Seamless Forecasting of Rainfall and Temperature for Adaptation of Farming Practices to Climate Variability

Volume 2 – SEAMLESS FORECASTS AND SUGARCANE

Report to the
WATER RESEARCH COMMISSION

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EXECUTIVE SUMMARY

BACKGROUND

The African population is one of the fastest growing in the world and the continent has a large potential for agricultural growth and development (Godfray et al., 2010). The definition of agricultural production strategies that will help prepare Africa for higher demand and worsening climate stresses must take into account various factors including political drive, infrastructure development, technical progress, social livelihood and economic growth. Apart from those, it is imperative to address climate change that directly impacts crop growth and food production in the long term, and in a similar measure climate variability that directly impacts year-by-year production.

Agriculture is highly sensitive to climatic parameters and numerous studies show that Africa will be highly affected by long-term climate changes, mostly in a negative manner (Iizumi et al., 2013; Zinyengere et al., 2013), and adaptation is required (Challinor et al., 2014). In addition to the exploration of long-term adaptation strategies in response to climate change, there is a demand for shorter time scale coping mechanisms, which would make agricultural systems more resilient in the face of climate variability (vs. climate change). Despite a number of limitations to be clearly understood, the value of seasonal forecasts is evident (Fraisse et al., 2006; Hansen and Indeje, 2004; Hansen et al., 2011; Klopper et al., 2006; Meinke and Stone, 2005; Patt and Gwata, 2002). The proposed research is designed to harness seasonal forecasts and impact models' numerical capacity to better prepare agricultural activities to climate variability.

RATIONALE

Repeated exposure to severe climate events combined with its financial and structural capacity to improve, makes of South Africa a major role player in exploiting climate and crop models' capacity to digest enormous data sets into useful tailored information needed for decision making. Although models are only a partial representation of reality, their exploration capacity is useful and they are already intensively used at larger time and/or space scales (e.g. AgMIP, Rosenzweig et al., 2014). Technical challenges such as forecast skill or spatial representation make shorter time scale studies more demanding. However, these temporal and spatial scales are indispensable to provide appropriate information that farming communities are continuously requesting. International research projects have identified those efforts as a priority to respond to climate risk vulnerability. Although, there are currently no projects in South Africa (see for example foreign initiatives CCAFS-CRAFT or US-AgroClimate), some solid regional studies have been performed at those scales, e.g. Archer et al., 2007; Ziervogel and Downing, 2004; Zuma-Netshiukhwi et al., 2013.

OBJECTIVES AND AIMS

The proposed research work directly follows on from a previous WRC project (Lumsden and Schulze, 2012), which explored the application of weather and climate forecasts in agricultural decision-making. This included applying weather and climate forecasts within hydrological models to produce hydrological forecasts.

This study explored, proposed and developed ways and approaches to leverage available seasonal forecast information, through robust climate-crop-water integrated assessment of agricultural and water systems, towards better farmers' preparedness to climate variability. The project also applied shorter range weather forecasts in this objective.

The number of partners involved in the project brings a large range of skills and expertise. Each aim is undertaken by the most relevant institution, with a clear effort towards regular community engagement.

No.	Aim	Report Sections
1	To rigorously document and improve accuracy and skill in, short (1-3 days) and medium (3-10 days) range weather forecasts.	Vol. 2 Ch. 3
2	To develop extended range (11 to 30 day) weather forecasts to facilitate fully seamless forecasting.	Vol. 2 Ch. 3
3	To render seasonal forecast data available to crop models, including the seasonal production at selected locations in SA.	Vol. 1 Ch. 2,3
4	To integrate seasonal forecasts into crop models for seasonal production scenarios, including the seasonal production at selected locations in SA.	Vol. 1 Ch. 4,5,6,7
5	To enhance the spatial and temporal resolution of seasonal climate forecasts.	Vol. 2 Ch. 3
6	To demonstrate the feasibility and evaluate the benefits of the climate-crop integrated approach virtually (models only with historical data) and in real conditions, at selected locations in SA.	Vol. 1 Ch. 8,9,10,11,12
7	To improve understanding of, and possible reduction in, hydrological forecast uncertainties and errors across different time ranges.	Vol. 2 Ch. 9
8	To develop and evaluate tailored hydrological and crop forecast products for application in decision-making across different time ranges in selected case studies in KwaZulu-Natal.	Vol. 2 Ch. 4,5,6,7,8
9	To summarise feedbacks, particularly on enablers and barriers, which can inform climate and agriculture experts and facilitate future climate-crop integration.	Vol. 1 Ch.13

METHODOLOGY

Stakeholder engagements from the inception to the end of the project tremendously helped to frame the research objectives and advancements, better fitting actual field constraints and farming communities' priorities. These engagements clearly allow to present the projects' advancement in the light of community feasibility and evaluating the benefits, barriers and enablers of the approach in the most grounded way possible. In addition to the smallholder farming communities engaged in Eastern Cape and Limpopo, stakeholders representing commercial perspectives were engaged in KwaZulu-Natal with respect to the application of hydrological forecasts in decision-making.

Integrating forecasts into hydro/crop models is one of the core research challenges of our project. Since it has been done on a long term climate change time scale, we know it is possible to couple seasonal forecasts with crop models. The challenge though comes from our intent to use the forecast-crop model combination as a tool to make crop-relevant weather-based information, or a crop forecast, to provide farming communities with a month to several months lead time decision tool. In this project a particular look was taken at the integration of seasonal forecasts with crop models (see for instance Vol. 1 Chapters 4 and 5). The major challenge in the integration lies in the capacity of the integrated tool/approach to process and produce *relevant* and *useful* information at this decision level.

Given the large workload and various ambitions and aims of the project, as well as the large number of partner institutions, the project execution was driven along two complementary directions:

Volume 1 – A seasonal time scale, led by The University of Cape Town, and mostly focusing on smallholder farmers of Alice, Eastern Cape and Lambani in Limpopo, with the support of the University of Fort Hare and the University of Venda, respectively.

Volume 2 – A seamless time scale, led by the University of KwaZulu-Natal and the CSIR, and focused mostly on commercial agriculture in KwaZulu-Natal, with the support of the University of Pretoria and the Agricultural Research Council.

RESULTS AND DISCUSSION

Volume 1 – Seasonal forecasts and smallholders

Throughout the project, and the various themes and approaches tested and developed, various enablers and barriers were faced. As rigorous as we make this process we acknowledge the complexity and local dependency of the following observations. We ground these observations in our experience through and beyond the project, and present it in a way that intent to highlight wider and more generic issues. In this volume 1, we build on the "month to season forecast" integration to crop models and related engagements in the Eastern Cape and Limpopo Province.

The scientific process started with grounding the research within two farming communities in Limpopo and Eastern Cape. The local partners and their network, as well as the direct engagement of the project team with the community, lead to better understanding of the community dynamics and aspirations. This local specific knowledge is related to two communities presented in Chapter 2 and Chapter 3 of this volume, and emphasise the heterogeneity of these communities, in terms of conditions and aspirations, as well as in terms of integration, acceptance and use of seasonal forecast information (see for instance Vol. 1 Chapters 6 and 7). This baseline is necessary to any scientific progress, so to clearly define a baseline, toward the building of a process that can be scaled up within a variable environment, such as is the South African agricultural production scene.

From this necessary understanding, the scientific process came to explore, understand, assimilate accessible numerical data and tools towards building approaches that ingest and digest seasonal forecast information, in order to reveal the most relevant possible information with decision potential, as well as facilitate its reception, understanding and use by farming communities. This would be the approach/methodological knowledge contribution of this project, mostly arising from the crops models' use (Chapter 4) with available seasonal forecasts (Chapter 5) and leading to the definition of (full or subset of) preferred crop management, per farm types, and with consistent response under varying seasonal forecasts (Chapter 12).

As a result of a multi-partner project, partners who have varying skills and interests, the knowledge contribution did not stop here. Significant contributions were made in terms of Indigenous Knowledge in both Limpopo and Eastern Cape, specifically in terms of agricultural decision making, and seasonal time scale, which adequately fit within this project objectives (Chapter 9). In some extent these advances connect with the numerical approach from a reception and a localisation perspective. The former relates to the relation of seasonal forecast with indigenous indicators and consequently the better understanding and assimilation of this information. The latter relates to the potential to ground a possible recommendation into a very specific and very local context either by translation or by further use of indigenous indicators. Such perspective, when/if applicable only improve acceptance and use of seasonal information.

This project also contributed to the highly relevant challenges of acceptance and use. This was addressed through the lens of Ecological Intensification (EI), with particular attention to the farm typology (Chapter 7). We discuss the particular potential of EI for small scale low input farmers, rigorously frame the strength or weakness of EI in that context, which directly feeds into acceptance and use of novel information/techniques (Chapter 10).

The communication of the science process and products always had a predominant role, and the project attracted scientific interrogation towards better communication of specifically seasonal forecast information to rural communities (Chapter 11).

Finally, a noticeable remote sensing effort was successfully lead, focusing on soil moisture and adaptive capacity mapping ambitions. The contribution builds on the significance of soil moisture as a decision parameter for farming communities and demonstrated the potential to use this approach with climate or seasonal forecast information (Chapter 8). Beside the knowledge contribution, this effort also points to a promising direction in the face of the field data scarcity often encountered in rural South Africa, many African countries and the developing world. Where numerical tools are very efficient and offer great accuracy where ground data is plentiful, these qualities are rightfully questionable where field data is scarce. A number of studies, supported by this one, suggested that the increased access and resolution of off-ground data sources could at least in part facilitate the use of data demanding approach, even where field data is scarce.

In academic terms, the project substantially supported capacity building (APPENDIX I), and led to national and international research publications (APPENDIX II).

<u>Volume 2 – Seamless forecasts and sugarcane</u>

The Mhlathuze catchment case study developed weather and climate forecasts at time ranges including 7-day, subseasonal and seasonal. The methodologies for developing the 7-day and seasonal forecasts (using the CCAM climate model and statistical downscaling of globally available climate forecasts, respectively) are fairly mature, while the forecasts at the subseasonal time scale represent a very new area of research. This time scale bridges the medium and seasonal time ranges, and thus there is a lot of overlap with these ranges in terms of the technical forecast development. The subseasonal forecasts were developed in CCAM as part of a separate seamless forecasting effort at the CSIR across all scales.

The 7-day weather forecasts were applied in the ACRU model linked to the Delft-FEWS hydrological forecasting system to produce forecasts of inflow to Goedertrouw Dam, and crop water and irrigation demand in two dependent subcatchments where sugarcane is grown. Seasonal forecasts of the storage in Goedertrouw Dam were also developed, this being a key need for forecasts amongst sugarcane stakeholders that were consulted. In a further piece of work, the potential to develop seasonal forecasts of sugarcane crop yield and water productivity using the AquaCrop model was explored.

The work done in the Mhlathuze case study was found to be technically challenging. These challenges included the hydrological modelling of the catchment, the development of the ACRU/Delft-FEWS forecasting system and attempting to produce seasonal forecasts of crop yield and water productivity with the AquaCrop model.

In terms of modelling the catchment, the operation of the Goedertrouw Dam was difficult to capture given the complex system of river releases for downstream irrigation and urban/industrial abstractions. Data describing the operation of the system was fairly limited, and required a number of assumptions to be made. Thus, the overall time required to configure the catchment in ACRU was longer than expected.

While the Delft-FEWS system is a powerful tool to enable hydrological forecasting (in terms of managing the large amounts of data associated with this activity), it is not a user-friendly system to configure. This situation is often found in modelling systems where there is a trade-off between utility and user friendliness. Hence the development of hydrological forecasting was somewhat delayed in the project. This resulted in there being little time within the project to convey final results and explore the implication of these with stakeholders. However the technical capacity to use this software that has been developed in the team during the project has been very valuable, and will continue to yield benefits in future hydrological forecasting efforts.

Another technical challenge experienced was in attempting to apply probabilistic-categorical seasonal climate forecasts in AquaCrop to produce crop yield forecasts. While there is value in utilizing a probabilistic climate forecast as uncertainty is quantified in the forecasts, models such as AquaCrop are not designed to utilize this kind of information, as they require a daily time series of weather information as input. It was thus not possible within the timeframe of the project to produce crop forecasts using AquaCrop.

Despite the technical challenges, the results of certain aspects of the agrohydrological forecasting in the Mhlathuze were encouraging. This was particularly so for the 7 day forecasts of crop water requirements, where the correlations with simulated historical values were high (R^2 above 0.8 for the two catchments assessed). Although the forecasts of Goedertrouw Dam inflows and net irrigation requirements at the 7 day time scale did not perform as well as those for crop water requirements, it is still believed they have potential to be useful in decision-making. Further research is required to evaluate the benefits of such application.

Research into developing seasonal forecasts of storage in Goedertrouw Dam revealed that there is predictability in autumn storage using the method developed. This method involved correlating historical summer rainfall with autumn storage. This correlation was made after analysing seasonal cycles of rainfall and dam storage and determining the strongest relationships present in the data. The method is simple to apply and forecasts can be produced quickly. A demonstration of how the forecasts could be applied in decision-making was given.

An alternative approach to producing seasonal dam storage forecasts would be to apply seasonal climate forecasts in ACRU. However, this would require downscaling of the seasonal climate forecasts to produce daily time series. This challenge was also encountered in the application of the AquaCrop model to produce crop forecasts. Methods are available to do this, such as through the use of historical analogue weather data or through the application of weather generators, however this adds another layer of complexity to the forecasting development process. The advantage of adopting this approach is that forecasts can potentially be developed for all seasons. The simulation-based approach also allows for exploring the potential to change the management of the dam, in response to forecasts.

CONCLUSIONS

This project is recognising water and its role in agricultural systems as complex systems evolving at the venture of various communities (e.g. academics or farmers), dealing with information of varying skills and relevance (e.g. skills of seasonal forecast or relevance of time scale), which must be communicated iteratively and facing communications challenges (e.g. language, concepts such as uncertainty, trust) and beyond. While importance and provision must be made for the inclusion of some extent of all those aspects, we believe the improvement of part of these aspects is taking a measurable role in the development of better managed agricultural systems, particularly under global (e.g. population increase, climate change) and national (e.g. wealth and food share, economic development) challenges.

All the good work and knowledge contributions only briefly highlighted above, are accompanied by many limitations and constraints that keep challenging such effort in terms of adoption, operationalization and scaling up amongst others. As the skill of seasonal forecast is varying in space and in time, as the decision maker (farming communities) are exercising in varying conditions and with varying priorities and uncertainties, nuances and reservations must necessarily come as part of the information. We recognise the importance of this complexity, and we are confident that this project contribution to knowledge is measurable and of direct value to future efforts directed to the empowerment of rural farming communities in South Africa.

This project demonstrated the value of using numerical tools, purposefully for the benefit of smallholder farming communities, with the imperative involvement of rural university and extension offices. This process, although clearly facing challenges for operationalization and scaling up, used the appropriate ingredients leading to future development. Amongst the multitude of ways this work can be taken forward, it seems evident that the success of national scale operationalization of this sort of approach must explicitly develop and involve the local university-extension link, which in turns will most likely reinforce the ownership of the combined numerical skills and local relevance.

The heterogeneity highlighted in this project is once again emphasized through the different audiences, decision makers, systems and consequently the responses to climatic factors. As much as better understanding, communication and integration of forecast information is useful for any decision maker, the capacity to produce such information and communicate it timeously is still technically very difficult, mostly due the large uncertainty involved, as well as the technical operationalization of the process, leading to low reliability of its execution on a regular basis. While the weather forecasts on (very) short time horizons remain accurate, its processing through modelling tool does not provide large added value while it requires large computation and interpretation efforts, if it is to improve the decision process. Although this remains a very interesting and promising research avenue for the future, the ambition to progress towards operationalization through better use of forecast information into the decision-making of agricultural practices, must account for the added value of the information produced, against its cost and reliability of production. At this time, operationalizing very short term climate-crop information is very demanding while its benefits for the farming communities are limited compared to the value of the original weather forecast. On the other hand operationalizing crop-based seasonal forecasts information, while being comparatively demanding to produce, offers measurable improvements of the use of seasonal forecast as well as sufficient time to produce it, communicate it, and hopefully integrate it to agricultural decisions.

This recommendation obviously must be considered in the light of the user interest for the information. Likely commercial farmers with extensive access to numerical tools and internet, will be much likely willing and capable of receiving short-term processed information. On the other hand farming communities with limited access to such tools and information on a regular basis, are more likely to prefer seasonal time scale information, through the extension offices, which play a determinant role in communication, interpretation, understanding and most likely integration of this information. While production of useful information, desired information, must be continued, there is no doubt that local stakeholders must be involved, including academics in local university, extension services, as well as farming communities in order to make this information relevant and useful but also to allow for local interpretation, communication and use. As much as the process can be run remotely, and the heavy computation should benefit from high computation capacities at national, governmental and/or educational institutions, the communication, the interpretation and as much expertise as possible must lie within local universities, local government institutions, and ultimately support and encourage the extension offices in their communication with the farming communities.

From a technical perspective, numerous ways exists to progress forward. We are confident that the combination of forecasts and water/crop modelling tools offer a tailored perspective on forecast information that allows for improved agricultural decisions.

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The University of KwaZulu-Natal, Council for Scientific and Industrial Research, the University of Fort Hare, the University of Venda, the University of Pretoria and the Agricultural Research Council (Institute for Soil, Climate & Water) for collaborating in the project.

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- Prof RE Schulze (UKZN)
- Mr AS Steyn (UFS)

The project team members:

- Mr T Lumsden (CSIR)
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- Dr L Zhou (UFH)
- Prof J Francis (UV)
- Prof W Landman (UP)
- Dr G Zuma-Netshiukhwi (ARC)

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CHAPTER 1. PROJECT INTRODUCTION AND OBJECTIVES

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1.1. Background

The African population is one of the fastest growing in the world and the continent has a large potential for agricultural growth and development (Godfray et al., 2010). The definition of agricultural production strategies that will help prepare Africa for higher demand and worsening climate stresses must take into account various factors including political drive, infrastructure development, technical progress, social livelihood and economic growth. Apart from those, it is imperative to address climate change that directly impacts crop growth and food production in the long term, and in a similar measure climate variability that directly impacts year-by-year production.

Agriculture is highly sensitive to climatic parameters and numerous studies show that Africa will be highly affected by long-term climate changes, mostly in a negative manner (Iizumi et al., 2013; Zinyengere et al., 2013), and adaptation is required (Challinor et al., 2014). In addition to the exploration of long-term adaptation strategies in response to climate change, there is a demand for shorter time scales coping mechanisms, which would make agricultural systems more resilient in the face of climate variability (vs. climate change). Despite a number of limitations to be clearly understood, the value of seasonal forecasts is evident (Fraisse et al., 2006; Hansen and Indeje, 2004; Hansen et al., 2011; Klopper et al., 2006; Meinke and Stone, 2005; Patt and Gwata, 2002). The proposed research is designed to harness seasonal forecasts and impact models numerical capacity to better prepare agricultural activities to climate variability.

South Africa's repeated exposure to severe climate events combined with its financial and structural capacity to improve, has a major role to play in exploiting climate and crop models capacity to digest enormous data into useful tailored information needed for decision making. Although models are only a partial representation of reality, their exploration capacity is useful and they are intensively used at larger time and/or space scales (e.g. AgMIP (Rosenzweig et al., 2014)). Technical challenges such as forecast skills or spatial representation makes shorter time scale studies more demanding. However, these time and space scales are indispensable to provide appropriate information that farming communities are continuously requesting. International research projects have identified those efforts as a priority to respond to climate risk vulnerability, however, there are currently no projects in South Africa, see for instance (CCAFS-CRAFT) or (US-AgroClimate). Some solid regional studies have been performed at those scales, e.g. (Archer et al., 2007; Ziervogel and Downing, 2004; Zuma-Netshiukhwi et al., 2013).

The proposed research work directly follows on from a previous WRC project (Lumsden and Schulze, 2012), which explored the application of weather and climate forecasts in agricultural decision-making. This included applying weather and climate forecasts within hydrological models to produce hydrological forecasts. This study explored, proposed and developed ways and approaches to leverage available seasonal forecasts information, through robust climate-crop-water integrated assessment of agricultural and water systems, towards better farmer's preparedness to climate variability. Shorter time scales were also considered in the study in an attempt to develop a seamless approach.

1.2. Contextualisation

The proposed study provides (i) a deep exploration of local farming communities' needs/expectations with regards to climate-crop seasonal forecasts; (ii) an advanced understanding of climate-crop integration for South African systems; and (iii) tested methodologies to produce agriculturally tailored seasonal forecast information. In the realization of these tasks, the project gives a critical importance to the development of long-term relevant solutions, which is supported by a clear understanding of short (day, weeks, seasonal, inter-annual) and long (decadal, multi-decadal) term challenges through community-driven research.

Unlike to global/continental integrated assessments that prove difficult to downscale with the appropriate local and regional characteristics, the final product of this smallholder-driven project provides local/district relevant information. This local relevance intents to facilitate project outputs replication towards the creation of provincial and national policies that better respond to community and district challenges. The achievement of methodological assessment in real-time conditions, emerges from regular connection with three communities, one in Limpopo, one in Eastern Cape and one in KwaZulu-Natal. Those engagements provided a unique platform for discussion between the research team and the local farming communities and authorities. Those exchanges both grounded local and national academics with field concerns and limitation, as they enabled for knowledge dissemination with farming communities and extension offices. Although this project focuses mainly on smallholder farming and seasonal time scales, it does also incorporate commercial agriculture and shorter time scales (short/medium range and sub-seasonal) through the KwaZulu-Natal case study.

1.3. General approach

1.3.1. Engagement with communities

Stakeholder engagements from the inception to the end of the project tremendously helped to frame the research objectives and advancements fitting actual field constraints and farming communities' priorities. The larger part of the approach annually engaged with two smallholder farming communities, one in Eastern Cape and one in Limpopo. Both provinces have been described as poor and most vulnerable to disasters (SALGA, 2011). Relationships prior to this project had already been developed through our collective, inter-university involvement with the South African Financial and Fiscal Commission funded project (FFC, 2014). These engagements clearly allow to present the projects advancement in the light of community feasibility and evaluating the benefits, barriers and enablers of the approach in the most grounded way possible. In addition to the smallholder farming communities engaged in

Eastern Cape and Limpopo, stakeholders representing commercial perspectives were engaged in KwaZulu-Natal with respect to the application of hydrological forecasts in decision-making.

The project recognises the long term nature of engagement with community, leading to building trust and strengthening exchange of relevant information. Consequently this project built on existing initiatives such as the establishment of the eDikeni water user association by the SA department of Water Affairs and Forestry in 2006, in Eastern Cape. Complementarily, the continued engagement supported through this project, and especially in in Limpopo and Eastern Cape, has explicitly be tuned to develop local universities connections with local communities and their extension officers. We believe it both serves the projects (better integration, for instance through languages), as well as it strengthen the long term engagement of communities with their most likely local university students and academics.

1.3.2. Integrating forecasts into hydro/crop models

Here lies one of the core research challenges of the project. It has been done so extensively on a long term climate change time scale, that we know it is possible to couple seasonal forecasts with crop models. The challenge though comes from the intent to use the forecast-crop model combination as a tool to make crop-relevant weather-based information, or a crop forecast, to provide farming communities with a month to several months lead time prevision tool.

