output from a coupled climate model, and antecedent rainfall in the catchment. Models were initially tested in a deterministic sense that does not consider any uncertainties in the forecasts. This first step is necessary in order to obtain an initial understanding of Vaal Dam predictability. However, seasonal forecasts are of a probabilistic nature, and so probabilistic forecast verification was also performed. Forecasts over a test period displayed attributes of discrimination and reliability, but the best prediction are made by using the antecedent rainfall in the catchment and only at short lead-times.

To summarize the results obtained with deterministic forecast models, we have found that:

1. There is a strong link between rainfall in the catchment and dam levels; as well as what happens downstream of the dam. This link is less pronounced during winter.
2. There is also a concurrent link between dam levels and downstream flows, but this link is strongest during the second half of summer and during autumn.
3. Real-time prediction for both dam levels and downstream flows is possible, but the predictability demonstrated here is mainly a result of using antecedent rainfall in the catchment as predictor in a statistical model, as opposed to using a climate model's forecasts or SSTs as predictors.

Past studies (see references in this document) have shown that high forecast skill can be obtained in certain catchments where ENSO forcing is contributing strongly to seasonal variability. For these cases, the use of output from climate models to predict river flows even outscore the use of antecedent rainfall in the catchment as predictor. In the Vaal Dam catchment, however, where ENSO forcing is not that strong, the use of climate models (and of tropical SST) did not improve on forecast models that use catchment rainfall as predictors. For such cases, antecedent rainfall is a critical component in the forecasts systems presented here and emphasises the importance of maintaining robust observational networks in the region (and elsewhere).

The three models that we evaluated are those with the highest correlation between forecast and observed and they are:

1. OND catchment rainfall predicting JFM dam levels,
2. OND catchment rainfall predicting JFM downstream flows,
3. NDJ catchment rainfall predicting FMA downstream flows.

A significant conclusion to be drawn here is that predictability is restricted to the second half of summer, going into autumn. This result is to be expected for models where antecedent rainfall is the best predictor. In a catchment where no or very little rainfall is usually received during winter and spring, rainfall during these seasons is subsequently not a good indicator of what is to be expected later on in the season.

The models' probabilistic forecast capabilities was tested over a 10-year test period and for extended lead-times. The main conclusions that can be drawn from probabilistic skill assessments are:

1. Forecast skill in terms of the models' discrimination attributes, show that only short lead-times are associated with usable skill.

2. Only high skill forecasts may be profitable to a forecast user, and in this case short lead-time forecasts and in particular for JFM dam levels.

This result is potentially a caveat that may result in such forecasts not being used by the dam's managers, especially if longer lead-time forecasts are required for optimal decision-making. There does not seem to be any value in making forecasts at short lead-times (we defined 1-month lead times here, but in fact it is less than that since the observed rainfall of the season used as predictor is only available in the first week of the season being predicted.

The work did not only focus on modelling but included a meeting with Rand Water. After our meeting, the following main conclusions may be drawn:

1. Although Rand Water does not manage the operations at the Vaal Dam, the added information that the forecast models can potentially provide will be of interest and benefit to them.
2. The meeting has resulted in Rand Water becoming aware of the forecasts that we produce on a monthly scale; and it is clear that they are interested in water quality fluctuations caused by inundation and drought. This gaining of knowledge by both parties is a positive consequence of the co-production process we have embarked on during our meeting with them.

Although we did have a meeting with Rand Water when we demonstrated the forecasting capabilities developed during the project, we did not develop forecasting systems tailored specific to their needs. However, we did make them aware of the predictability identified and they have become aware of the operational forecasts of the Vaal Dam being produced at the University of Pretoria. Follow up meetings with Rand Water and other invested parties should happen so that the predictability identified here can be further applied and forecasting systems further developed in a true co-development process.

6.2 RECOMMENDATIONS

The work has clearly demonstrated a seasonal forecast capability for the Vaal Dam, given the following restrictions:

1. Observed antecedent rainfall in the Vaal Dam catchment is a good predictor in linear statistical models.
2. Forecasts are mostly skilful mainly during the second half of summer going into autumn.
3. Forecasts work best, and can be used at lowest risk, only at very short lead-times.

Since forecasts for the second half of summer, going into autumn, have been shown to be skilful, the planning of water release downstream can benefit from such forecasts, albeit at a short lead-time. The observation that high rainfall totals may have been observed during summer over the catchment can help with such planning. However, the forecast models presented here are not able to provide guidance on hydro-climate variability during spring or during winter. Sophisticated hydrological models should be configured to see if they can assist with seasonal forecasts for the Vaal Dam during these seasons and also to see if such models can improve on the forecasts presented here. Until such time, simple linear models may be the only viable way to make skilful seasonal forecasts for the Vaal Dam.

Given these limitations, it is important that modellers should (atmospheric and hydrologists) more actively engage with the dam's managers in order to start a process of co-development of seasonal forecast products most suitable for improved decision-making in areas where climate variability affects dam fluctuations.

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