Numerical integration

A number of technical solutions exist to integrate forecasts information with numerical impact models. In this project a particular look was taken at the integration of seasonal forecasts with crop models (see for instance Vol. 1 Chapters 4 and 5). The major challenge in the integration lies in the capacity of the integrated tool/approach to process and produce *relevant* and *useful* information. This project, once again confirms that usefulness varies from one location to another, due to seasonal forecasts skills, data availability for calibrating the models and other factors. This variability of conditions and farmer’s ambitions is addressed in this project through engagements, and resulted in the definition of farmer’s typologies (see Vol. 1 Chapters 6 and 7).

Forecast lead times

A common staple crop growing period takes about 3-5 months, and some of the critical management decisions are taken up to a few months before sowing. This project’s efforts target both very short (day to week) operational decision time scale, as well as intermediate (month to several months) tactical decision time scales.

Data time step resolution

Process-based models strength lies in the step-by-step modelling of the modelled interacting processes. The time step used is a compromise of time/computing complexity and process description. AquaCrop, DSSAT and APSIM for instance use a daily time step, though they can deal with monthly data as well, through the use of a weather generator for instance. In order to limit as much as possible the inner-processing of data from seasonal forecast to crop forecast, we preferred the use and production of daily time step resolution seasonal forecast.

1.3.3. Institutional repartition of work

Given the large workload and various ambitions and aims of the project, the project team was driven along two complementary directions.

Volume 1 – A seasonal time scale, led by The University of Cape Town, and mostly focusing on smallholder farmers of Alice, Eastern Cape and Lambani in Limpopo, with the support of the University of Fort Hare, the University of Venda, respectively.

Volume 2 – A seamless time scale, led by the University of KwaZulu-Natal and the CSIR, focused mostly on commercial agriculture in KwaZulu-Natal, with the support of the University of Pretoria and the Agricultural Research Council.

The first direction lead to numerous advances using Alice in Eastern Cape and Lambani in Limpopo as case study, and this is reported in Vol. 1 Chapters 2 and 3 put in place the basis of the study reporting on site descriptions and engagements. Chapters 4, 5, 6 and 7 are reporting on the technical aspects allowing to connect crop models with seasonal forecasts, in a context of climate change and climate variability, with a clear ambition to improve the systems. Chapters 8, 9, 10, 11 and 12 report the different ways implemented at different levels, to improve the use of seasonal forecast information by smallholder farmers in these locations. Chapter 8 is reporting on the use of remote sensing data to map soil moisture and adaptive capacity in Eastern Cape. Chapter 9 is exploring the current use of local indigenous knowledge related to weather forecast In Eastern Cape and in Limpopo. Chapter 10 is studying the potential of ecological intensification in those areas. Chapter 11 is interested in the communication of seasonal forecast information to rural communities. Chapter 12 is advancing an approach to make cropping decisions in response to seasonal forecasts. Chapter 13 finally brings together concluding remarks related to seasonal forecasts use to help cropping decision making, specifically with smallholder farmers on the basis of Alice and Lambani case study in Eastern Cape and Limpopo.

The KwaZulu-Natal case study (Vol. 2) was focused on the Mhlathuze catchment in the north of the province. The case study commenced in Chapter 2 with a description of the catchment and the stakeholder engagement undertaken in the project. In Chapter 3 the development and refinement of weather and climate forecasts is detailed. The configuration and verification of the ACRU hydrological model under observed climate conditions is then covered in Chapter 4. Chapter 5 details the linking of ACRU to Delft-FEWS, a hydrological forecasting framework. Chapter 6 then presents the results of short to medium range agrohydrological forecasting, while Chapter 7 presents the results of seasonal dam storage forecasting. Chapter 8 explores the potential to produce seasonal forecasts of crop yield and water productivity for the Empangeni area. Efforts to understand and reduce uncertainties and errors in agrohydrological forecasting are then described in Chapter 9, before conclusions are drawn on the Mhlathuze case study (and more broadly) in the final chapter.

1.4. Aims

The number of partners involved in the project brings together a large range of skills and expertise. Each aim is undertaken by the most relevant institution, with a clear effort towards regular community engagement.

AIM 1 – TO RIGOROUSLY DOCUMENT AND IMPROVE ACCURACY AND SKILL IN, SHORT (1-3 DAYS) AND MEDIUM (3-10 DAYS) RANGE WEATHER FORECASTS (FEEDING INTO AIM 7 and 8)

The aim to improve weather forecasts focused on the 1-7 day lead time which spans both the short and medium time ranges. This aim was linked to the KwaZulu-Natal case study where a variety of time ranges (short range to seasonal) were considered in the endeavour to develop seamless forecasting for application in agricultural decision-making. Although the aim was linked to the KwaZulu-Natal case study, the weather forecasting research was conducted over a much larger domain (southern Africa) given the synoptic scale of the processes that influence weather at a particular location.

The conformal-cubic atmospheric model (CCAM) numerical weather prediction system was applied in the effort to improve short/medium range weather forecasts (Vol. 2, Section 3.1). These efforts focused on increasing the spatial resolution of forecasting and on making refinements to the cumulus parameterization and aerosol schemes.

AIM 2 – TO DEVELOP EXTENDED RANGE (11 TO 30 DAYS) WEATHER FORECASTS TO FACILITATE FULLY SEAMLESS FORECASTING (FEEDING INTO AIM 7 and 8)

The forecasts developed under this aim (as part of the KwaZulu-Natal case study) are more appropriately classified as “sub-seasonal” forecasts, rather than extended range forecasts which have a strict definition pertaining to the 11-30 day forecast period. The forecasts developed are for a 40 day period. This is in keeping with sub-seasonal forecasts which can range from 40 to 60 days into the future. CCAM, coupled to the CSIRO sophisticated dynamic land-surface model referred to as Atmosphere Biosphere Land Exchange model (CABLE), was applied in the effort to develop sub-seasonal forecasts (Vol. 2, Section 3.2). The sub-seasonal time-scale holds the particular challenge of falling between the shorter range time scales, where initial conditions are the most important consideration in determining forecast skill, and the seasonal time-scale, where boundary conditions are crucial for model skill. As the sub-seasonal time range bridges the medium and seasonal time ranges, this effort is closely linked to forecast development efforts at those time ranges. Hence the work on sub-seasonal forecasting is reported in the context of developing seamless forecasting and includes results across the different time ranges.

AIM 3 – TO RENDER SEASONAL FORECASTS DATA AVAILABLE TO CROP MODELS, INCLUDING THE SEASONAL PRODUCTION AT 2 LOCATIONS IN SA

This aim, and forecasts used for the smallholder case study in Eastern Cape and Limpopo, does not include the improvement of the currently available seasonal forecasts. However, feedback on the enablers and barriers faced in the development of the climate-crop integrated assessment are provided to encourage seasonal forecast providers and agricultural experts to take those into consideration for future advancements (aim 9). Although the project intention was to use a South African seasonal forecast products, a lack of specific legal sharing framework, and the irregularity of forecast production, made this mostly impossible. Given the project ambition to provide an approach accessible to any user, we used free and accessible CFSv2 forecasts[1]. This effort was tailored for two communities, one in Eastern Cape and one in Limpopo (see respectively Vol. 1 Chapter 2 and 3), and particularly grounded through the annual engagement with local farming communities.

AIM 4 – TO INTEGRATE SEASONAL FORECASTS INTO CROP MODELS FOR SEASONAL PRODUCTION SCENARIOS, INCLUDING THE SEASONAL PRODUCTION AT 2 LOCATIONS IN SA

After considering multiple process-based crop models, the project proceeded to calibrate 2 DSSAT, and AquaCrop (see Vol. 1 Chapter 4). The DSSAT suite of model was taken forward and integrated with seasonal forecasts (see Vol. 1 Chapter 5). The capacity of DSSAT to simulate large numbers of conditions allows the exploration of large numbers of seasonal scenarios, combined with a number of possible agricultural actions, hence bringing out a notion of confidence and risk related to the presented climate-crop integrated assessments (see Aim 6). Engagements were once again, a major driver toward the calibration, validation and interpretation of the numerical approach. It translates for instance, through the farmer's typologies defined in both Eastern Cape and Limpopo, specifically with a perspective emphasising the climate variability awareness (see Vol. 1 Chapter 6) and the potential to use Ecological Intensification (see Vol. 1 Chapter 7).

AIM 5 – TO ENHANCE THE SPATIAL AND TEMPORAL RESOLUTION OF SEASONAL CLIMATE FORECASTS (FEEDING INTO AIM 7 and 8)

Owing to changes in the composition of the project team, the methodology employed (Vol. 2, Section 3.3) moved away from the use of climate models run at SAWS, and instead utilized the output of coupled global models contributing to the North American Multi-Model Ensemble. However, statistical post-processing was still utilized (as originally envisaged) to downscale the global forecast data to a scale more appropriate for use in catchment-scale agro-hydrological forecasting. More specifically, linear statistical procedures were applied to downscale and improve hindcasts (re-forecasts) from the coupled ocean-atmosphere models for the SADC region. This involved the use of Model output statistics to improve the raw climate model output through mean and variance bias correction. The enhancement of seasonal climate forecasts under this aim was directed at the KwaZulu-Natal case study.

[1] http://cfs.ncep.noaa.gov/

AIM 6 – TO DEMONSTRATE THE FEASIBILITY AND EVALUATE THE BENEFITS OF THE CLIMATE-CROP INTEGRATED APPROACH VIRTUALLY (MODELS ONLY WITH HISTORICAL DATA) AND IN REAL CONDITIONS, AT 2 LOCATIONS IN SA

The richness of the human resources and skills collected in this project has allowed to use the combination of seasonal forecast information with crop models and other technologies, in ways not necessarily foreseen at the inception (i.e. indigenous knowledge). This variety of approaches and directions are all grounded in engagements with communities and tailored in return for those very communities, making the overall project ambition to improve preparedness to climate variability local specific and valuable. In Eastern Cape, it includes the mapping of soil moisture through remote sensing data (see Vol. 1 Chapter 8), the documentation and use of indigenous knowledge to improve seasonal decision making in Eastern Cape and Limpopo (Vol. 1 Chapter 9), as well as the exploration of ecological intensification acceptance and use, and the production of crop forecast for the 2017-2018 growing season.

AIM 7 – TO IMPROVE UNDERSTANDING OF, AND POSSIBLE REDUCTION IN, HYDROLOGICAL FORECAST UNCERTAINTIES AND ERRORS ACROSS DIFFERENT TIME RANGES (FEEDING INTO AIM 8)

Research to understand and reduce uncertainty and error in hydrological forecasting in the KwaZulu-Natal case study (Chapter 9) focused initially on characterizing the error in the weather/climate forecasts that are used as input to the hydrological forecasting process. These assessments were approached from a hydrological perspective, which is different to how such forecasts are typically assessed by weather/climate scientists. Other work to address uncertainties and error focused on improved initialization of hydrological models for hydrological forecasting, and on the benefit of incorporating temperature forecasts into the hydrological forecasting framework.

AIM 8 – TO DEVELOP AND EVALUATE TAILORED HYDROLOGICAL AND CROP FORECAST PRODUCTS FOR APPLICATION IN DECISION-MAKING ACROSS DIFFERENT TIME RANGES IN ONE OR MORE CASE STUDIES IN KWAZULU-NATAL

The Mhlathuze catchment was chosen as a case study for the development of tailored agrohydrological forecasts. These forecasts were primarily aimed at irrigated sugarcane agriculture, as this is a major economic activity in the catchment, and is also a substantial water user. Therefore, any improvements to the management of water and crops in the sector that can be brought about by the availability of agrohydrological forecast has the potential to return economic and environmental benefits. These benefits would extend to the management of water in general in the catchment.

In terms of developing tailored agrohydrological forecasts, engagement with stakeholders revealed the need for seasonal forecasts of the Goedertrouw dam, and the possible benefit that could be derived from developing shorter term forecasts of irrigation water demand for irrigation scheduling purposes. Agrohydrological forecasts were developed through the application of the ACRU hydrological model, coupled to the Delft-FEWS hydrological forecasting system. This involved modelling the hydrology of the Mhlathuze catchment, including dams and abstractions of water for various users (especially irrigation). Coupling ACRU to Delft-FEWS aided in applying ACRU in a forecasting context. The possibility of forecasting seasonal sugarcane yields and water productivity using the AquaCrop model, was also explored.

AIM 9 – TO FEEDBACK ENABLERS AND BARRIERS TO CLIMATE AND AGRICULTURE EXPERTS TO FACILITATE FUTURE CLIMATE-CROP INTEGRATION

Throughout the whole project, and the various themes and approaches tested and developed, particular attention was given to the enablers and barriers faced. A rigorous collection and details about these enablers and barriers is presented. Relying on the research team wide range of expertise and their professional connections to relevant institutions across South Africa, those feedback are presented as recommendations for improvement and supported by the concrete advances of the project and its engagement with communities. Despite the simple methodology required to provide complete and useful feedback, they rely on regular and frequent questioning through the various steps taken for the realization of the project, understanding the reason of choices made along the way and the consequent recommendation to improve future advances in the field of climate-crop integration.

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CHAPTER 2. DESCRIPTION OF THE MHLATHUZE CATCHMENT AND ENGAGEMENT WITH STAKEHOLDERS

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2.1. Catchment description

The Mhlathuze catchment is situated in the north of KwaZulu-Natal and lies approximately 160 km north of Durban and ± 35 km south of the St. Lucia Estuary (Figure 2-1). The Mhlathuze catchment forms part of the Usutu to Mhlathuze Water Management Area (WMA). The catchment has an area of approximately 4209 km^2, with nine quaternary sub-catchments each between 250-650 km^2 in size, and has three major towns namely, Richards Bay, Empangeni and Melmoth. The catchment has an altitudinal range of approximately 1612 m.a.s.l. in the upper reaches of the WMA which borders Swaziland and gradually drops in altitude to the ocean (Figure 2-1). Mean Annual Precipitation (MAP) of the catchment ranges from about 800 mm in the upper and middle parts of the catchment, to approximately 1 400 mm near the coast (Figure 2-2), and has a Mean Annual Runoff of 938 million m^3 with a Mean Annual Temperature range of 12 and 14°C in the west to 20 and 22°C at the coast.

Some important vegetation types, notably the Ngongoni veld (upper, more undeveloped areas) and coastal forest and thornveld (coastal, developed areas) are found in the catchment. Important afromontane forests are found along the southern fringes of the catchment. Land use in the catchment is dominated by afforestation and irrigated crops (predominantly sugarcane and citrus), with most of the irrigated areas located on the banks of the main stem of the Mhlathuze River below the Goedertrouw Dam. The main commercial enterprises in the catchment are sugarcane (dryland and irrigated), maize and timber. There are approximately 400 km^2 of pine and wattle forestry plantations upstream of the Goedertrouw Dam. Subsistence farming in rural areas consists mainly of livestock farming. About 37% of the population is rural, 3% occupies farms and 59% are urban.

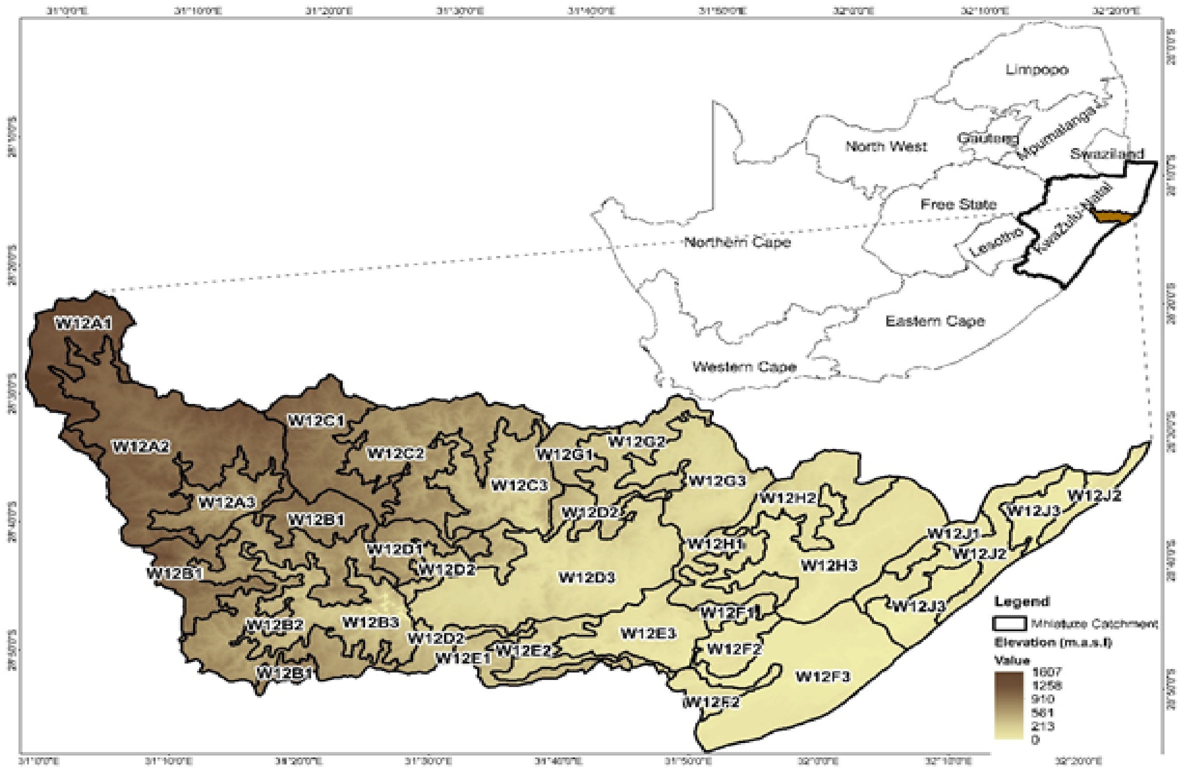

Figure 2-1 Location and altitudinal range of the Mhlathuze catchment in KwaZulu-Natal

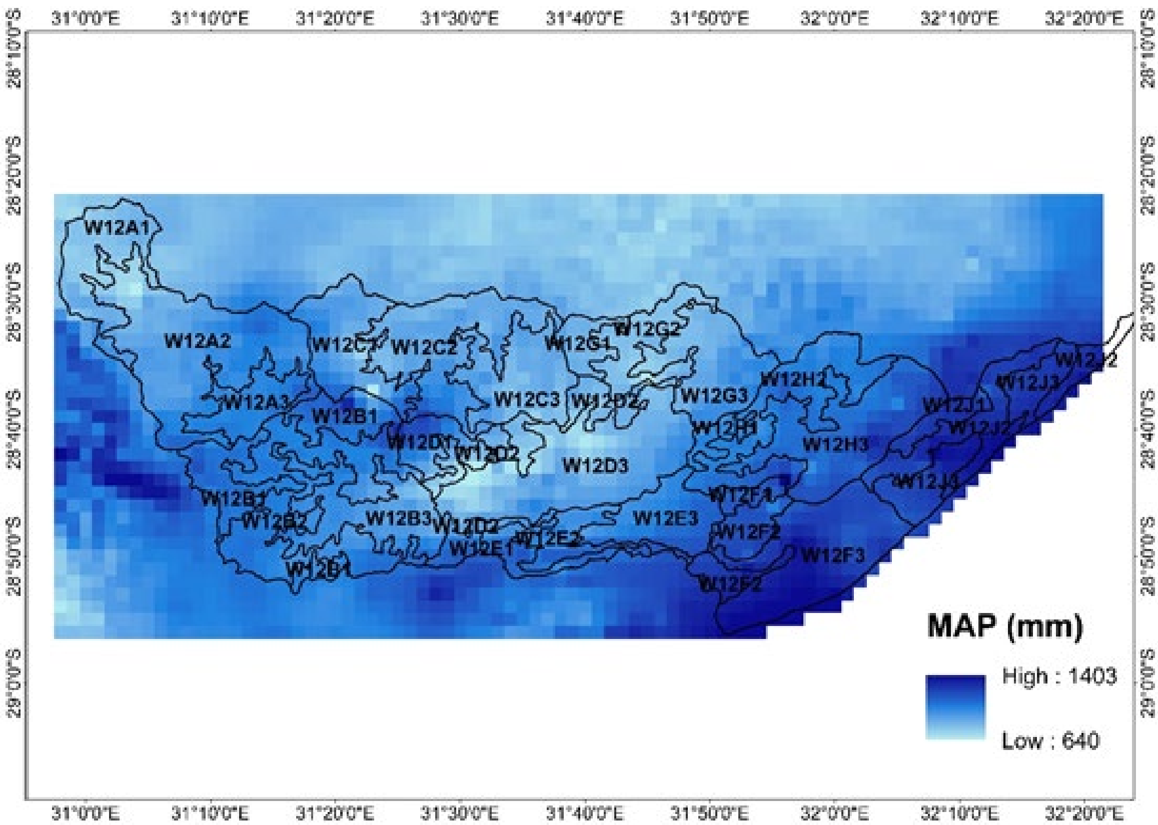

Figure 2-2 Mean Annual Precipitation of the Mhlathuze catchment

The main water supply system in the Mhlathuze catchment consists of the Goedertrouw Dam, with a capacity of approximately 300 million m^3, the Mhlathuze weir, and the Thukela-Mhlathuze Emergency Transfer Scheme, which pumps water from the Thukela River to the Goedertrouw Dam. The Goedertrouw Dam was constructed in the late 1970s to provide water for irrigation downstream. Upstream to the Goedertrouw Dam is the Mvuzane River inflow where the Thukela Transfer Scheme discharges into the Mvuzane River. The Thukela-Goedertrouw Transfer System is used to augment the dam level when it drops as a result of high water demand. During the drought of 1994 the emergency augmentation scheme was put in place (commissioned in 1997) that has the capacity to deliver approximately 40 million m^3/a at a rate of approximately 1.2 m^3/s to the Mvuzane stream. The only second use of the scheme was necessary during the second half of the 2014 calendar year, as a result of minimum summer rainfall received and low raw water resources. In that year, KZN was officially declared to be in a drought. This drought had an adverse effect on the Mhlathuze Water systems with the Goedertrouw Dam dropping to below 65% for the first time since it was commissioned. The Thukela Transfer Scheme was then put into operation, supplying a total capacity of 0.94 m^3/l. The transferred water is allocated for urban and industrial use (DWAF, 2000).

The natural lakes in the catchment also contribute to the yield of the system. The latest yield estimate of this system, including the lakes, is 270 million m^3/annum at a 1:100 assurance after allowing for the ecological water requirements below the Goedertrouw Dam and including the transfer from the Thukela River. Three coastal lakes are sources for abstraction in this strategic area: Lake Mzingazi, Lake Nsezi and Lake Cubhu.

There are several large industries in the catchment namely Mondi's Richards Bay and Flexton Pulp mills, Richards Bay iron and Titanium Works, Iscor, Tongaat Hulett, Alusaf and Felixton sugar mill. Richards Bay Minerals and Ticoris Hillendale Mine have extensive mining operations in the coastal dunes. Richards Bay and Ninians quarries are open cast quarries in the Mhlathuze catchment.

Water scarcity remains the predicament in many area of South Africa, where different industries competes for water, demand for domestic water use, crops competes with other crops, for example sugarcane competes with other crop for water. It has become evident that dryland production unaccompanied with supplementary irrigation may lead to crop failure which contributes to economic loss. Thus, the importance of decision support initiatives with the utilisation of weather forecasts, climate predictions and crop simulation models are critical for the provision of a variety of scenarios based on given weather and climatic conditions (Lapola et al., 2009). Such provision facilitates the interpretation of the impact of sugarcane production, irrigation strategies on water resources, accessibility and profitability.

The KwaZulu-Natal province is one of two provinces that are distinguished as having sugarcane as a major land use. However, the changing climate conditions lead to decision making becoming more complex as water restriction policies and water management rules are enforced, resulting in water becoming more scarce and very expensive (Schmidt, 2001). The Mhlathuze Catchment constitutes of five irrigation entities that utilise and facilitate the distribution and use of water below Goedertrouw Dam. These five irrigation entities are mainly utilised for sugarcane irrigation and several irrigated citrus farms. The irrigation schemes are listed in order of distance from the dam.

- Nkwaleni Scheme
- Umfuli
- Heatonville
- Inkasa Irrigators
- Lower Mhlathuze Scheme

Inkasa Irrigation Scheme (IIS) is predominantly constituted of small scale irrigators engaged in sugarcane production. Within IIS the most developed areas with significant sugarcane productivity are Biyela, Kwadlama and Mzimela.

Agricultural productivity and in this case, sugarcane productivity is linked to appropriate irrigation strategies, which are also highly influenced by soil types, climate and water availability. The role of decision support tools becomes more significant in decision making amongst producers, and to inform policy makers. Lack of access to information and tools could be a limiting factor toward improved sugarcane productivity and poverty alleviation within the Mhlathuze catchment. It is therefore necessary to investigate the application of weather forecasts, climate prediction and agrohydrological models to develop forecasts that can potentially enhance tactical and operational decision making.

2.2. Stakeholder engagement

Stakeholder engagement in the Mhlathuze case study focused on ascertaining the needs for agrohydrological forecasting information in the catchment, and also on gathering information on crop and water resources management to ensure the representativeness of the agrohydrological modelling conducted in the study. The findings of this engagement is presented in different sub-sections below for the various aspects covered.

2.2.1. Ascertaining the needs for agrohydrological forecasting

As alluded to previously, the KZN case study was focused on the Mhlathuze catchment in the north of the province. The focus was mainly on applying weather and climate forecasts to commercial irrigated sugarcane, but did to some extent include small scale growers.

To ascertain the needs for agrohydrological forecasting information for the sugarcane sector in the catchment, staff at the South African Sugarcane Research Institute (SASRI) were consulted during various small group meetings. SASRI is mandated to serve the agricultural research needs of the sugar industry, encompassing both commercial and small growers. The research staff consulted include Dr Abraham Singels (Principal Agronomist), Mr Matthew Jones (Systems Modeller), Mr Aresti Paraskevopoulos (Scientific Programmer) and Mr Phil Sithole (Agrometeorologist). During the course of these discussions it was established that a need exists for the development of seasonal forecasts of the storage volume of the Goedertrouw Dam. This dam has a full supply capacity of 301 million m^3 and primarily supplies water for urban, industrial and irrigation purposes. The potential applications of seasonal dam storage forecasts are discussed under relevant headings below.

The needs for short to medium range (0-7 day) agrohydrological forecasts in the catchment centre on water demand forecasts for irrigation scheduling. A brief discussion on this is presented after the discussion on seasonal dam storage forecasting.

2.2.1.1. Seasonal forecasts of the storage volume of Goedertrouw Dam

Two potential applications of seasonal dam storage forecasts were identified in discussions with SASRI staff. The first of these include improving the irrigation water availability estimates that are assumed in the crop yield forecasts produced for the area. These forecasts are generated as part of the operational industry-wide crop yield forecasting system developed by SASRI. The second relates to the potential to improve on-farm allocation of irrigation water. Information related to these applications that was gleaned from discussions with SASRI, and from literature provided by Dr Singels, is presented in the following subsections.

Application to crop yield forecasting

The SASRI crop yield forecasts (Bezuidenhout and Singels, 2007) are generated at the scale of Homogeneous Climate Zones (HCZ) that have been delineated for the industry. The HCZ forecasts are then aggregated to the level of the sugarcane mills to which those HCZ are associated. Finally, the mill level forecasts are aggregated to produce a national forecast for the industry.

The SASRI forecasts are used for a variety of purposes:

- Mill operators use the forecasts to determine the annual mill opening and closing dates. The selected start date and duration of the milling season have an important influence on the quality of the cane that is crushed and the profitability of the milling.
- At a national scale the forecasts are used to estimate crop payments from millers to growers and also to estimate tax rebates for communal small scale growers. In these situations, crop forecasts help to anticipate and streamline large financial transactions.
- International marketers use the forecast prior to and during the start of the milling season to exploit price hedging, forward-sell surplus sugar at higher profit margins and cut expenditure on freight.
- Potentially, the crop yield forecasts could also be used to develop more efficient haulage schedules and to tailor agronomic practices to the expected climate

Seasonal climate forecasts are combined with a sugarcane yield model, CANESIM, to generate crop yield forecasts. CANESIM is configured to run in all the HCZ delineated across the sugar industry (there are approximately 48 HCZ). The Canesim model is a daily time step, point-based simulation model predominantly driven by water. For input, it requires soil available water holding capacity (TAM in mm) and daily temperature, rainfall and reference evaporative demand. The model accounts for partial canopy conditions and soil water content using a single layer soil profile. Yield is calculated as a function of transpiration (Bezuidenhout and Singels, 2007). The model has been validated at mill level and was found to produce excellent simulation results (Gers et al., 2001).

A map of the HCZ delineated for the sugar industry is given in Figure 2-3. There are three HCZ that are of relevance to the Mhlathuze catchment, i.e. they overlap the boundary of the catchment and the irrigated cane grown within the HCZ are supplied by water from the catchment. These HCZ are highlighted on the map.

The names of the three HCZ that are relevant to the Mhlathuze are given in Table 2-1, together with the areas of rainfed and irrigated cane that are assumed to be in each HCZ for crop forecasting purposes. The three HCZ mostly supply cane to the Felixton mill (located in Empangeni HCZ), but the Empangeni HCZ also supplies a small amount of rainfed cane to the Umfolozi Mill (located north east of the Empangeni HCZ).

Table 2-1 Homogeneous climate zones relevant to the Mhlathuze catchment and the areas of rainfed and irrigated cane within them that are assumed for crop forecasting purposes

HCZ No.	HCZ Name	Rainfed Area (ha)	Irrigated Area (ha)
18	Heatonville	1330	4050
19	Empangeni	8200	1100
20	Nkwaleni	0	2950

At present, very simple assumptions are made in the SASRI sugarcane yield forecasting system regarding the availability of irrigation water. It is assumed that water supply levels at the time of generating a forecast will persist for the remainder of the current summer (October to March) or winter (April to August). For the following summer, irrigation applications are set at 80% of the maximum permissible amount when current supplies are good or at 50% when current supplies are poor. For the following winter, irrigation applications are set to 50% of the maximum permissible amount when current supplies are good or to half the summer amount when current supplies are low.

A way to improve the estimation of available irrigation water supplies in the SASRI crop forecasting system, would be to apply seasonal climate forecasts in a hydrological model to generate forecasts of water availability. For the three HCZ overlapping the Mhlathuze catchment, SASRI assume that irrigation water is sourced from the Goedertrouw Dam (located on the main stem of the Mhlathuze River). If the storage volume of the dam is forecast, then it may be possible to provide improved estimates of the water available for irrigation represented in the crop forecasting system (taking into account any water restrictions in place). The modelling of the dam, and the catchment supplying it, would need to take into account the other (non-agricultural) water users in the area.

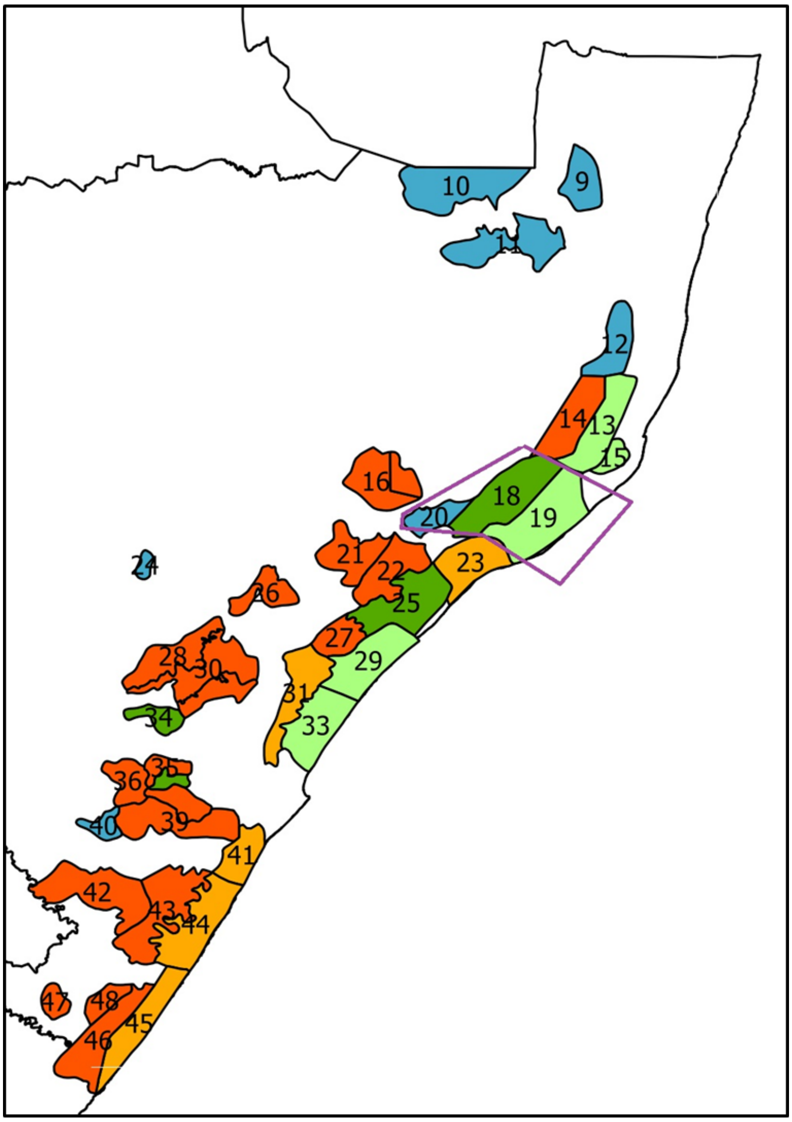

Figure 2-3 Homogeneous climate zones in the South African sugar industry with zones relevant to the Mhlathuze catchment highlighted (source: SASRI)

Application to on-farm allocation of water for irrigation

Another potential application of irrigation water availability forecasts would be to support an on-farm irrigation water allocation tool developed by SASRI. This tool requires an indication of the availability of irrigation water at seasonal and longer time scales. The tool, which was developed concurrent to this project, aims to help farmers decide how to allocate water to their different fields, particularly in times when water is in short supply. The tool requires information such as the farm size, the fields on the farm, the soils, crop cycles and recorded and expected weather. Using a relatively simple crop model and an economic optimisation algorithm, the tool makes recommendations on how best to allocate water to the various fields on the farm.

2.2.1.2. Short to medium range agrohydrological forecasts

A need for short to medium range agrohydrological forecasts (e.g. 7 day forecasts) centres on crop water demand for irrigation scheduling purposes. More specifically, such forecasts could be focused on soil moisture, evapotranspiration or irrigation water demand. A soil moisture forecast could further be useful in decisions relating to expected in-field trafficability of agricultural machinery. Within the context of sugarcane, soil trafficability is an important consideration in harvest scheduling. The harvesting of sugarcane needs to be carefully scheduled as any delays between harvesting of the cane and crushing it at the mill leads to rapid deterioration in the cane quality.

Another possible application of short to medium range weather forecasts would be the prediction of wet/dry day sequencing. This information could potentially be useful in decisions related to pesticide and fertilizer applications, sugarcane burning and fire break burning.

2.2.2. Obtaining information on crop and water resources management

Communication with the SASRI extension officer for the Zululand North region, Mr Tshifhiwa Radzilani, yielded information regarding the crop and water resources management within the Mhlathuze catchment. In response to the selected questions regarding crop management, Mr Tshifhiwa indicated that crop cycles are practised for a period of 12 to 15 months within the catchment and irrigation water is sourced from a combination of the Goedertrouw Dam as well as the Mhlathuze river below the Dam, both of which forms part of the Mhlathuze Water Supply System. Water for domestic, agricultural and industrial purposes is abstracted directly from the Goedertrouw Dam to the canal and abstractions directly from the river to agricultural fields and farm balancing dams for storage. The methods of irrigation application scheduling involve a combination of direct and indirect soil water measurements such as the use of neutron probes, tensiometers, capacitance probes, and estimations through water budget calculators and the use of daily ET measurements from automatic weather stations and crop models. Various irrigation system hardwares are used within the catchment include dragline systems, semi-permanent irrigation systems, surface drip irrigation systems, sub-surface drip systems and centre pivots.

Exact volume demands for other sectors were not known, however, what was known is that approximately 40% of the water from the dam and Mhlathuze river system has been allocated by Government for industrial and municipal purposes and the balance for agricultural use. Information on the annual volumes of water transferred into the Goedertrouw dam for the Thukela transfer scheme was unknown as well as how the annual volume of water from the scheme is distributed throughout the year. Additionally, information with regards to user/sector prioritization during periods of reduced water availability, for example during dry years, was unknown, as well as the timings of dam releases and the associated volumes.

To compensate for the missing information the most recent study on the Mhlathuze catchment titled “Modelling support for Licensing Scenarios by the Department of Water Affairs (DWA) in 2012, which was a follow-on study from the uMhlathuze Water Availability Assessment study (MWAAS) by DWA in 2009, was used. The study provided technical support to its Regional Office in the application of the model developed during the MWAAS to assist with water reallocation, provision of analytical support in the management of the water resources, and also to offer a support function in the water use licence evaluation process. The study focussed on a technical water resource analysis of the uMhlathuze, Amatikulu and Mlalazi river basins. A detailed surface water hydrology assessment was undertaken and a detailed Water Resources Yield Model (WRYM) was configured for the catchment. From the study, both estimated and allocated volumes of total water use for the urban, agricultural and industrial sectors for the year 2013, as well as estimated annual volumes and timings of annual water transfers from the Thukela into the Goedertrouw Dam were obtained. These were used to improve the configuration of the ACRU model for agrohydrological modelling purposes.

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CHAPTER 3. REFINEMENT OF WEATHER AND CLIMATE FORECASTS

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3.1. Weather forecasts

3.1.1. Description of the improved CCAM numerical weather prediction system

The numerical weather prediction (NWP) model applied at the CSIR to address Aim 1 of the project (to improve short/medium range weather forecasts) is the conformal-cubic atmospheric model (CCAM), a variable-resolution global climate model (GCM) developed by the CSIRO (McGregor, 2005; McGregor and Dix, 2001, 2008). The model solves the hydrostatic primitive equations using a semi-implicit semi-Lagrangian solution procedure, and includes a comprehensive set of physical parameterizations. The GFDL parameterization for long-wave and shortwave radiation (Schwarzkopf and Fels, 1991) is employed, with interactive cloud distributions determined by the liquid and ice-water scheme of Rotstayn (1997). The model employs a stability-dependent boundary layer scheme based on Monin-Obukhov similarity theory (McGregor et al., 1993). CCAM runs coupled to a dynamic land-surface model CABLE (CSIRO Atmosphere Biosphere Land Exchange model). The cumulus convection scheme uses mass-flux closure, as described by McGregor (2003), and includes both downdrafts and detrainment. CCAM may be employed in quasi-uniform mode or in stretched mode by utilising the Schmidt (1977) transformation.

CCAM may be applied at quasi-uniform resolution, or alternatively in stretched-grid mode to obtain high resolution over an area of interest. Figure 3-1 shows the model grid that was

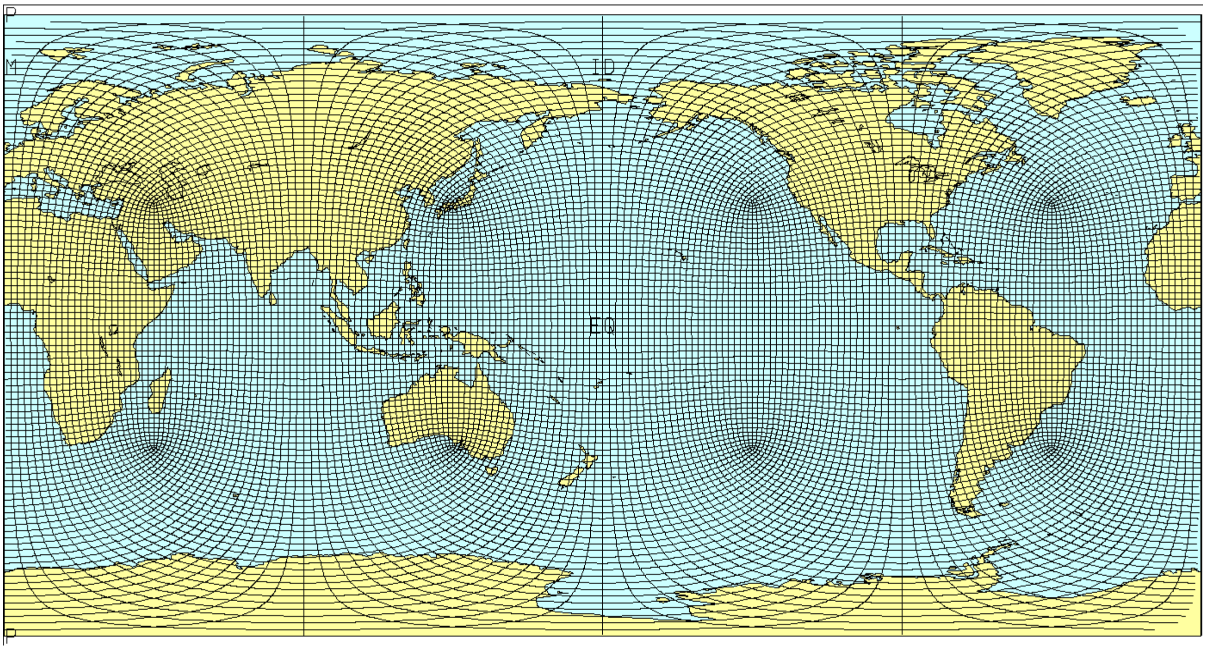

Figure 3-1 C192 quasi-uniform conformal-cubic grid, providing a horizontal resolution of about 50 km resolution globally (every 4th grid point is shown)

used for the quasi-uniform forecasts applied in the project (every 4th grid point is shown), of C192 resolution (about 50 km in the horizontal). CCAM's ability to realistically simulate present-day southern African climate has been extensively demonstrated (e.g. Engelbrecht et al., 2009; Engelbrecht et al., 2011; Engelbrecht et al., 2013; Malherbe et al., 2013; Winsemius et al., 2013; Engelbrecht et al., 2015).

For daily operational weather forecasting activities at CSIR the model is initialized with atmospheric conditions at 0000, 0600, 1200 and 1800 UTC, as obtained from the Global Forecasting System (GFS) made available by the USA's National Oceanic and Atmospheric Administration (NOAA). The improved system for application in the project produces a global forecast at 50 km spatial resolution (previously the model had 50 km resolution only over an extended southern African domain). The variable resolution capabilities of CCAM subsequently allow the model to run at higher resolution over a selected region using the lower resolution forecast to provide boundary conditions in the far-field. In the new extended forecast system, this technique is applied to downscale from global 50 km resolution forecasts to forecasts of 8 km resolution over South Africa (compared to the old system that offered 15 km resolution over South Africa). The short-range forecasts are issued 7 days ahead.

3.1.2. Results

Hindcasts were performed to test the accuracy and skill of the new high resolution forecast system for 2013-2016. These included comparing the performance of different cumulus parameterisation settings in terms of the effect on the model's ability to forecast rainfall totals. Similarly, the impact of including a prognostic aerosol scheme on forecast accuracy and skill was investigated. The latter investigation stems from the notion that a more realistic description of the availability of condensation nuclei may impact on the model's ability to skilfully forecast rainfall. The model bias in forecasting rainfall over South Africa is shown in Figure 3-2, for the cases of three different cumulus parameterisation settings applied with and without prognostic aerosols. It is clear that the model has a general positive bias when forecasting rainfall over South Africa, with the bias exceeding 100 mm per year over much of the eastern interior. General negative biases are present over the Limpopo river basin, and over the winter rainfall region of the southwestern Cape. Moreover, two of the convection parameterisation biases (conv=1 and conv=2) result in the simulation of a spurious rainfall maximum to the west of Lesotho. The presence of prognostic aerosols in the forecast scheme does not have a significant effect on the bias calculated for the respective hindcasts. Overall, the hindcasts performed with conv=0 yield the most realistic representation of rainfall totals over South Africa.

The model bias in simulating rainfall over Africa is shown in Figure 3-3. As before, the bias was calculated for the hindcasts performed at 50 km resolution globally. The figure reveals that a bias similar to the wet bias over South Africa also occurs over the subtropical North Africa. Over the latter region, the presence of aerosols significantly increases the wet bias. Moreover, the hindcasts exhibit a general negative bias over much of tropical Africa, which extends in the east to northern Mozambique. The enhanced positive bias that result over North Africa in the presence of aerosols suggest that conv=0 without the use of prognostic aerosols may currently be the preferred settings for the operational forecast system applied at the CSIR.

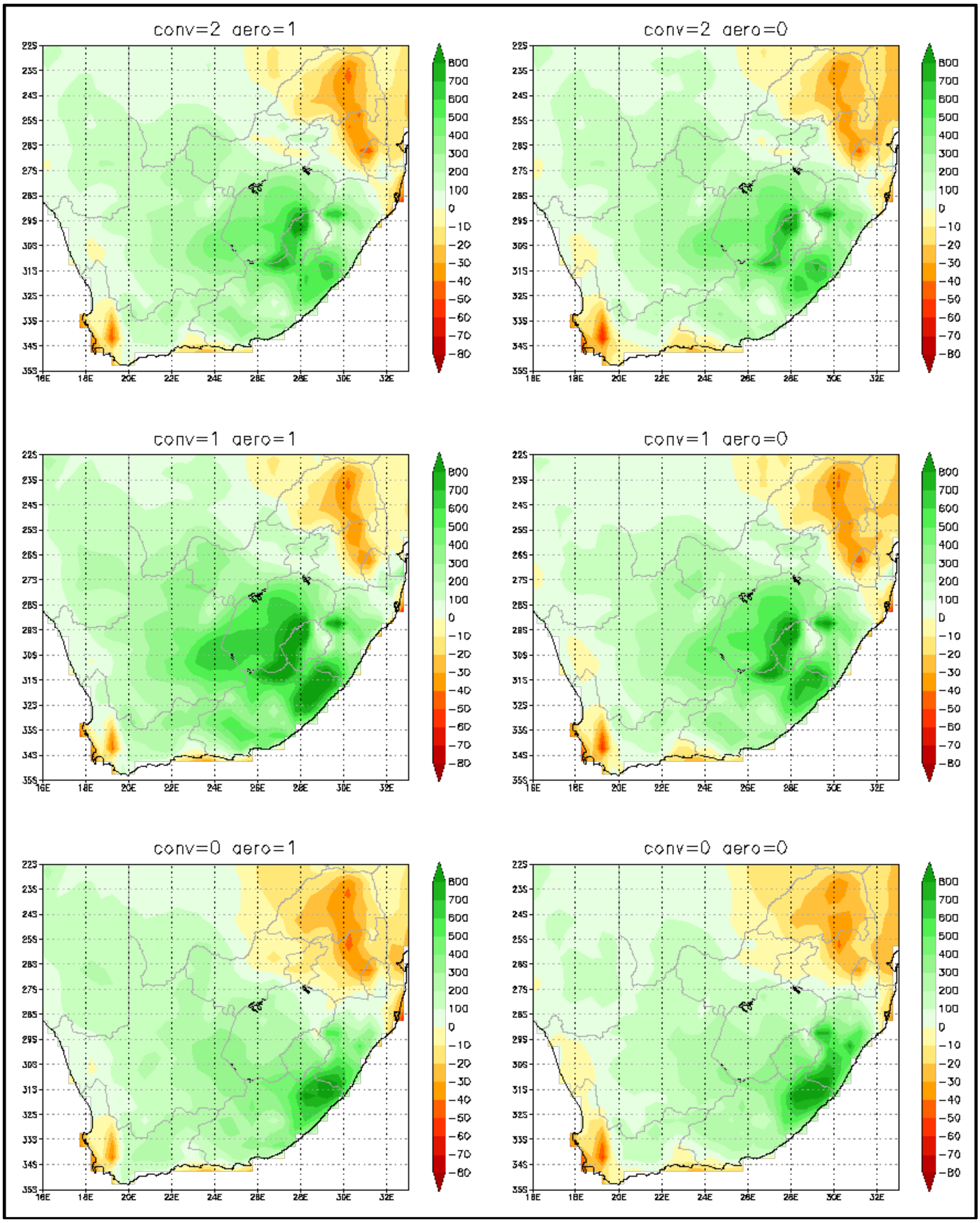

Figure 3-2 CCAM bias (mm) in simulating rainfall totals over South Africa for the period 2013 to 2016, across three different cumulus convection schemes with a prognostic aerosol scheme applied (left), and across three different cumulus schemes applied in the absence of aerosol forcing (right). The hindcasts were obtained at 50 km resolution globally.

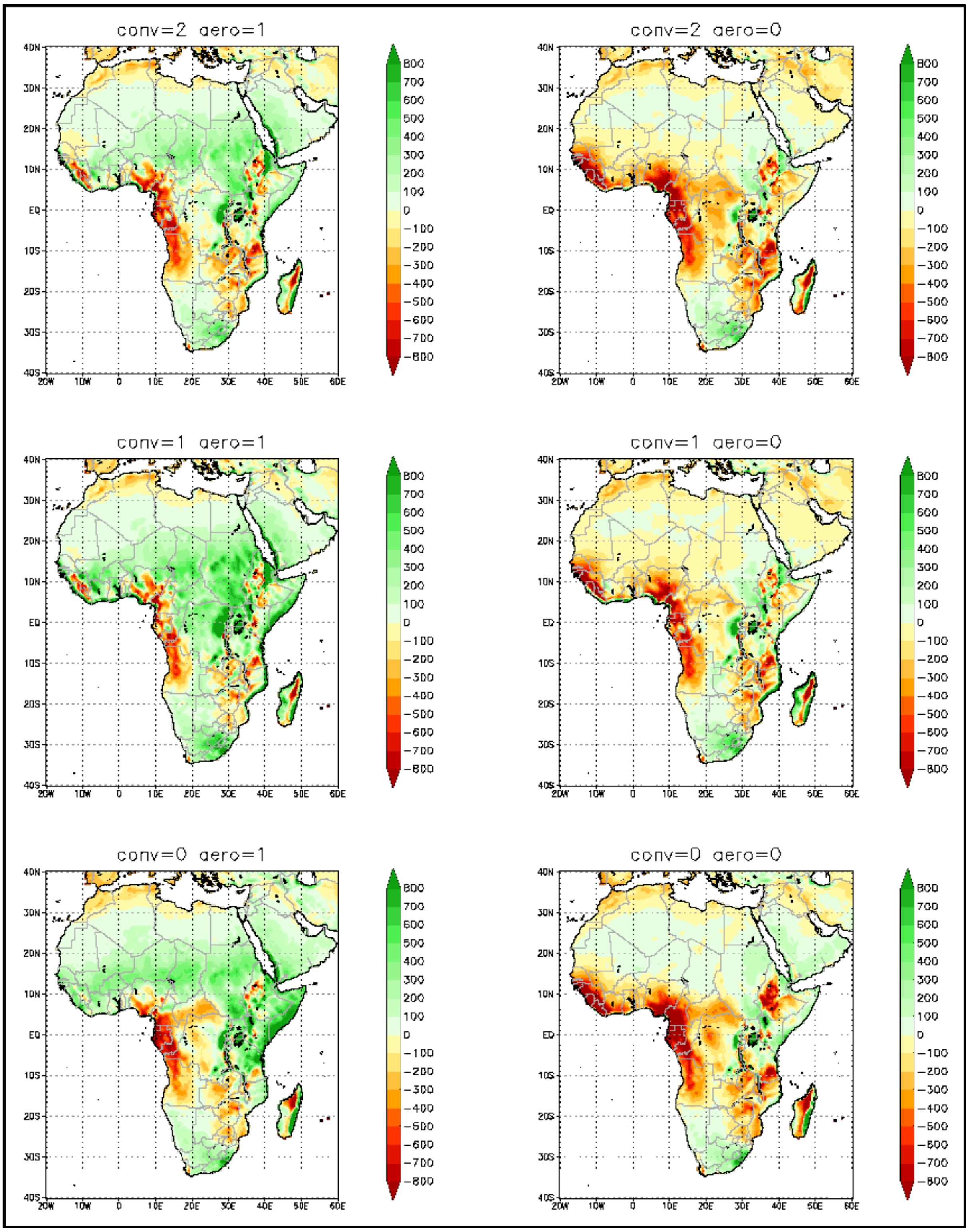

Figure 3-3 CCAM bias (mm) in simulating rainfall totals over Africa for the period 2013 to 2016, across three different cumulus convection schemes with a prognostic aerosol scheme applied (left), and across three different cumulus schemes applied in the absence of aerosol forcing (right). The hindcasts were obtained at 50 km resolution globally.

A comparison between the 50 km and 8 km CCAM simulations is shown in Figure 3-4, for a region over northeastern South Africa. It can be seen in the corresponding observations that a rainfall maximum extends from Lesotho into the Mpumalanga and Limpopo Drakensberg. This feature is not present in the 50 km resolution simulations, but is well represented in the 8 km resolution simulations. These results indicate the potential for the CSIR 8 km resolution forecasts to add value and skill over regions of steep topography in particular.

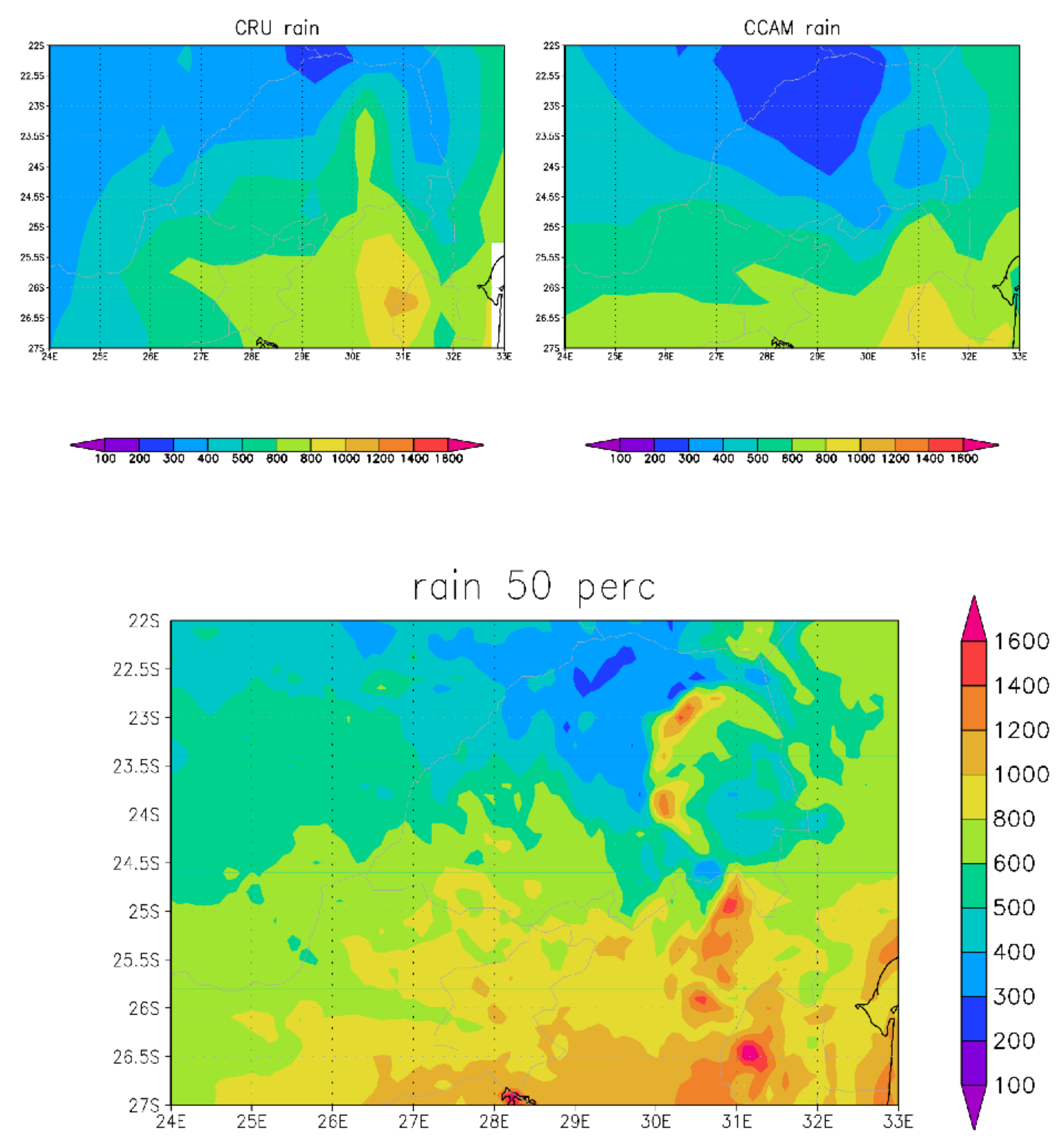

Figure 3-4 CCAM average simulated rainfall totals (mm) compared to observations for northeastern South Africa. The simulated 50 km resolution totals (top right) can be compared to observations from weather stations (top left) and 8 km resolution simulations (bottom).

3.1.3. Conclusion

The impact of varying cumulus parameterizations, introducing a prognostic aerosol scheme and increasing the horizontal resolution of CCAM have all been investigated in efforts to improve the short to medium range forecasting capability of CCAM. The accuracy (bias) associated with these model variations has been determined and documented, and has aided in developing an optimum model configuration for forecasting purposes.

Two sets of CCAM 7 day forecasts were made available during the course of the project for agrohydrological forecasting in the Mhlathuze catchment. The first set consisted of 15 km resolution forecasts for the period 2013-2016 (all year round) for rainfall and maximum and minimum temperature. The second set were higher resolution 8 km forecasts for the same period (2013-2016), but only including rainfall (i.e. excluding temperature) for the summer (Dec-Jan-Feb) months. The first and second sets of forecasts were provided in text and netCDF formats, respectively.

3.2. Sub-seasonal forecasts

3.2.1. Background

African climate exhibits a high degree of natural variability and is prone to the occurrence of droughts and floods. Recent severe droughts in the Horn of Africa and the Sahel (e.g. Lyon and DeWitt, 2012; Williams et al., 2012) are vivid examples of Africa's vulnerability to climate variability. Moreover, the 2015/16 El Niño event and resulting heat-waves and drought over southern Africa emphasized how global warming and climate change may function to intensify the impacts of drought events over Africa. In fact, the austral summer (December to February) of 2015/16 has been the warmest ever recorded over southern Africa, and were associated with a high frequency of heat wave events that impacted significantly on crop yield, livestock mortality and human comfort. The multi-faceted repercussions of the 2015/16 southern Africa and the 2017 persistent Western Cape devastating droughts and how these type of extremes probably intensify over the region under global warming scenario (Engelbrecht et al., 2015) attests to the importance of having skilful and reliable early warning systems for the region. Weather and climate information across time scales are thus useful instruments to inform the planning, development, management and running of climate sensitive segments of the economy (Winsemius et al., 2014; Bett et al., 2017; Clark et al., 2017).

This section describes the development of a seamless forecasting system that ranging from short weather forecast to climate change time scales using a single dynamic core at the Council Scientific and Industrial Research (CSIR) Natural Resources and the Environment (NRE), Climate Studies, Modelling and Environmental Health group by placing more emphasis on the extended range time scale. The seasonal forecasting, relatively matured, effort in South Africa goes back as early as the 1990s. Already then, a number of local institutions developed objective seasonal forecast techniques which were based entirely on statistical methods. A variety of forecasting systems were subsequently developed over the years, including systems that incorporated dynamical global climate models (e.g. Beraki et al.,2014, 2016) and statistical downscaling models (Landman and Beraki, 2010). Local seasonal forecasting efforts and the use of atmospheric general circulation models (AGCMs) in South Africa from a historical perspective are recently reviewed by Landman (2014). This extensive modelling endeavour is motivated primarily by the fact that numerous (observational and numerical) studies over the past couple of decades (e.g. Klopper et al., 1998; Landman and Goddard, 2002; Tennant and Hewitson, 2002; Reason and Rouault, 2005) conclusively shown the existence of potential predictability over the region, in the midst of strong hydrodynamical instabilities associated with mid-latitude baroclinicity, due to the tropical heat modulation on the mid-latitude circulation whose signature peaks during the austral mid-summer (Shukla, 1981; Mason et al., 1996). The southern Africa regions climate is therefore driven by the slowly evolving components of the climate system (Palmer and Anderson, 1994; Barnston et al., 1999). Most of the signature of these slowly evolving systems is believed to originate from the ocean and thus the interaction between the ocean and the atmosphere is of paramount importance in the context of climate predictions (Goddard et al., 2001).

Despite weather forecast in the extended-range time scale has been a topic of considerable interest (e.g. Deque and Royer, 1992; Landman & Tennant, 2000; Tracton et al., 1989; Zeng et al., 1993) since first studied by Shukla (1981), its progress has stalled. The hiatus is presumably attributed to lack of reasonable intelligence in climate models. Because extended-range forecast (ERF) is arguably the most complex part of Numerical Weather Prediction (NWP) since the physical basis for this time-scale is not as clear as for medium-range (3-10 days) and seasonal forecasts. Theoretically, the underlying logic to exercise this type of prediction resides on the assumption that the time range 11 to 30 days is still short enough that the atmosphere retains some memory of its initial state and it is, presumably, long enough that the slowly evolving boundary conditions have an impact on the atmospheric circulation (Beraki and Olivier, 2009). To bridge the gap, the World Weather Research Programme (WWRP) and World Climate Research Programme (WCRP) launched a joint research initiative in 2013, the Subseasonal to Seasonal Prediction Project (S2S). The main goal of this project is to improve forecast skill and understanding of the subseasonal to seasonal time scale, and to promote its uptake by operational centres and exploitation by the applications communities (see Vitart et al., 2016). Nonetheless, most of the S2S community endeavours on the continent were concentrating mostly over the western and central Africa (e.g. Kamsu-Tamo et al., 2014; Olaniyan et al., 2018). For the most part predictability for individual calendar months is the only recently published work on sub-seasonal time scales over southern Africa (e.g. Phakula et al., 2018) which suggests the S2S southern African region is still in its infancy.

In pursuit of improving predictive skill effort stemmed from the work first initiated by Beraki and Olivier (2009) locally, the study revisits a numerical experimentation framework that uses ultra-high resolution dynamical downscaling paradigm. These computationally intensive model simulations have been conducted at the Centre for High Performance for Computing (CHPC) of South Africa based in Cape Town. Dynamical downscaling for seasonal forecast (in operational context) was first attempted locally by Kgatuke et al. (2008) and more recently by Ratnam et al. (2016). As opposed to these previous studies, which used Limited Area Model (LAM), our study employs a stretched-grid model referred to as conformal-cubic atmospheric model (CCAM; McGregor, 2005a). The CCAM has been undergone a significant improvements in dynamics and physics over recent years and is intensively used in climate change studies locally (e.g. Engelbrecht et al., 2015).

3.2.2. Model description and experimental design

3.2.2.1. AGCM description

The climate model used in the study is the CSIRO (Commonwealth Scientific and Industrial Research Organisation in Australia) CCAM (McGregor, 2005a). This stretched grid atmospheric climate model is coupled to the CSIRO sophisticated dynamic land-surface model referred to as Atmosphere Biosphere Land Exchange model (CABLE). The CCAM AGCM (Atmospheric General Circulation Model), which is σ-coordinate model, employs a semi-implicit semi-Lagrangian method to solve the hydrostatic primitive equations (a nonhydrostatic version also exists). It uses an R-grid (reversible staggering for the wind components) for good gravity wave dispersion behaviour (McGregor, 2005b). The GFDL parameterizations for long-wave and short-wave radiation are used, with interactive cloud distributions determined by the liquid and ice-water scheme of Rotstayn (1997). A stability-dependent boundary layer scheme based on Monin Obukhov similarity theory is used (McGregor et al., 1993), together with the non-local treatment of Holtslag and Boville (1993). The cumulus convection scheme uses a mass-flux closure, as described by McGregor (2003), and includes downdrafts, entrainment and detrainment. CCAM includes a prognostic aerosol scheme, and can be applied consistently with the emission inventories and radiative forcing specifications of the Coupled Model Intercomparison Project Phase Five (CMIP5). CABLE includes a dynamic river routing scheme adapted from the CSIRO Mk3.5 CGCM (ocean-atmosphere Coupled Global Circulation Model).

3.2.2.2. Driving CGCM description

The CCAM-CABLE Model was forced with predicted sea-ice concentration (SIC) and sea surface temperatures (SSTs) acquired from the outputs of the SINTEX-F2v ensemble seasonal prediction system (Doi et al., 2014, 2016). It is based on the SINTEX-F2 CGCM (Sasaki et al., 2013, 2014, 2015). The atmospheric component is ECHAM5 (Roeckner et al., 2003), and the oceanic component is the Nucleus for European Modelling of the Ocean (NEMO) system (Madec, 2006). The atmospheric component has T106 horizontal resolution (approximately horizontal resolution of 125 km at equator) with 31 vertical levels. The oceanic component employs the ORCA05 grid, which uses a tripolar grid with 0.58 zonal resolution and 0.58 cosine (latitude) meridional resolution with 31 vertical levels. The atmospheric and oceanic components are coupled with data exchanged every 2 hours, including SST, sea ice fraction, freshwater, surface heat, surface current, and momentum fluxes, by means of the Ocean Atmosphere Sea Ice Soil, version 3 (OASIS3; Valcke et al., 2004), coupler. We refer the reader to Doi et al. (2016) for complete description of the CGCM experimentation.

3.2.2.3. Retroactive forecasts design

The AGCM retroactive experiment consists of 18 ensembles integrations of 6 months in length, which are built as a function of both atmospheric states (ICs) and boundary forcing (BCs; Beraki et al., 2016). This model configuration offers a better description of uncertainties that may arise from the initial and boundary forcings. The uncertainties that arise from the ICs are accounted for by taking 6 consecutive daily realistic atmospheric states back from the forecast date in each month and year. For the November hindcasts, for instance the atmospheric ICs cover the period from November 1 to 6 for 15 years starting from 2000 to 2014. To minimize potential climate drift, the CCAM-CABLE is nudged at its surface to the SINTEX-F2 CGCM SSTs, using the spectral nudging method of Thatcher and McGregor (2009, 2010). Furthermore, all climate simulations are forced by the time-varying CO_2 and ozone (O_3) fields provided through the CMIP5 archive for the period 1870-2100. The atmospheric ICs are acquired from the NCEP (National Centers for Environmental Prediction), Department of Energy (DOE) Atmospheric Model Intercomparison Project (AMIP) II Reanalysis (R2) dataset (Kanamitsu et al., 2002). The NCEP/DOE atmospheric states are transformed to the CCAM CABLE quasi-uniform (C96) horizontal resolution (approximately 105 km^2) and 25 vertical sigma layers similarly to Beraki et al. (2014).

Forcing the AGCM with all ensemble realizations of the SINTEX-F2 CGCM is presumably computationally inhibiting. This is due to a double fold increase in the AGCM integrations by the size of atmospheric ICs as it is also important to account for uncertainties arising from the atmospheric states. Hence, the prescription of the SST scenarios follows a manner that optimizes the representation of the uncertainty envelope and also taking into account computational constraints. The background error here is estimated from the standard deviation of the 6 CGCM ensemble integrations and subsequently added/subtracted to the ensemble mean anomalies. It is also worth noting that the SIC and SST anomalies are superimposed to the AMIP observed climatology to minimize the biases in the boundary forcings (Beraki et al., 2016; Ratnam et al., 2017). In the CGCM experiment, as noted in Doi et al. (2016), uncertainties in ocean vertical mixing estimations, ocean physics is perturbed in two different ways by considering or neglecting ocean vertical mixing induced by small vertical-scale structures (SVSs) within and above the equatorial thermocline (Sasaki et al., 2012). This similar paradigm also ensures the quantification of uncertainties of both initial conditions and model physics for forecasts.

The most striking advantage of the CCAM is that, as noted earlier, it embraces a dynamic kernel and physics all cast on a cube-based grid and can be applied either at quasi-uniform horizontal resolution to function as a global climate model, (here we use C96 resolution approximately corresponds 105 km^2), or in stretched-grid mode to function as a high-resolution regional climate model (RCM). In the current ultra-high resolution experiment, the CCAM uses C192 stretched-grid configuration which is a resolution approximately about 8 km^2 over the Southern Africa where the centre of the panel is placed, while it has coarse resolution elsewhere, as shown Figure 3-5. To arrive at this high-resolution, the C192 experiment is constrained with the C96 integration of the AGCM in order to maintain numerical stability and achieve a balanced simulation consistent with the driving AGCM reinforced with spectral nudging technique of Thatcher and McGregor (2010) while the RCM is allowed to freely develop self-dynamics coherent to the expected regional details.

3.2.2.4. Verifying Observed data

Climate Hazards Group InfraRed Precipitation (CHIRP) is quasi-global rainfall dataset. Spanning 50°S-50°N (and all longitudes), starting in 1981 to near-present, CHIRP(S) incorporates 0.05° resolution satellite imagery without (with) in-situ station data to create gridded rainfall time series for trend analysis and seasonal drought monitoring (Funk et al., 2015). We use the version that doesn’t include station data (due to the quality concern and lack of homogeneity in in-situ observation coverage over the southern Africa sub-continent (J. Malherbe, 2018, personal communication).

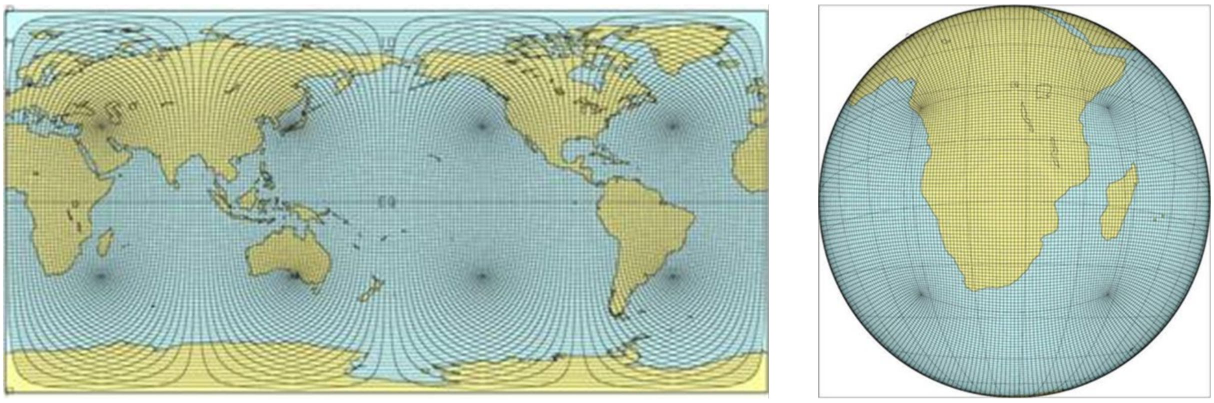

Figure 3-5 Example of C96 quasi-uniform global resolution (about 100 km; left) and C192 stretched-grid resolution zooming in over southern Africa (about 8 km; right) while coarse resolution elsewhere

3.2.3. Results and discussion

3.2.3.1. Climatological representation

The results presented in this section are taken from the November initialized C96 (quasi-uniform resolution; only for the seasonal time scale included) global and C192 regional (8k resolution over southern Africa) CCAM hindcast simulations for the 15 years from 2000 to 2014. In this study, the lead time in a seasonal prediction context is defined from the starting month when the model is initialized (Beraki et al., 2006). While the S2S time scale is from day 11 to 30 from the model initialization date (20 Nov to 9 Dec for each year). The Nov initialized hindcast which embrace the vicinity of mid-summer is to assess the performance of the model simulations since the region has profound tropical influence and **noncable** ENSO (El-Niño Southern Oscillation) signature (Shukla, 1981; Mason et al., 1996).

Figure 3-6 compares the model climatological simulation and corresponding observation both for the ERF and seasonal time scales. For the former, the model and observation a good level of agreement on the climatological representation of daily rainfall accumulations. However, the model has a tendency to overestimate (underestimate) daily rainfall totals over the eastern part of South Africa adjacent to the eastern border of Lesotho and north-western part of the domain. For the seasonal time scale, it is shown that the model C192 configuration tends to show better climatological representation on the southern Africa region (Figure 3-6(d)) relative to the C96 CCAM configuration Figure 3-6(e). The latter particularly extends the rainfall regime to southern Namibia and western South Africa. We also shown rainfall over the surrounding Oceans to gain better insight into how the mid-summer rainfall regime is captured in the model. Both model simulations overestimated rainfall over Indian Ocean and its surround noticeably over Mozambique Channel while underestimating precipitation climatology over the Central part of the model domain (eastern-Angola, southern-Zambia, northern-Zimbabwe and -Mozambique). Nonetheless, the model global precipitation pattern reasonably resembles the Climate Research Unit (CRU 4.1; Harries et al., 2013) and the Global Precipitation Climatology Project (GPCP; Huffman et al., 2001) global observed data (not shown). It is worth noting however that the findings presented here are based on the preliminary results of the numerical experimentation. More extensive model simulations that include 50 km global resolution with a different convective scheme, interactive aerosol dynamic scheme are underway.

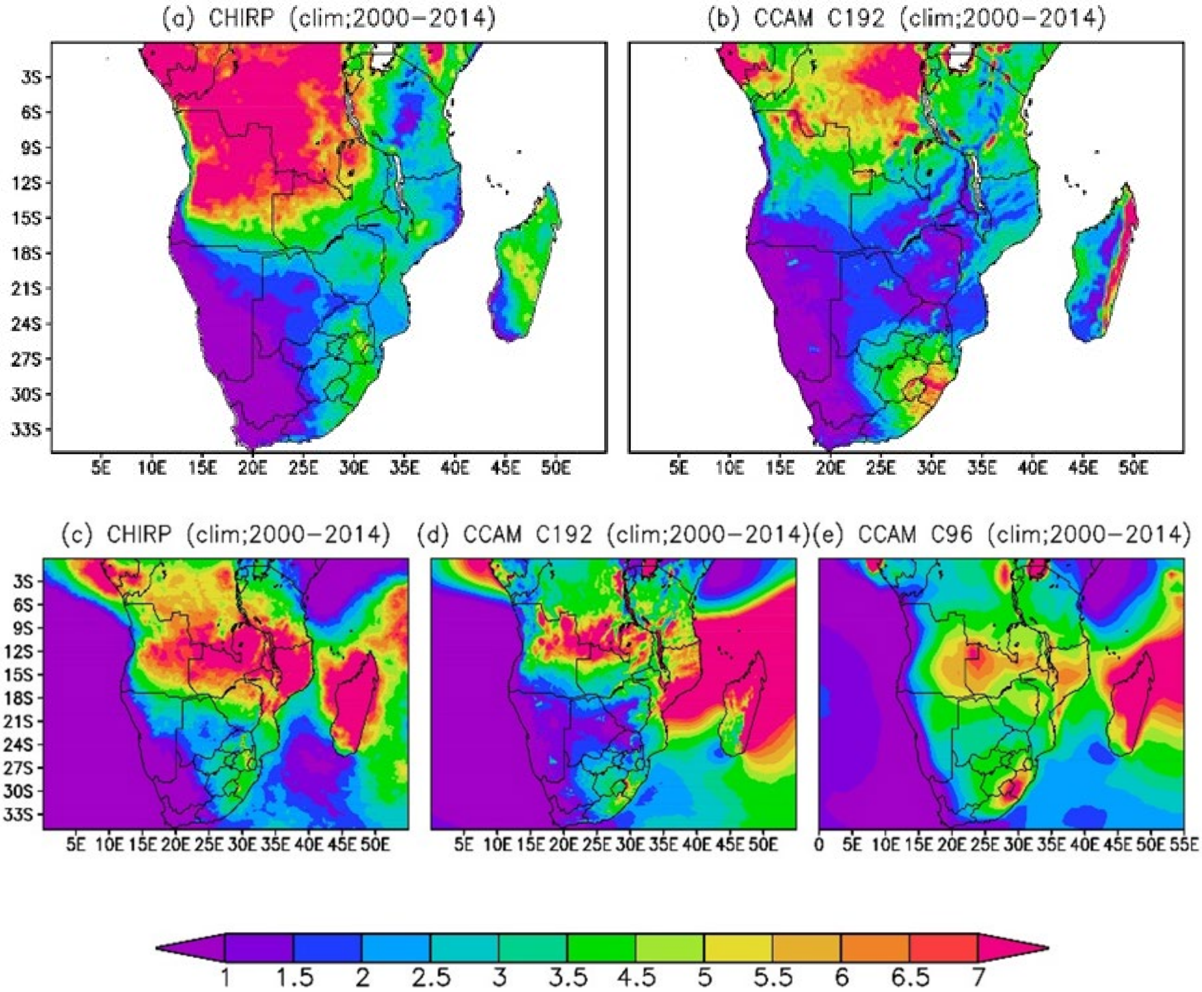

Figure 3-6 Daily Precipitation (mm/day) averaged over the 20 days spanning the date from 20 Nov to 9 Dec (2000-2014; a,b) and DJF 2000/01 to DJF 2012/13 (c-e). The observation is taken from CHIRP satellite estimates and ensemble mean CCAM-CABLE as showing in the title of each plot.

3.2.3.2. Retroactive forecast skill

The CCAM's C192 performance is investigated for both the ERF for the noted period and mid-austral summer one month lead. The verification is based on 270 (15 years × 18 ensemble members) model retroactive forecasts each consisting of 6-month integrations in order to establish forecast lead-times of up to 4 months. Each ensemble set emulates a set of operational forecasts issued on the 6 of November each year starting from 2000 to 2014. The model bias in the mean annual cycle was removed from the model forecasts prior to comparing the statistics, i.e. computing the anomalies of the model about its own drifted climatology as a function of different initialization time and lead-months (Wang et al., 2002; Schneider et al., 2003; DeWitt, 2005; Beraki et al., 2014, 2016).

The model evaluation is done probabilistically because climate prediction is assumed to be inherently probabilistic and applicably judges the model's ability or weakness in an operational context. Figure 3-7 presents the ability of the model to discriminate events from non-events using the relative operating characteristic area (ROC; Mason and Graham, 1999).

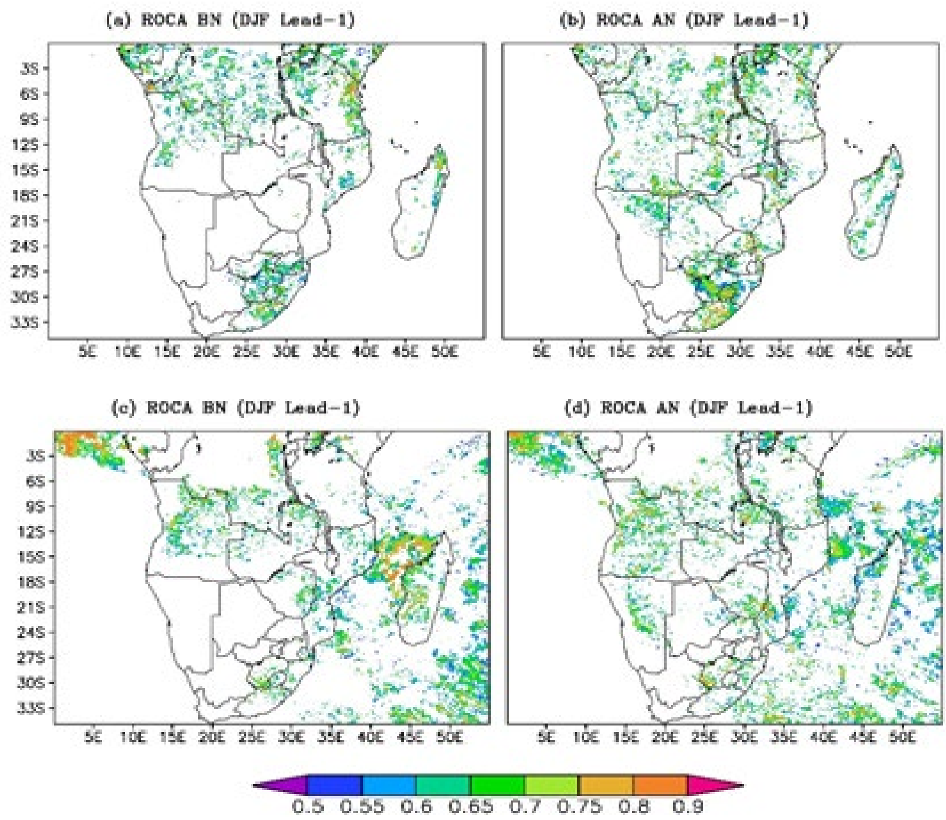

Figure 3-7 Southern Africa skill distribution as measured with ROC area daily accumulated rainfall (mm/day) the CCAM 8 km horizontal resolution for ERF (top) and seasonal (bottom) time scales for (a,c) below- and (b,d) above-normal categories. Only statistically significant values at the 95% level shades are shown.

It is noticeable that the model is skilful in discriminating below- and above-normal rainfall conditions over the southern Africa region where the tropical rainfall bearing system apparently associated with the seasonal migration of the ITCZ (Inter Tropical Convergence Zone) and tropical temperate trough (TTT; Harrison, 1984; Washington and Todd, 1999; Tyson and Preston-Whyte, 2000; Reason et al., 2006; Manhique et al., 2011). However, the C96 probabilistic skill is marginal (not shown) which suggests that the dynamical downscaling may be able to further augment the quality of forecast and potentially offer a better climate prediction strategy despite its computational cost. Furthermore, the extended-range time scale probabilistic skill is deeper for both categories over the summer rainfall region of South Africa relative to the corresponding seasonal probabilistic skill. The skill concentration decay toward as the simulation time progresses in time attests to the importance of resolution to shorter time scales and role of low frequency component of the atmospheric initial condition (Shukla, 1981) and longer time scales are presumably explained more by robustness of external forcings and their coupled interactions (such as ocean-atmosphere, land-atmosphere; Beraki et al., 2014, 2016). The ROC applied to probabilistic forecasts indicates whether the forecast probability was higher when an event such as a flood or drought season occurred compared to when it did not occur. ROC scores for the rainfall categories for example represent the respective areas beneath the ROC curve that is produced by plotting the forecast hit rates against the false alarm rates. If the area would be≤0.5, the forecasts have no skill, and for a maximum ROC score of 1.0, perfect discrimination has been obtained. As in Beraki et al. (2014), the significance test is conducted using a variant of the Mann-Whitney non-parametric procedure that explicitly accounts for variance adjustment caused by incidents of ties (Mason and Graham, 2002; Wilks, 2011).

3.2.4. Conclusion

In this section, we have tested an ultra-high resolution stretched-grid climate model applied to a seamless forecasting system strategy that encompasses both the extended-range and seasonal time scales in an attempt to realize a skilful and informative probabilistic climate prediction system for the Southern Africa region. The primary motivation for pursuing this computationally expensive model configuration, lies in the fact that this level of detail (if rigorously skilful) is vital for various climate application endeavours, and may have far-reaching positive implications. The numerical experimentation first employed CCAM (C92 quasi-uniform) global simulations forced with the SINTEX-F2 CGCM predicted SSTs and SICs, constrained with time-varying CO_2 and ozone and initialized with realistic atmospheric and land surface states. Subsequently, the CCAM C92 has driven the very same model's C192 ultra-resolution regional configuration in order to achieve a result that is stable and consistent with the synoptic patterns of the driving GCM. Furthermore, a spectral nudging technique was applied to minimize the potential climate drift. The AGCM probabilistic forecasts for the austral summer season for daily accumulated rainfall were fairly skilful particularly for the extended-range time scale. The model was able to discriminate significantly wet and dry episodes over the southern Africa region that is particularly dominated by tropical rainfall bearing systems which are believed to embrace noticeable ENSO signature. Climatologically, the dynamical downscaling was also found to further improve the rainfall pattern simulated by its driving GCM.

An output of the research was a 20 year (2000-2014) series of 40 day forecasts initialized on the first of November of each year and covering the period 1 November to 10 December. The forecasts incorporated rainfall, maximum temperature and minimum temperature, and consisted of an 18 member ensemble and an ensemble mean.

3.2.5. Recommendations and future plans

The work presented here is based on the preliminary results of the numerical experimentation. More extensive model simulations are underway that include 50 km global resolution with a different convective scheme, interactive aerosol dynamic scheme in order to maximize the predictive skill of the 8 km configuration presented in this section. In addition, the result suggests that a bias correction technique and statistical remapping procedure may be needed to minimise the systematic model errors and deepen model intelligence. Nonetheless, since ultra-resolution dynamical downscaling is computationally expensive, its predictive skill should be compared against a baseline skill level achievable by a statistical downscaling technique to justify its deployment in a seasonal forecasting paradigm, though the potential skill enhancement demonstrated on the extended-range time scale suggests that even increasing to finer resolution may be beneficial for future consideration.

The CSIR has been in the process of developing the next generation of seamless forecasting system with more emphasis for subseasonal to decadal time scales based on the state-of-the-art Variable-resolution Earth System Model (VrESM). The VrESM will support the future climate modelling research drive of the CSIR to advance the South African scientific contribution and develop multi-disciplinary research capability in South Africa. The use of ESMs (the highest hierarchy in contemporary climate modelling science in terms of complexity) are not widely practiced at the seasonal to inter-annual climate time scales due to computational consideration and complexity. However, under a global warming scenario, seasonal and interannual climate variability may undergo some behavioural changes or adjustments and need to be explicitly accounted for in climate model simulations. It is primarily motivated by the advances made in climate research during the past decade, which have led to the understanding that modelling and predicting a given climate anomaly over any region is incomplete without a proper treatment of the effects of SST, sea ice, snow cover, soil wetness, vegetation, stratospheric processes, and atmospheric composition (carbon dioxide, ozone, etc.). The approach is highly relevant to the contemporary international research agenda and particularly the research thrust of the World Climate Research Programme (WCRP) Working Group on Subseasonal to Interdecadal Climate Predictions (WGSIP).

3.3. Seasonal climate forecasts

Statistical downscaling of seasonal values, for both averages (e.g. maximum temperatures) and totals (e.g. rainfall), have been found to improve the seasonal-to-interannual forecast skill of global climate models (e.g. Landman and Goddard, 2002). In this project, the effort to improve seasonal climate forecasts (Aim 5) involved applying linear statistical procedures to downscale and improve hindcasts (re-forecasts) from coupled ocean-atmosphere models over SADC. Detail on the methods applied over the region include model output statistics (MOS; Landman et al., 2012; Lazenby et al., 2014) and improving raw climate model output through mean and variance bias correction.

A collection of hindcasts from a coupled ocean-atmosphere model of the North American Multi-Model Ensemble (NMME, Kirtman et al., 2014), the GFDL-CM2.5-FLOR-B01, and from the ECHAM4.5-MOM3-DC2 (DeWitt, 2005) are used to statistically downscale to a higher spatial resolution than the resolution of these coupled models. The resolution of the models vary from about 1°x1° to 2.8°x2.8°, while the downscaling or recalibration is performed on gridded data at a resolution of about 0.5°. The latter data is from the Climatic Research Unit (CRU) TS3.1 data set (Mitchell and Jones, 2005). The hindcasts are for monthly data from the early 1980s and are available for 12 ensemble members and for lead-times up to 11 months. We are using only 1- to 3-month lead-times hindcasts. The SADC area is from 15/17°S to 35°S; 11°E to 41°E.

The capability to produce high resolution forecasts was first demonstrated by presenting two types of maps. The first type is a set of examples that shows typical model skill after downscaling has been performed over a 30-year cross-validation period from 1982/83 to 2011/12 for the December to February (DJF) season. The second type shows DJF downscaled forecasts for SADC that could have been made at a 1-month lead-time (i.e. forecasts issued in November) during the El Niño season of 2009/10 and of the La Niña season of 2010/11.

Figure 3-8 shows the Spearman's correlations between downscaled rainfall (left) and maximum temperatures (right) hindcasts over the 30 year period and the observed CRU data. The downscaled hindcasts have been cross-validated with a 5-year-out window design. Take note that the resolution of the downscaled results can be seen on the maps.

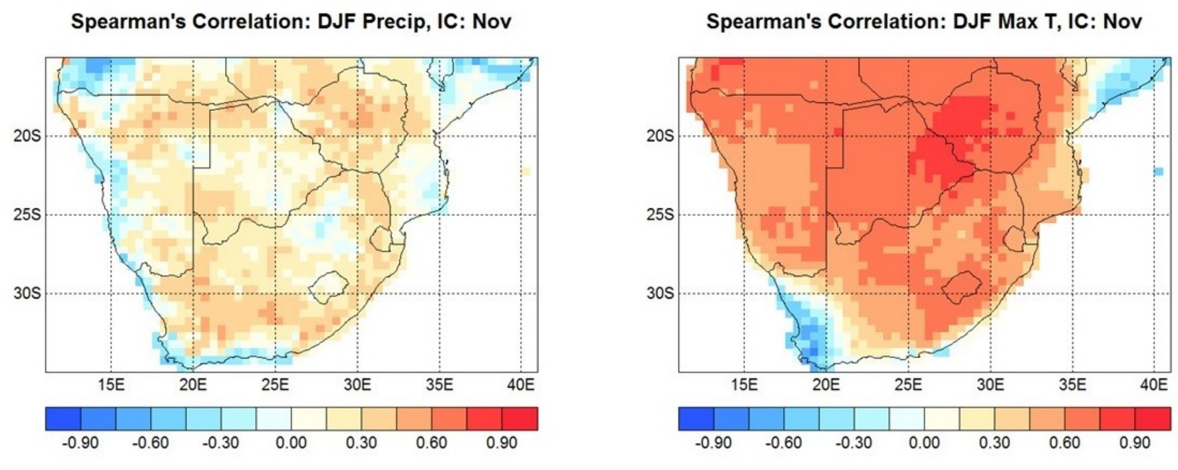

Figure 3-8 Spearman's correlations between CRU data and downscaled values (using ECHAM-MOM3 output as predictor in statistical downscaling model). The map on the left is for downscaled DJF rainfall totals, and the map on the right for DJF averaged maximum temperatures. These maps represent skill at a 1-month lead-time.

Probabilistic forecasts for SADC for the 2009/10 (El Niño) and 2010/11 (La Niña) seasons are presented next. Forecasts from two approaches and for two coupled models are presented. The first approach involves statistical downscaling coupled model output to the CRU resolution and the second approach involves applying bias corrections to the coupled models' rainfall forecasts. The downscaling is done by using the 850 hPa geopotential height fields of the

ECHAM4.5-MOM3-DC2 coupled model as predictor in a canonical correlation analysis (CCA) linear post-processing model, and the rainfall fields of the GFDL-CM2.5-FLOR-B01 coupled model in a separate CCA post-processing model. The probabilistic rainfall forecasts for the 2009/10 season are shown in Figure 3-9.

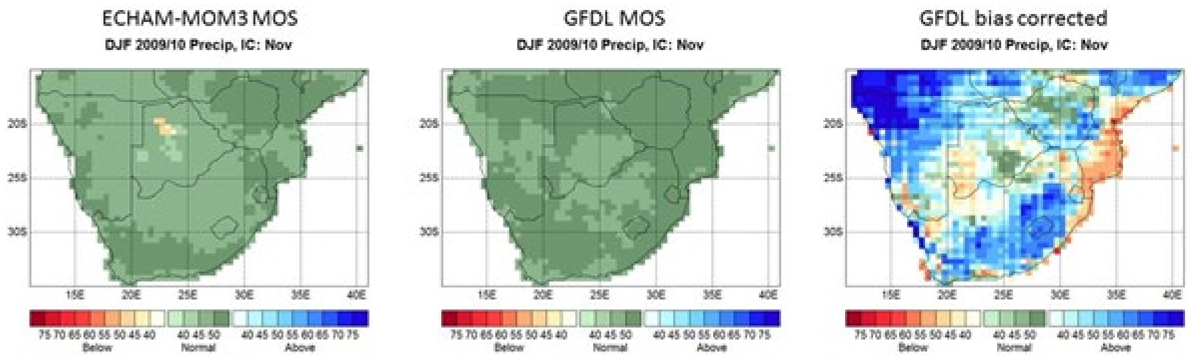

Figure 3-9. Probabilistic forecasts for 2009/10 DJF rainfall. Initialization month is November. The maps on the left and middle are forecasts obtained by statistically downscaling coupled model output to the CRU resolution. The map on the right is a forecast obtained by correcting biases of the GFDL coupled model. The bar at the bottom of each map shows the predicted probabilities for three categories (Below: ≤ the 25th percentile of the climatological record; Above: ≥ the 75th percentile of the climatological record; Normal: between the two outer categories).

The 2009/10 DJF period was not a typical El Niño drought season over SADC. The downscaled rainfall forecasts of Figure 3-9 reflect this outcome, although the bias corrected forecast (map on the right of Figure 3-9) is more favourable for a wet season than is the case for the downscaled forecasts where predominantly near-normal rainfall totals are predicted. Rainfall forecasts for the 2010/11 La Niña season are shown in Figure 3-10. Here we see that the downscaled and bias corrected forecasts are in agreement and show enhanced probabilities for a wet DJF season. In fact, 2010/11 was a season of serious flooding over parts of SADC (Muchuru et al., 2016).

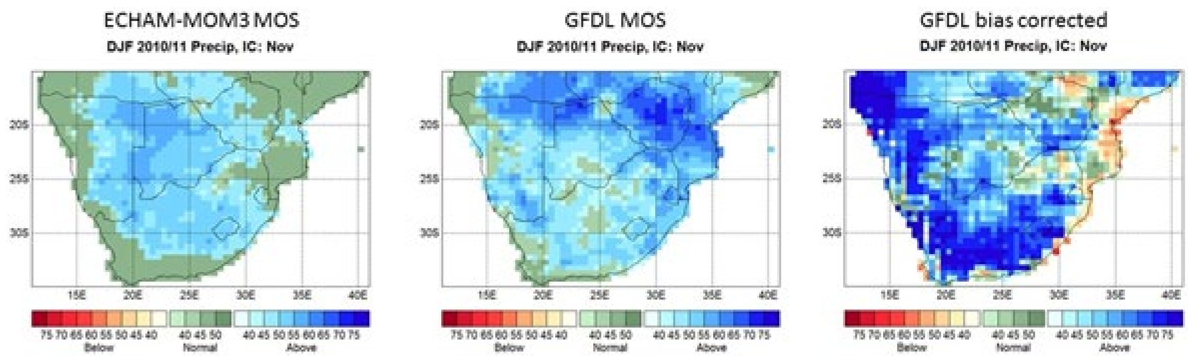

Figure 3-10 As for Figure 3-9, but for 2010/11

Our downscaling capability is also demonstrated for maximum temperatures. Figure 3-11 shows the temperature forecasts for the two ENSO seasons. These examples show a typical ENSO pattern of hot conditions during El Niño and cool conditions during La Niña-enhanced probabilities for the above (below) maximum temperature category to materialize during El Niño (La Niña).

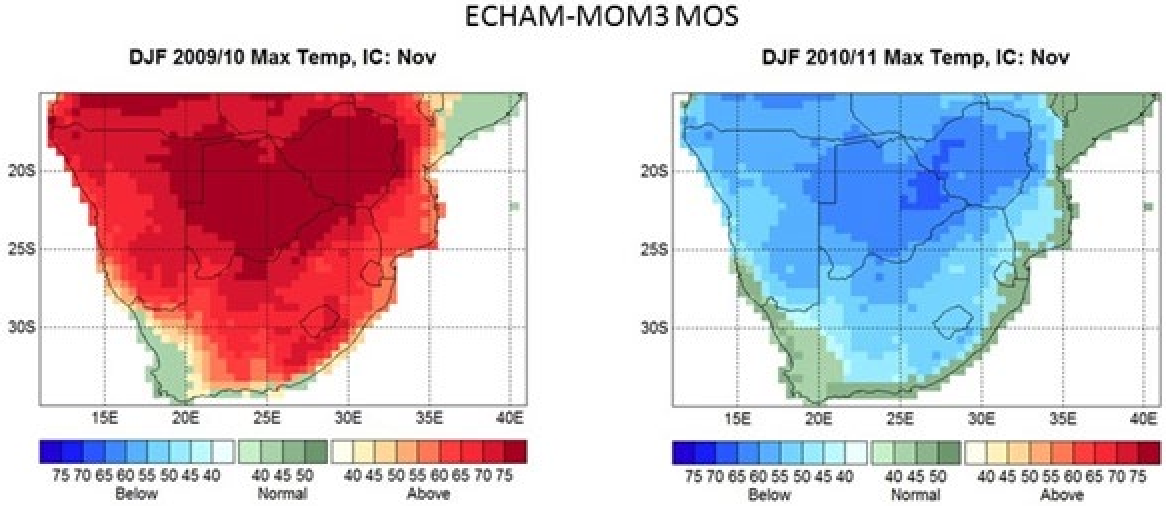

Figure 3-11 Downscaled maximum temperature forecasts for the two ENSO seasons. Downscaling is done by using the 850 hPa geopotential height fields of the ECHAM4.5-MOM3-DC2 coupled model is input in a linear statistical post-processing model. The bar below each map represents the predicted probabilities for each category.

The results presented here show that the capability to improve on the horizontal resolution of coupled ocean-atmosphere models has been developed in the project. Also demonstrated are two statistical methods of downscaling: from predicted low-level circulation to rainfall/temperature through linear methods, and bias correcting rainfall/temperature hindcasts of the coupled model. We focus on the bias correction approach since the NMME project do not make available low-level circulation data (e.g. 850 hPa geopotential height fields) for real-time predictions. However, as is shown below, bias correction has the ability to provide skilful downscaling models.

The above results are presented for a 30-year cross-validation period. Next we will demonstrate skill for the DJF season over a 20-year retro-active forecast period from 1993/94 to 2012/13. The retro-active forecast and verification procedures applied here are very similar to those described before (Landman et al., 2014). Here the initial training period is over 13 years from 1980/81 to 1992/93, and the training period is incremented for each hindcast over the 20 years by one year. Figure 3-12 shows the initial training (stand-alone red line) and hindcast period (red line and associated green line). This figure shows the deterministic retro-active hindcasts for the grid-point indicated on the figure which is located just off the Limpopo River. Take note that the longer lead DJF rainfall hindcast (initialisation of the coupled model in September) has a slightly higher skill level (higher correlation) than the shorter lead hindcast initialised in November. Such an occurrence of seemingly more skilful hindcasts at longer lead-times may be a function of the relatively short verification period and is often the case when predicting variables such as rainfall for which forecast skill is marginal. This discrepancy is not seen for the high skill hindcasts for maximum temperatures shown in Figure 3-13.

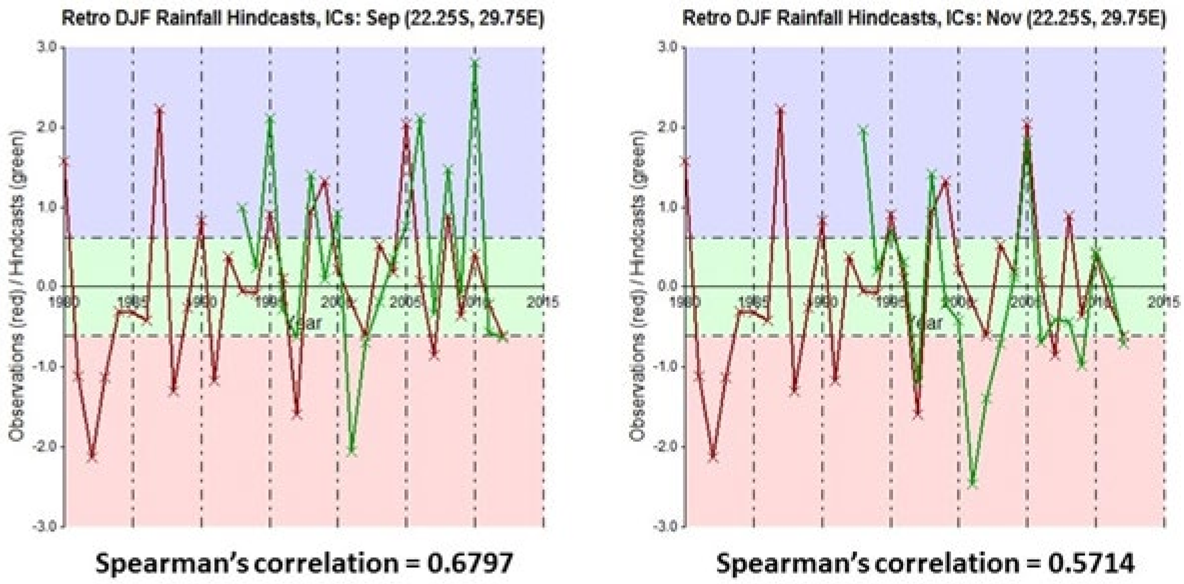

Figure 3-12 Retro-active hindcasts for DJF rainfall at the grid-point lat-long indicated on the figure. The hindcasts and the observations are normalised values. The three categories as specified in the text are respectively shown as blue (above-normal), green (near-normal) and red (below-normal).

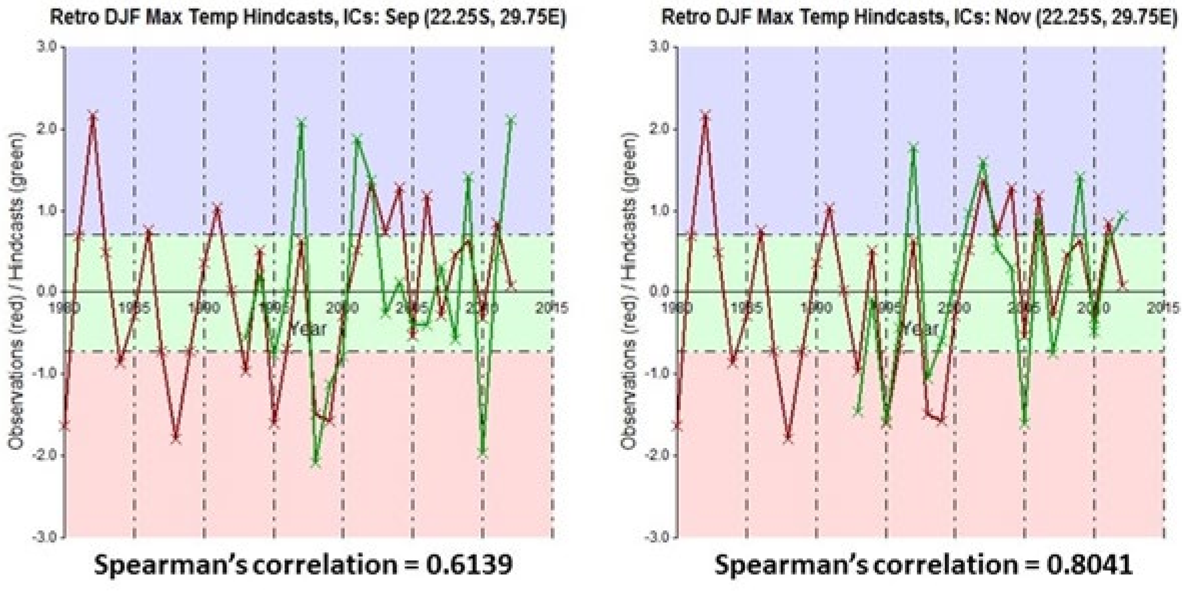

Figure 3-13 As for Figure 3-12, but for maximum temperatures

Seasonal maximum temperatures over SADC are highly predictable when compared with seasonal rainfall as well as with seasonal minimum temperatures (Lazenby et al., 2014). This result that maximum temperatures skill is superior to that of minimum temperatures is also found here for the grid-point near the Limpopo River (compare Figures 3-13 and 3-14). In fact, seasonal minimum temperature hindcast skill at the specific location is even lower than rainfall hindcast skill.

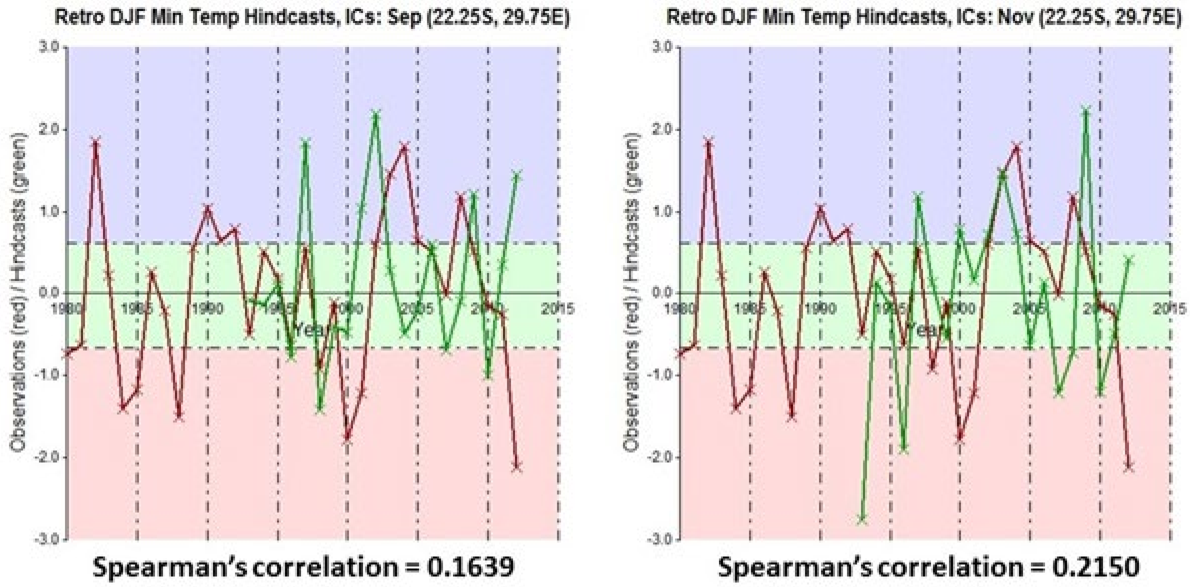

Figure 3-14. As for Figure 3-13, but for minimum temperatures

Seasonal forecasts are of a probabilistic nature and so should be judged probabilistically. Here we present relative operating characteristic (ROC; Mason and Graham, 2002) scores over SADC for DJF rainfall (Figure 3-15), maximum (Figure 3-16) and minimum temperatures (Figure 3-17) at a one-month lead-time as calculated over the 20-year verification period presented in Figures. 3-12 to 3-14. ROC scores (the area below the ROC graph) is a function of hit rates against false-alarm rates. For good forecasts the hit rate will accumulate faster than the false-alarm rate, resulting in high ROC scores. For perfect discrimination (whether the hindcasts are discernibly different given different outcomes) the ROC score would be 1.0, and for no skill the ROC score would be 0.5 or less. ROC applied to probabilistic forecasts indicates whether the forecast probability was consistently higher when, for example, a flood or drought season occurred compared to when it did not occur. Although the ROC is a verification procedure recommended by the World Meteorological Organisation, it has been criticised because the reliability of the forecast probabilities is ignored. Although reliability estimates, along with other skill estimates are not provided in this report, these can be easily calculated for the 20-year hindcast period.

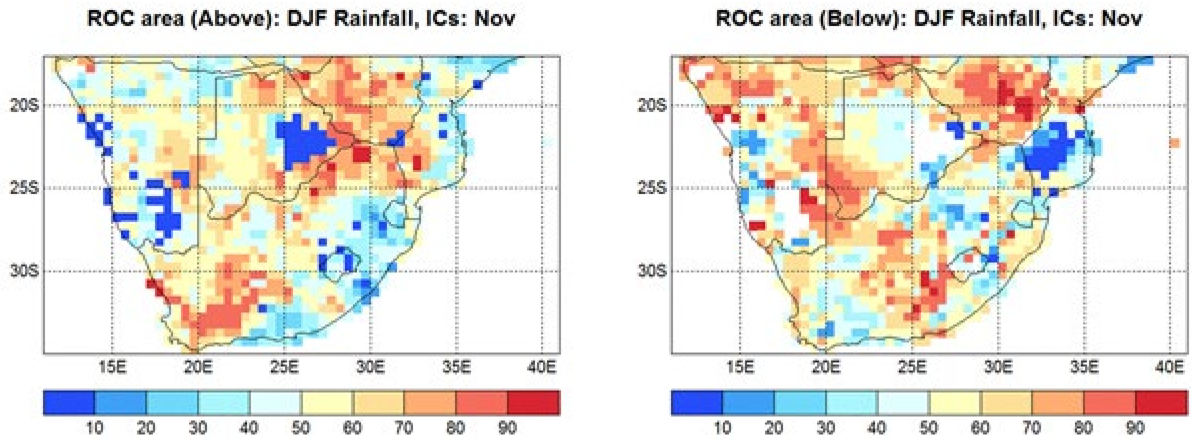

Figure 3-15 ROC scores for above- and below-normal DJF rainfall hindcasts as calculated over the 20-year period specified in the text. The ROC score at each grid box needs to be higher than 0.5 in order for a forecast system to be regarded skilful at the specific grid box.

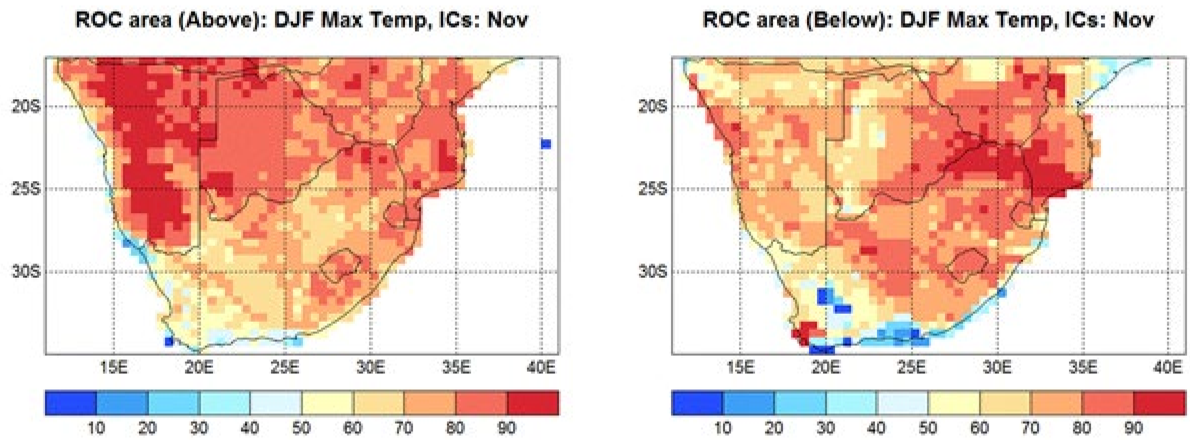

Figure 3-16 As for Figure 3-15, but for maximum temperatures

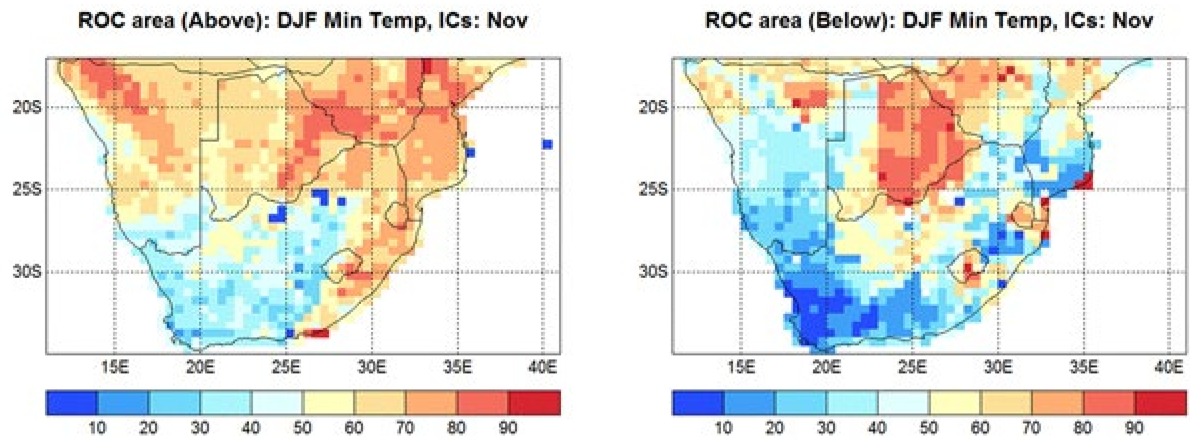

Figure 3-17 As for Figure 3-16, but for minimum temperatures

An indication of the relative levels of model skill in predicting seasonal rainfall, minimum and maximum temperatures over SADC have been presented here, albeit over a restricted subset of DJF seasons. However, the project has generated hindcasts for all three-month overlapping seasons from Jan-Feb-Mar to Dec-Jan-Feb (12 in total) and for lead-times from one to three months. These hindcasts require temporal downscaling to be suitable for use in a hydrological model such as ACRU.

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CHAPTER 4. CONFIGURATION AND VERIFICATION OF THE ACRU MODEL IN THE MHLATHUZE CATCHMENT

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4.1. Overview of the ACRU model

The ACRU agrohydrological model is sensitive to weather, soils and land cover, and can simulate irrigation processes, catchment streamflow and reservoir water balances. It is thus suited to developing agrohydrological forecasts for the Mhlathuze catchment, including forecasts of the level of the Goedertrouw Dam.

As a conceptual-physical soil water budget model, ACRU (Schulze, 1995 and updates) integrates various water budgeting and runoff producing components of the terrestrial hydrological system, as well as operational aspects of water resource management, all with risk analysis (Schulze, 1995; Smithers and Schulze, 2004). The model was designed as a daily time-step, two layer soil water budgeting model which has been structured to be sensitive to land use changes on soil moisture, evaporative rates and runoff regimes. The model has been considerably updated from original versions to its present status (Smithers and Schulze, 2004) in order to simulate those components and processes of the hydrological cycle which are affected by the soil water budget, such as stormflow, baseflow, irrigation demand, sediment yield or crop yield, and to output any of those components on a daily basis (where relevant), or as monthly and annual totals of the daily values. A summary of the concepts of the ACRU model with respect to inputs, operational modes, simulation options and objectives is given in Figure 4-1, and Figure 4-2 represents a schematic of the multi-layer soil water budgeting by partitioning and redistribution of soil water, as conceptualised in the ACRU model.

4.2. Disaggregation of the Mhlathuze catchment for ACRU modelling

South Africa, Swaziland and Lesotho have been delineated into nested hierarchical catchments or hydrological unit boundaries by the South African Department of Water and Sanitation (DWS) for the planning and management of water resources. This hierarchical system of catchments range from primary, through to secondary and tertiary and finally to Quaternary catchments. A total of 1946 Quaternary catchments cover South Africa, Swaziland and Lesotho. Until recently, the quaternary catchments were the smallest operational units. With substantial datasets linked to these scaled catchments, they are used in a wide range of studies, for example, hydrological modelling, climate change and water resource management. However, the need for sub-quaternary level scale information was highlighted.

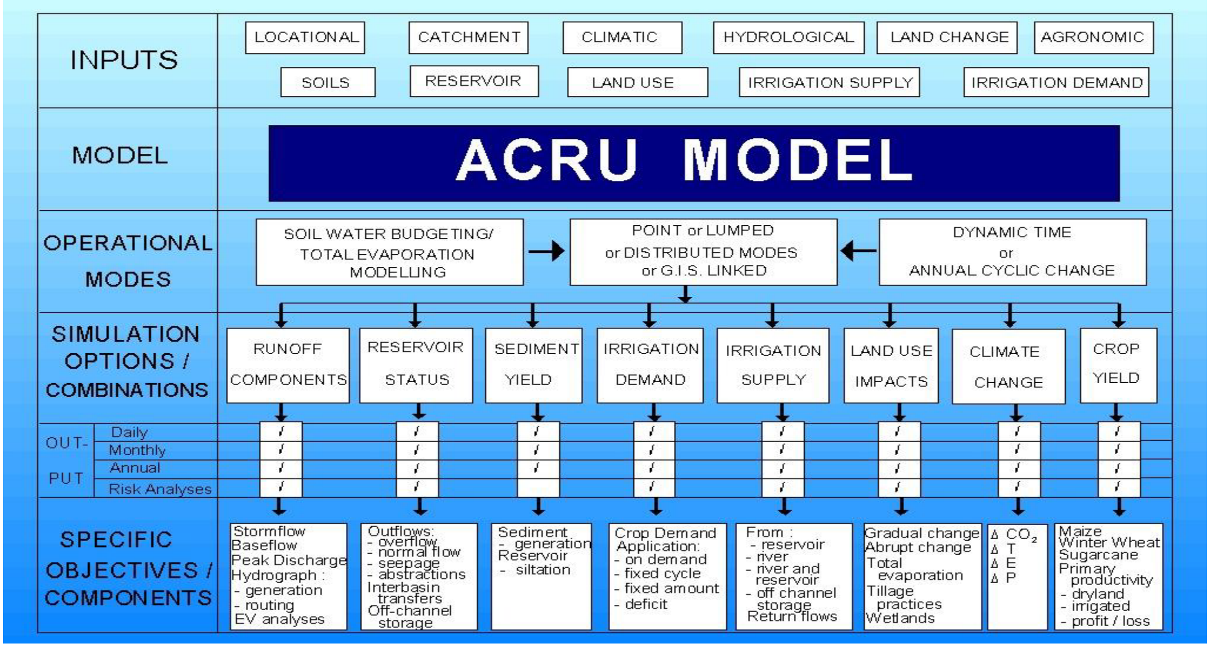

Figure 4-1 The ACRU agrohydrological model: Schematic of inputs, modes of operation, simulation options and objectives / components (Schulze, 1995)

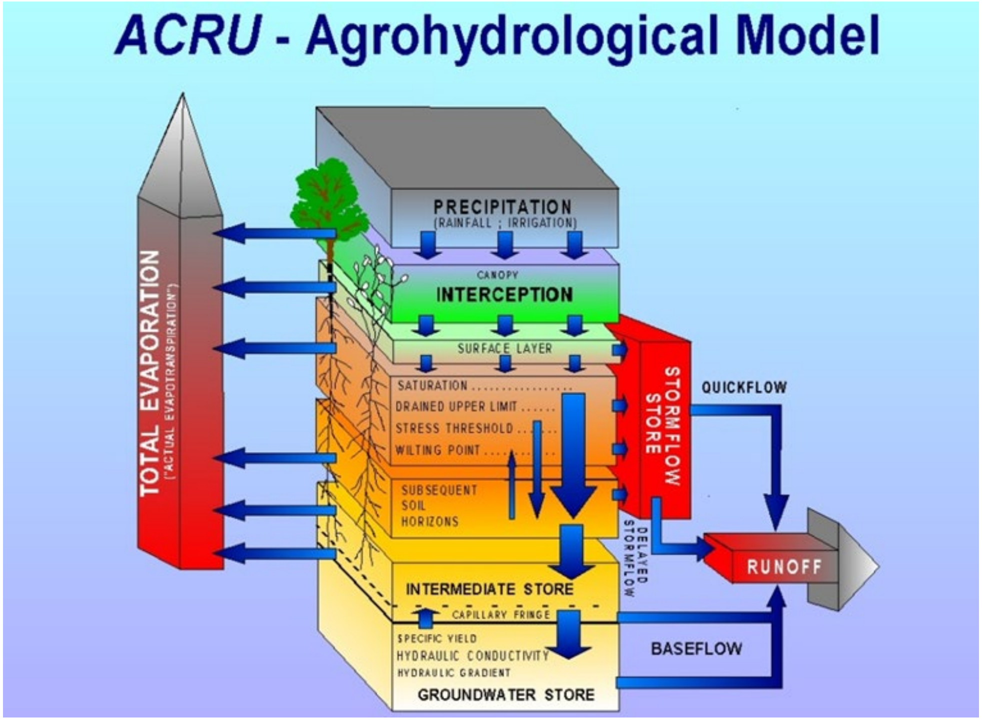

Figure 4-2 The ACRU agrohydrological model: Schematic of its multi-layer soil water budgeting and partitioning and redistribution of soil water (Schulze, 1995)

Disaggregation of fourth level quaternary catchments into fifth level quinary catchments, which are hydrologically more homogenous catchments, was therefore performed. Following the altitudinally-driven delineation of hydrologically interlinked quinary catchments for South

Africa, Swaziland and Lesotho, the previously developed Quaternary Catchment Database was expanded to a Quinary Catchments Database. This database includes hydrological variables such as rainfall, potential evaporation, crop growth and transpiration parameters, soil attributes, stormflow response variables and daily and monthly temperature information. The weather variables are available for a 50 year period from 1950 to 1999. A total of 27 Quinary catchments exist within the Mhlathuze catchment (Figure 4-3).

The quinary catchments are numbered in a downstream order in a similar manner to the quaternary catchments. For example, in quinary catchment W12A3:

- the letter W denotes the primary drainage region;
- the number 1 indicates that the quinary catchment lies within the secondary drainage region number 1;
- the number 2 indicates that the quinary catchment lies within the 2nd tertiary drainage region of the secondary drainage region number 1;
- the letter A indicates the quaternary catchment within the tertiary drainage region; and
- the number 3 indicates the lower quinary catchment within the quaternary catchment A (each quaternary catchment is divided into an upper, middle and lower quinary catchment).

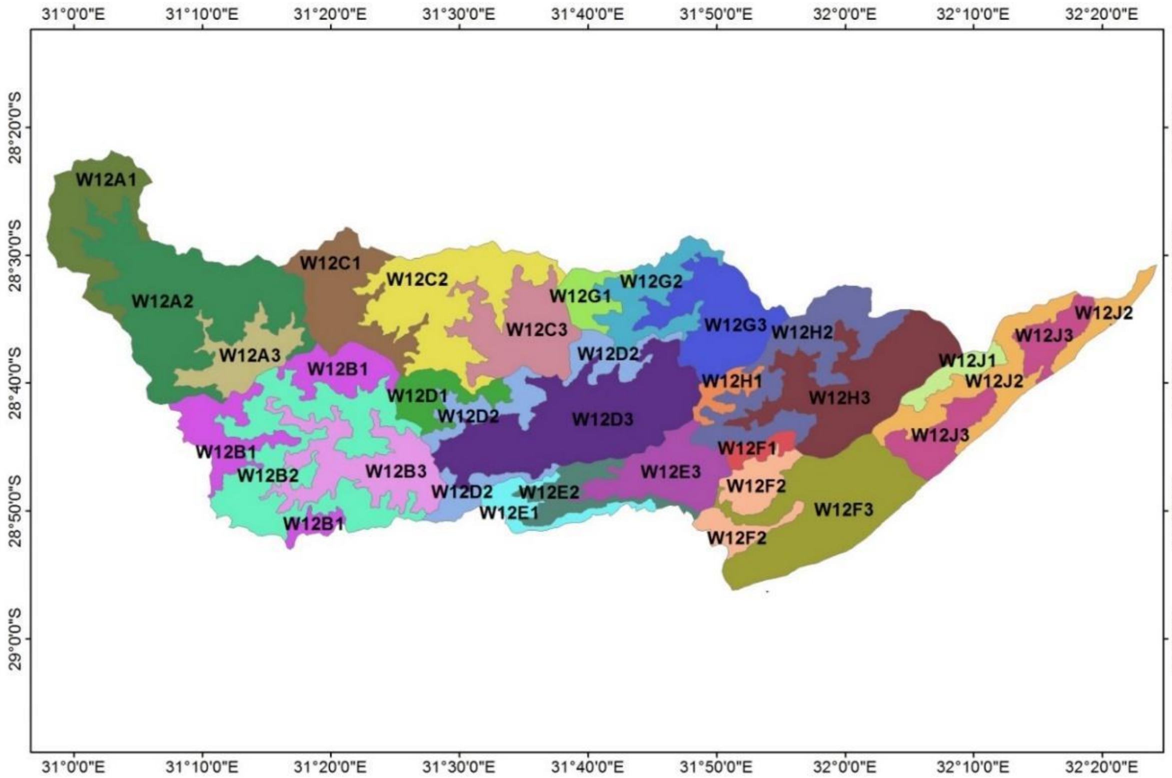

Figure 4-3 Quinary catchments in the Mhlathuze catchment

4.3. Input data to ACRU

4.3.1. Observed weather and streamflow data

In terms of weather data the ACRU model minimally requires inputs of daily rainfall and monthly means of daily maximum and minimum temperature (Schulze, 1995). Daily rainfall is the most important input into the daily time step ACRU model as hydrological responses are most sensitive to this input. For forecasting purposes, it is necessary to obtain up-to-date daily rainfall input for each quinary catchment. This requires the selection of currently active rain gauges within and around the catchment. These stations would not necessarily be the same as the stations included in the Quinary Catchments Database, since some of the latter have been discontinued or are no longer the most suitable stations to represent particular quinary catchments. Sources of rainfall data for active stations within and around the catchment area include SASRI and South African Weather Services (SAWS) rain gauges. The final set of active rainfall stations selected to represent rainfall in the various parts of the catchment all had a record of greater than 10 years in length. These stations included a total of 13 SASRI and SAWS stations (Figure 4-4) for the study period from the 1 January 1997 to 31 May 2010. The selection was based on the reliability of the historical record, together with the altitude and proximity of the station to the relevant quinary catchment and/or streamflow gauge. Rainfall data for the period pre-2000 was obtained from the Lynch (2004) database (where data were available for active stations), while data post-1999 was obtained directly from the organisation managing the station (SASRI or SAWS). This ensured the longest record possible for the selected stations since records obtained directly from the data providers did not necessarily extend to the beginning of the station's record.

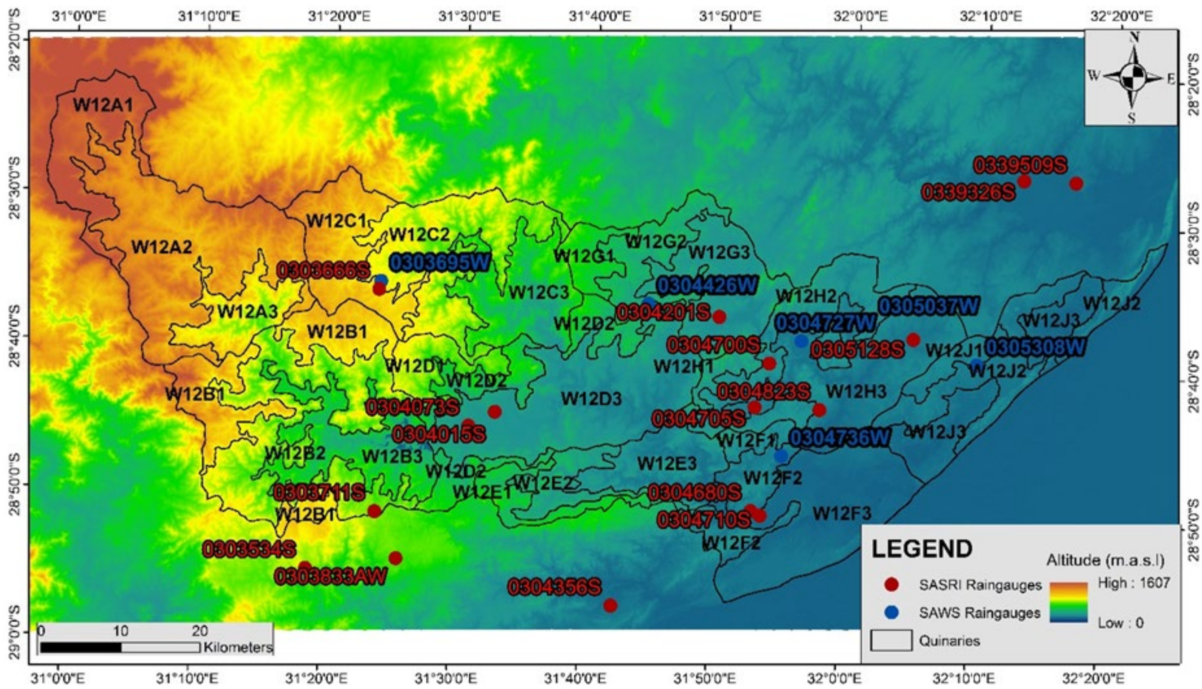

Figure 4-4 Active SASRI and SAWS rain gauges selected to represent rainfall in the Mhlathuze catchment

The ACRU model allows for the option to invoke rainfall adjustment factors (CORPPTs) on a month-by-month basis for a more improved representation of the rainfall in each subcatchment. These CORPPTs were calculated by dividing each quinary's median monthly rainfall by the median monthly rainfall of the rainfall station representing that quinary (Table 4-1). The median monthly rainfall of each quinary catchment was obtained from the monthly raster surfaces produced by Lynch (2004).

Since daily A-pan and maximum and minimum temperature records were not available for the catchment after the year 2000, the option to use mean monthly totals of daily A-pan equivalent evaporation (unscreened) was invoked in the ACRU model. These mean monthly data are available in the Quinary Catchments Database.

Observed daily streamflow data were available for four weirs within the catchment (Table 4-2). Historical records extend as far back as 1948 and run to the present. Weirs W1H005 and W1H028 were selected as locations for the verification of the ACRU model (Figure 4-5). This was based on the aim to accurately simulate locations of key land uses as well as reservoir storage levels and water availability after abstractions below Goedertrouw Dam.

Table 4-1 Selected rainfall driver stations for each catchment and the associated month-by-month adjustment (CORPPT)

subcat	Altitude	MAP	Correlation (Median monthly	Driver station	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC
5089	1257	802	0.996	0303695W	0.98	0.97	1.00	1.00	1.06	0.82	0.69	1.20	0.99	1.05	1.10	1.05
5090	1026	907.8	0.997	Entumeni Sugar Estate	1.01	0.97	1.02	0.89	1.09	0.84	0.75	1.00	0.97	0.90	0.97	1.01
5091	748	996.09	0.988	Eshowe Woodgarth	1.34	1.20	1.17	1.27	1.26	0.87	0.86	1.03	1.02	1.33	1.13	1.13
5092	862	1035	0.995	Eshowee Brocklee Farm	1.03	0.93	0.98	1.04	0.90	0.78	0.78	0.79	0.93	1.08	1.03	0.99
5092	863	1035	0.995	Eshowee-Brocklee	1.00	0.95	0.97	1.04	0.88	0.78	0.78	0.89	0.97	1.05	0.99	0.94
5092	862	1035	0.997	Eshowee-Brocklee	1.06	1.03	1.03	1.12	0.88	0.81	0.78	0.89	0.97	1.13	1.11	1.06
5093	602	997	0.996	Eshowee Brocklee Farm	1.03	0.98	0.99	1.06	0.85	0.81	0.78	0.86	0.97	1.12	1.06	1.02
5094	367	931	0.994	Eshowee-Brocklee	1.10	1.05	1.02	1.12	0.85	0.85	0.78	0.91	1.02	1.18	1.16	1.14
5095	907	910	0.992	Entumeni Sugar Estate	1.07	1.01	1.04	0.92	1.21	0.79	0.75	0.78	0.82	0.92	0.98	1.09
5096	639	888	1.00	Entumeni Sugar Estate	1.10	1.03	1.07	0.94	1.03	0.84	0.75	0.86	0.88	1.01	1.08	1.12
5097	374	846.82	0.980	Kwambonambi	1.10	1.05	1.02	1.33	1.26	1.41	1.28	1.15	1.01	1.19	1.12	0.89
5098	584	964	0.992	Eshowee-Brocklee	1.00	0.95	1.01	1.10	0.81	0.93	0.85	0.89	0.95	1.14	1.07	1.07
5099	329	979	0.975	Mtubatuba	1.21	1.09	0.93	1.22	0.86	1.16	0.93	0.95	0.84	1.14	1.17	1.00
5099	329	844	0.99	Nkwaleni	1.12	1.15	1.18	1.31	1.19	1.39	1.23	0.98	0.94	1.12	1.14	0.97
5099	328	845	0.99	INYONI	1.12	1.12	1.06	1.23	1.27	1.00	1.02	1.13	1.19	1.27	1.35	1.16
5100	139	831	0.99	Kulu Halt	1.11	1.05	1.03	1.30	1.12	1.20	1.23	1.11	0.92	1.14	1.10	0.99
5101	341	1175	0.98	0304727W	1.14	1.19	0.97	0.92	0.99	1.06	0.82	0.91	0.89	0.91	0.98	1.16
5102	212	1020	0.992	0304736W	0.93	0.88	0.86	1.00	1.02	0.90	0.99	0.84	0.81	0.90	0.83	0.86
5103	91	1026	0.984	0305308W	0.94	0.99	1.02	1.22	1.18	1.08	1.10	1.08	0.91	1.00	1.05	0.99
5104	396	826	0.989	KULU HALT	1.13	1.05	1.03	1.32	1.12	1.25	1.29	1.15	0.95	1.15	1.15	1.05
5105	255	783	0.995	0304736W	1.14	1.10	1.09	1.32	1.29	1.13	1.23	1.18	1.16	1.25	1.16	1.15
5106	149	867	0.988	Ukulu properties	1.04	1.04	1.01	1.02	0.96	0.89	0.85	0.88	0.90	1.19	1.21	1.06
5107	178	979	0.978	0305308W	0.94	0.97	1.07	1.32	1.27	1.27	1.16	1.19	1.03	1.15	1.12	1.04
5108	111	1021	0.993	Empangeni Mill	1.23	1.16	1.11	1.06	0.84	0.86	0.70	0.84	0.82	1.01	1.16	1.06
5109	56	1094	0.977	0305308W	0.89	0.93	1.00	1.17	1.01	0.98	0.94	0.98	0.88	1.03	1.05	1.06
5110	107	1123	0.974	0305308W	0.88	0.93	0.93	1.13	1.00	0.88	0.92	0.92	0.88	0.97	1.07	1.08
5111	64	1175	0.982	0305308W	0.90	0.93	0.92	1.05	0.97	0.85	0.86	0.88	0.83	0.91	1.04	1.03
5111	64	1175	0.984	0305308W	0.88	0.90	0.87	0.93	0.91	0.74	0.78	0.76	0.72	0.81	0.93	0.94
5112	21	1227	0.974	0305308W	0.87	0.89	0.83	0.92	0.82	0.72	0.72	0.76	0.76	0.89	1.01	0.99
5113	80.47	1203	0.937	0305308W	0.83	0.86	0.92	0.96	0.77	0.74	0.72	0.76	0.72	0.91	1.08	1.12
5114	57.83	1242	0.957	0305308W	0.79	0.83	0.89	0.90	0.79	0.69	0.69	0.75	0.78	0.89	1.01	1.03
5114	57.83	1242	0.94	0305308W	0.82	0.85	0.89	0.93	0.74	0.72	0.69	0.75	0.78	0.90	1.08	1.11
5115	28.16	1214	0.94	0305308W	0.81	0.86	0.92	0.93	0.83	0.72	0.70	0.78	0.80	0.94	1.09	1.11
5115	28.16	1214	0.943	0305308W	0.95	0.94	0.86	0.93	0.69	0.72	0.71	0.78	0.83	0.93	1.08	1.11

Table 4-2 Observed weir information within the Mhlathuze catchment

Weir	Quinary	River	Area (km^2)	Latitude	Longitude	Start Date
W1H005	W12C2	Mfulazane River at Golden Reef	45	-28.57207	31.39257	1948-08-11
W1H028	W12B3	Mhlathuze River below Goedertrouw Dam	1273	-28.76635	31.46666	1979-10-30
W1H009	W12D3	Mhlathuze River at Riverview	2408	-28.74817	31.74563	1960-11-02
W1H032	W12F3	Mhlathuze River at Umhlathuze Valley	2678	-28.80128	31.95539	1993-02-02

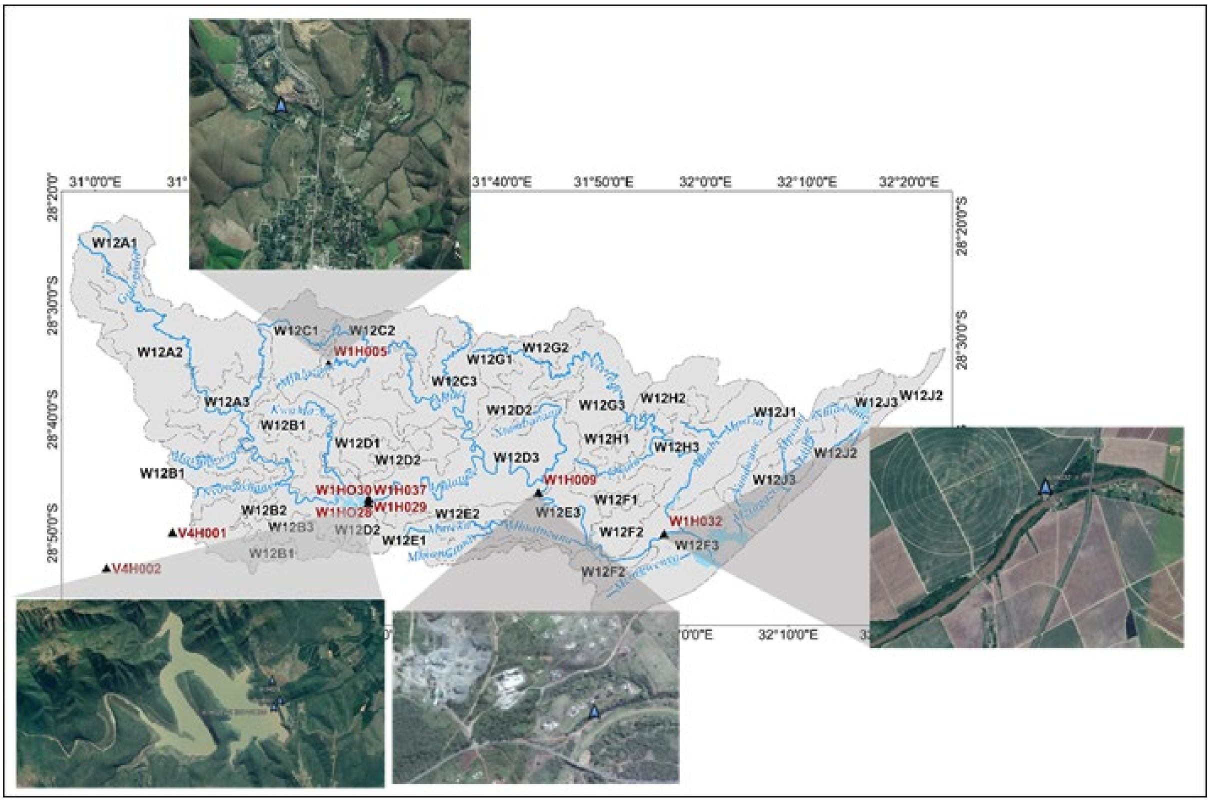

Figure 4-5 Locations of weirs within the Mhlathuze catchment selected for verification analysis (W1H005 and W1H028). Other weirs in the catchment are also indicated (W1H009 and W1H032).

4.3.2. Land Cover

Land cover plays an important role in the processes of plant and soil water evaporation. In ACRU modelling, relevant above-ground processes include evaporation of intercepted water, soil water evaporation and transpiration, while below ground processes include root water uptake and associated plant stress thresholds.

Information on present land cover in the Mhlathuze catchment was sourced from the National Land Cover (2001) database. When initially extracting land cover information from the National Land Cover (NLC) database there were 40 land cover categories found in the catchment (Table 4-3). For modelling purposes it was decided to lump similar categories together so that the number of land cover units represented in the modelling would be more manageable. The lumped land cover categories included natural vegetation, forestry plantations, dryland sugarcane, irrigated sugarcane, subsistence farming, urban (formal), urban (informal), waterbodies, mines and estuaries. A map showing the lumped land cover categories in the Mhlathuze catchment is given in Figure 4-6.

Information was also extracted from the Acocks Veld Type (1988) map of South Africa and is mapped in Figure 4-7 for the Mhlathuze catchment. This information was used to develop a second configuration of ACRU in the Mhlathuze catchment. This configuration simulates what streamflow would be in the catchment under natural (undisturbed) conditions.

Subsequent to producing the map of land cover in Figure 4-6, the areas of plantation forestry in the catchment were disaggregated into the different tree species present in the catchment (acacia, pine, eucalyptus) to reflect their varying water use patterns. The breakdown of the areas of different land covers in each quinary catchment (including the distinction between forest species) is shown in Table 4-4 where sugarcane includes only dryland while commercial irrigated group included the irrigated cane and other irrigated crops The different land covers in a quinary catchment were represented as Hydrological Response Units (HRUs) in the ACRU model configuration. The hydrological attributes of land cover that ACRU requires include monthly means of crop coefficients, canopy interception loss (mm) per rainday and fractions of active roots in the topsoil horizon. In addition, the effective total rooting depth and fraction of Plant Available Water (PAW) at which plant stress sets in, are also required.

For the estimation of canopy interception loss in ACRU, the monthly interception loss parameter (VEGINT) for each land cover was used. These values were obtained from Smithers and Schulze (2004). The option to enhance evaporation for forest canopies was invoked for the commercial forestry within the catchment. This is due to the faster rates of evaporation of intercepted water on forested surfaces as compared to the available energy from reference potential evaporation.

Table 4-3 Initial land cover categories extracted from the National Land Cover (2001) database

Land Cover Categories
Bare Rock and Soil (erosion : dongas / gullies)
Bare Rock and Soil (erosion : sheet)
Bare Rock and Soil (natural)
Cultivated, permanent, commercial, dryland
Cultivated, permanent, commercial, irrigated
Cultivated, permanent, commercial, sugarcane
Cultivated, temporary, commercial, dryland
Cultivated, temporary, commercial, irrigated
Cultivated, temporary, subsistence, dryland
Degraded Forest & Woodland
Degraded Thicket, Bushland, etc.
Degraded Unimproved (natural) Grassland
Forest (indigenous)
Forest Plantations (Acacia spp)
Forest Plantations (clearfelled)
Forest Plantations (Eucalyptus spp)
Forest Plantations (Other / mixed spp)
Forest Plantations (Pine spp)
Improved Grassland
Mines & Quarries (mine tailings, waste dumps)
Mines & Quarries (surface-based mining)
Thicket, Bushland, Bush Clumps, High Fynbos
Unimproved (natural) Grassland
Urban / Built-up (residential)
Urban / Built-up (residential, formal suburbs)
Urban / Built-up (residential, formal township)
Urban / Built-up (residential, hostels)
Urban / Built-up (residential, informal township)
Urban / Built-up (residential, mixed)
Urban / Built-up (rural cluster)
Urban / Built-up (smallholdings, grassland)
Urban / Built-up (smallholdings, thicket, bushland)
Urban / Built-up (smallholdings, woodland)
Urban / Built-up, (commercial, education, health, IT)
Urban / Built-up, (commercial, mercantile)
Urban / Built-up, (industrial / transport : heavy)
Urban / Built-up, (industrial / transport : light)
Waterbodies
Wetlands
Woodland (previously termed Forest and Woodland)

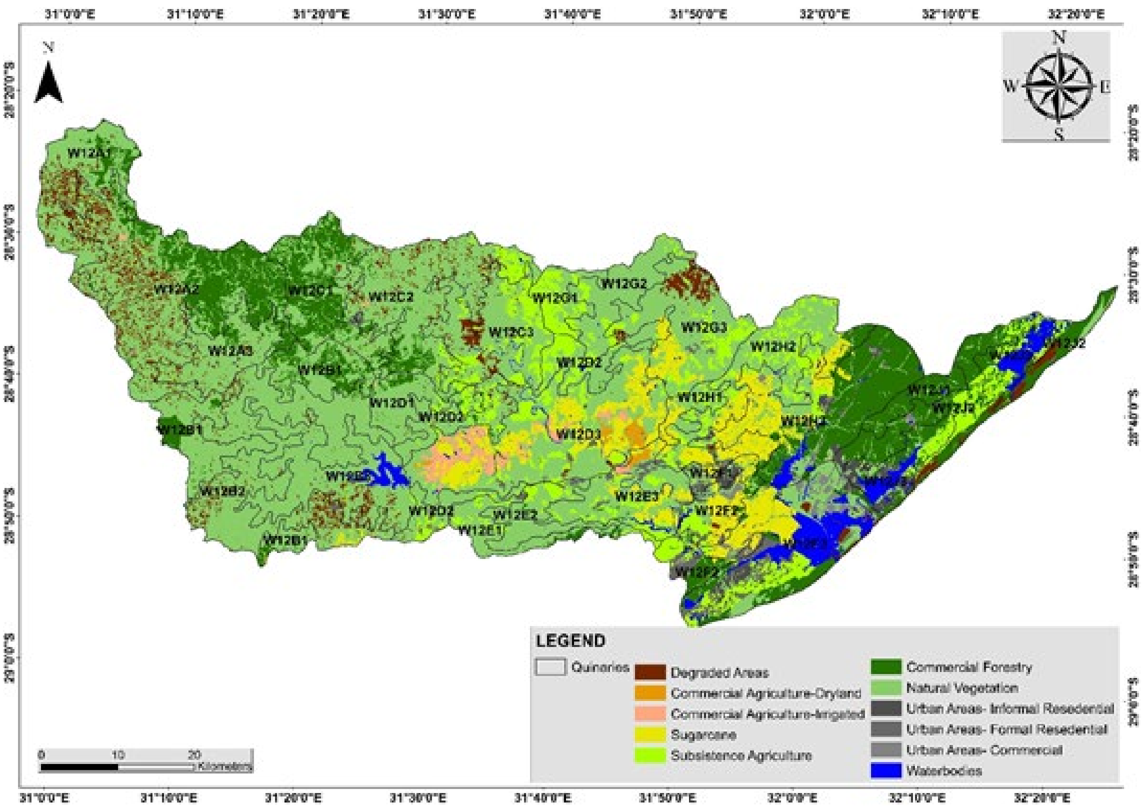

Figure 4-6 Lumped land cover categories in the Mhlathuze catchment (after National Land Cover, 2001)

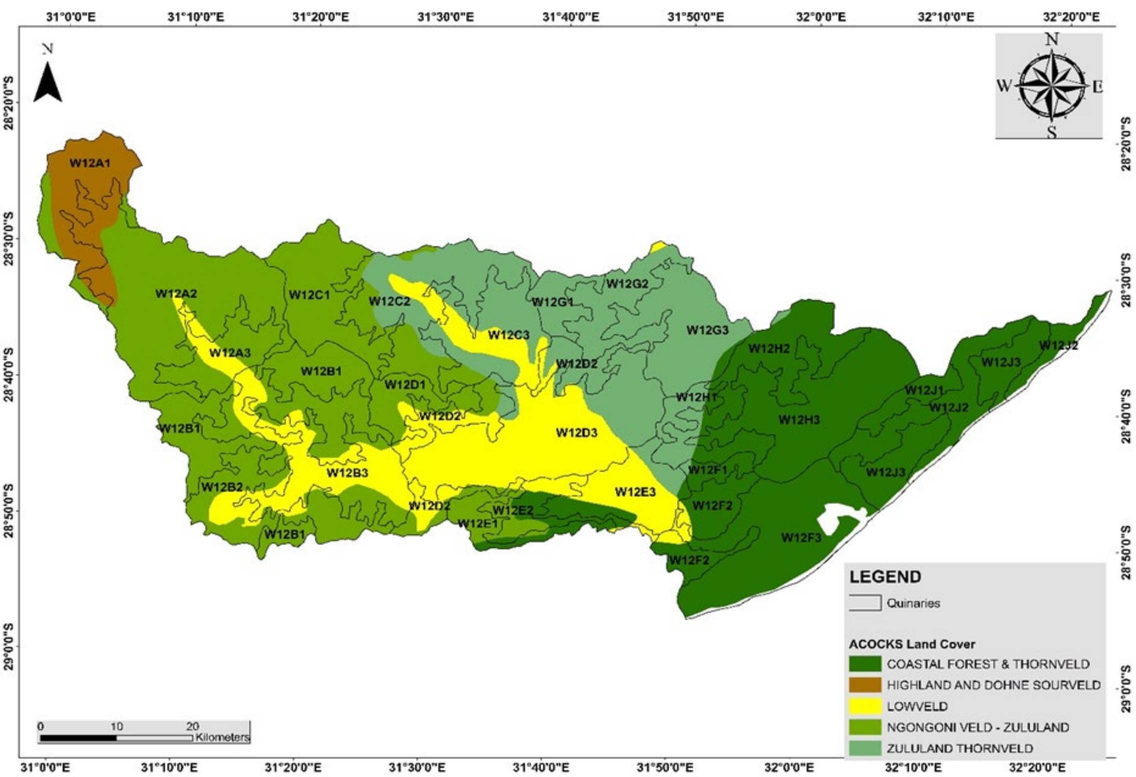

Figure 4-7 Acocks Veld Types in the Mhlathuze catchment (after Acocks, 1988)

Table 4-4 Areas (km^2) of the land cover HRUs represented in the ACRU model for each quinary (sub) catchment in the Mhlathuze catchment based on information from the NLC (2001) map of South Africa. Key physiographic data (area, MAP, average altitude) and weir numbers (where appropriate) are also given for each quinary catchment.

	W12A1	W12A2	W12A3	W12B1	W12B2	W12B3	W12C1	W12C2	W12C3	W12D1	W12D2	W12D3	W12E1	W12E2
Area(km2)	149.36	381.85	94.25	189.90	294.95	173.72	162.55	243.74	165.90	67.91	153.67	349.47	54.30	69.15
MAP (mm p.a)	784	933	1019	1037	999	924	891	876	810	1065	817	860	1071	1035
Average Altitude (m.a.s.l.)	1257.29	1026.68	748.03	862.52	601.97	366.75	906.87	639.21	374.10	584.34	328.69	138.56	341.95	211.89
Weir						W1HO28		W1HO05				W1HO09		
LAND USE (%)														
Commercial forestry	14.83	37.67	15.41	60.30	2.47	0.03	67.08	12.58	1.00	15.30	2.24	0.02	0.20	0.35
Comercial agriculture														
Sucarcane	0.00	0.07	0.00	25.72	4.35	0.00	18.11	5.45	0.00	3.39	0.73	24.64	0.01	0.96
Commercial	0.50	0.62	0.31	0.45	0.00	0.00	0.35	0.05	0.00	0.23	0.00	0.58	0.00	0.00
Orchards	0.00	0.00	0.00	0.20	0.08	0.00	0.44	0.28	0.00	0.15	0.38	7.28	0.00	0.00
Subsistence Agriculture	8.14	14.73	0.34	15.87	2.64	1.12	0.14	3.04	4.43	2.17	22.46	5.04	5.04	5.74
Natural Vegetation	68.61	37.50	82.23	151.73	83.81	83.79	12.24	72.71	84.96	61.53	215.77	54.76	75.07	73.90
Degraded Area	0.19	0.11	0.30	0.10	0.08	0.11	0.02	0.07	0.09	0.03	0.11	0.12	0.05	0.03
Urban Areas														
Built up(CBD industrial)	0.00	0.07	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00
Formal Resedential	0.03	0.09	0.00	0.03	0.00	0.00	0.49	0.54	0.00	0.00	0.00	0.00	0.00	0.00
Informal Rural Resedential Areas	6.78	8.00	1.10	45.10	6.56	8.31	0.69	5.20	8.47	17.19	57.28	6.14	19.50	18.56
Water Bodies	0.92	1.15	0.32	0.50	0.02	6.63	0.43	0.08	1.05	0.01	1.03	1.41	0.13	0.46

	W12E3	W12F1	W12F2	W12F3	W12G1	W12G2	W12G3	W12H1	W12H2	W12H3	W12J1	W12J2	W12J3	W12J3
Area(km2)	126.26	47.71	95.32	31.72	195.23	260.22	39.39	38.56	125.02	56.95	73.72	163.75	56.95	130.71
MAP (mm p.a)	1070	786	1182	1030	1117	1155	1170	1182	1182	1281	1226	1240	1240	1240
Average Altitude (m.a.s.l.)	91.26	395.56	71.60	178.20	111.26	56.58	107.90	63.80	63.80	20.80	80.47	57.83	28.16	28.16
Weir										W1HO32				
LAND USE (%)														
Commercial forestry	0.01	1.19	16.96	0.04	5.57	50.83	1.92	6.33	32.01	9.13	96.97	129.57	60.93	85.34
Comercial agriculture														
Sucarcane	19.75	0.00	21.75	21.65	30.70	18.13	31.22	52.15	1.02	16.22	0.31	0.14	0.00	0.00
Commercial	0.00	0.00	0.00	0.00	0.11	0.16	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Orchards	0.05	0.00	0.00	0.00	0.03	0.08	0.05	3.02	0.52	0.30	0.00	0.00	0.00	0.00
Subsistence Agriculture	6.74	11.19	0.00	8.80	10.21	1.08	1.22	1.50	4.40	1.35	0.00	0.21	0.07	0.09
Natural Vegetation	55.58	65.53	14.27	50.82	32.69	20.20	15.54	17.16	25.14	41.48	2.62	44.42	23.00	47.90
Degraded Area	0.13	0.04	0.00	0.04	0.04	0.24	0.06	0.73	1.99	2.02	0.10	16.14	2.41	4.27
Urban Areas														
Built up(CBD industrial)	0.05	0.00	0.00	0.05	0.45	0.35	1.82	3.47	1.12	3.89	0.00	0.45	0.00	0.53
Formal Resedential	0.02	0.00	0.00	0.05	0.55	0.48	17.67	2.88	0.36	0.76	0.00	1.81	0.00	12.70
Informal Rural Resedential Areas	16.93	21.92	22.19	18.27	19.41	5.86	30.25	11.24	32.94	14.38	0.00	5.56	3.17	24.97
Water Bodies	0.75	0.12	1.22	0.28	0.26	2.61	0.25	1.52	0.48	10.47	0.00	1.71	10.42	24.20

Evaporation in ACRU is represented as a combination of both evaporation from the soil surface (E_s) and evaporation from the plant surface (E_t). When E_s and E_t are described together, the term total evaporation (E) is used, where $E = E_s + E_t$. Vegetation water use is estimated as the product of reference potential evaporation (calculated from meteorological variables) and a set of crop coefficients. The crop coefficient K_{cm} is expressed as a ratio of maximum evaporation from a plant at a given growth stage to the reference potential evaporation. The fraction of plant available water (PAW) at which total evaporation is assumed to drop below maximum evaporation was set to 40% of the PAW. Monthly values of K_{cm} are required as input to the model. These monthly values are then transformed by the model into daily values using Fourier analysis.

The fraction of root mass distribution in the topsoil (ROOTA) is required as an input into the ACRU model on a monthly time scale, from which the fraction for the subsoil is calculated internally. In the model, soil water is extracted from both soil horizons simultaneously. Under stressed conditions, if the top soil is below the stress threshold, the subsoil's contribution to total evaporation is enhanced to compensate, and is above that computed for its root mass fraction. The opposite is true in conditions where the subsoil is below the stress threshold.

Estimates of surface litter / mulch cover are required on a month-to-month basis as a percentage when the option to calculate E_t and E_s as separate entities is invoked. This layer retards soil water evaporation losses. The index of infiltrability of rainfall into the soil is required in the model on a monthly time scale and is dependent on groundcover characteristics and rainfall intensity. Monthly values of the different vegetation inputs required by the ACRU model (discussed above) are given in Table 4-5 for the vegetated land covers in the Mhlathuze catchment. These inputs were derived from the ACRU User Manual, various publications and from expert opinion. The Acocks land cover information for the catchment (Figure 4-7) was used to provide a breakdown of the ACRU vegetation inputs for the natural vegetation class appearing in the NLC map of the catchment (Figure 4-6).

Table 4-5 Monthly values of the vegetation inputs required by ACRU for each of the vegetated land covers in the Mhlathuze catchment

Land Use	Variable	Monthly Values											
		J	F	M	A	M	J	J	A	S	O	N	D
Natural Vegetation													
Highland and Dohne Sourveld	CAY	0.7	0.7	0.7	0.5	0.3	0.2	0.2	0.2	0.5	0.7	0.7	0.7
	VEGINT	1.6	1.6	1.4	1.2	1.2	1.0	1.0	1.0	1.3	1.6	1.6	1.6
	ROOTA	0.9	0.9	0.9	1.0	1.0	1.0	1.0	1.0	1.0	0.9	0.9	0.9
	COIAM	0.2	0.2	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.2
Ngongoni Veld-Zulu Land	CAY	0.7	0.7	0.7	0.7	0.6	0.5	0.5	0.6	0.6	0.7	0.7	0.7
	VEGINT	1.4	1.4	1.4	1.4	1.4	1.4	1.4	1.4	1.4	1.4	1.4	1.4
	ROOTA	0.9	0.9	0.9	0.9	1.0	1.0	1.0	1.0	0.9	0.9	0.9	0.9
	COIAM	0.2	0.2	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.2
Lowveld	CAY	0.8	0.8	0.8	0.7	0.6	0.4	0.4	0.4	0.6	0.8	0.8	0.8
	VEGINT	2.5	2.5	2.5	2.1	1.9	1.9	1.9	1.9	2.1	2.5	2.5	2.5
	ROOTA	0.8	0.8	0.8	0.9	0.9	0.9	0.9	0.9	0.9	0.8	0.8	0.8
	COIAM	0.2	0.2	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.2
Zululand Thornveld	CAY	0.8	0.8	0.8	0.7	0.7	0.5	0.5	0.6	0.8	0.8	0.8	0.8
	VEGINT	2.4	2.4	2.4	2.1	1.8	1.8	1.8	1.8	2.2	2.4	2.4	2.4
	ROOTA	0.8	0.8	0.8	0.8	0.9	0.9	0.9	0.9	0.8	0.8	0.8	0.8
	COIAM	0.2	0.2	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.2
Lowveld Sour Bushveld	CAY	0.8	0.8	0.8	0.7	0.7	0.6	0.6	0.6	0.6	0.8	0.8	0.8
	VEGINT	2.5	2.5	2.5	2.4	2.2	2.0	2.0	2.2	2.4	2.5	2.5	2.5
	ROOTA	0.8	0.8	0.8	0.9	0.9	0.9	0.9	0.9	0.9	0.8	0.8	0.8
	COIAM	0.2	0.2	0.2	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.2	0.2
Coastal Forest and Thornveld	CAY	0.9	0.9	0.9	0.9	0.8	0.7	0.7	0.8	0.9	0.9	0.9	0.9
	VEGINT	3.1	3.1	3.1	3.1	2.5	2.0	2.0	2.5	3.1	3.1	3.1	3.1
	ROOTA	0.8	0.8	0.8	0.8	0.8	0.8	0.8	0.8	0.8	0.8	0.8	0.8
	COIAM	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3
Commercial Forestry													
Eucalyptus	CAY	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9
	VEGINT	3.4	3.4	3.4	3.4	3.4	3.4	3.4	3.4	3.4	3.4	3.4	3.4
	ROOTA	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5
	COIAM	0.2	0.2	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.2	0.2
Pine	CAY	0.7	0.7	0.7	0.7	0.6	0.5	0.5	0.6	0.6	0.7	0.7	0.7
	VEGINT	1.4	1.4	1.4	1.4	1.3	1.2	1.2	1.3	1.4	1.4	1.4	1.4
	ROOTA	0.9	0.9	0.9	0.9	1.0	1.0	1.0	1.0	0.9	0.9	0.9	0.9
	COIAM	0.2	0.2	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.2

Table 4-5 Continued

Land Use	Variable	Monthly Values											
		J	F	M	A	M	J	J	A	S	O	N	D
Agriculture													
Permanent Irrigated (Citrus)	CAY	0.8	0.8	0.8	0.7	0.6	0.5	0.5	0.5	0.6	0.7	0.8	0.8
Commercial Agriculture	VEGINT	1.4	1.4	1.4	1.2	1.0	1.0	1.0	0.8	0.0	0.0	0.8	1.4
	ROOTA	0.8	0.9	1.0	1.0	1.0	1.0	1.0	1.0	1.0	0.9	0.8	0.7
	COIAM	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3
Sugarcane	CAY	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9
Commercial Sugarcane (RBAY+North)	VEGINT	2.0	2.0	2.0	2.0	2.0	2.0	2.0	2.0	2.0	2.0	2.0	2.0
	ROOTA	0.8	0.8	0.8	0.8	0.8	0.8	0.8	0.8	0.8	0.8	0.8	0.8
	COIAM	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4
Subsistence Agriculture	CAY	0.9	0.8	0.5	0.4	0.2	0.2	0.2	0.2	0.2	0.2	0.3	0.6
	VEGINT	1.1	1.1	1.0	1.0	0.6	0.5	0.5	0.5	0.5	0.0	0.5	1.0
	ROOTA	0.8	0.8	0.9	0.9	1.0	1.0	1.0	1.0	1.0	1.0	1.0	0.9
	COIAM	0.2	0.2	0.3	0.3	0.3	0.3	0.2	0.2	0.2	0.4	0.3	0.3
Dryland temporary	CAY	1.1	1.0	0.6	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.8
commercial agriculture	VEGINT	0.8	1.3	1.3	1.1	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.4
	ROOTA	0.8	0.8	0.8	0.9	1.0	1.0	1.0	1.0	1.0	1.0	1.0	0.9
	COIAM	0.2	0.2	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.4	0.3	0.3

4.3.3. Soils and drainage

The ACRU model is a daily multi-layer soil water budget model operating with two soil layers; topsoil and subsoil. Processes of evaporation and transpiration take place within these two active soil layers resulting in root development and soil water extraction. The soil and drainage properties required by the model include; the thickness of the soil layers, permanent wilting point, drained upper limit, fraction of soil water to be redistributed daily from the topsoil to the subsoil and then from the subsoil to the groundwater store. The soils and drainage parameters used in ACRU are given in Table 4-6 for each quinary catchment.

Table 4-6 ACRU soil and drainage parameters for each quinary catchment in the Mhlathuze catchment

Quinary	DEPAHO	DEPBHO	WP1	WP2	FC1	FC2	PO1	PO2	ABRESP	BFRESP
W12A1	0.3	0.52	0.167	0.195	0.264	0.298	0.415	0.42	0.32	0.32
W12A2	0.3	0.53	0.154	0.184	0.249	0.284	0.423	0.42	0.37	0.37
W12A3	0.3	0.52	0.162	0.182	0.254	0.276	0.421	0.416	0.37	0.37
W12B1	0.3	0.49	0.161	0.181	0.256	0.279	0.419	0.417	0.37	0.37
W12B2	0.3	0.38	0.155	0.156	0.246	0.251	0.431	0.418	0.35	0.35
W12B3	0.29	0.26	0.147	0.139	0.236	0.231	0.443	0.421	0.32	0.32
W12C1	0.3	0.53	0.148	0.174	0.244	0.272	0.423	0.414	0.38	0.38
W12C2	0.3	0.33	0.139	0.134	0.231	0.228	0.44	0.42	0.34	0.34
W12C3	0.3	0.4	0.134	0.13	0.225	0.224	0.447	0.426	0.37	0.37
W12D1	0.3	0.38	0.154	0.16	0.252	0.263	0.423	0.416	0.34	0.34
W12D2	0.29	0.24	0.144	0.137	0.235	0.231	0.441	0.419	0.31	0.31
W12D3	0.3	0.41	0.189	0.217	0.267	0.291	0.428	0.433	0.32	0.32
W12E1	0.3	0.29	0.16	0.153	0.251	0.246	0.427	0.419	0.31	0.31
W12E2	0.3	0.35	0.164	0.159	0.255	0.251	0.426	0.424	0.33	0.33
W12E3	0.3	0.41	0.181	0.196	0.263	0.275	0.425	0.426	0.32	0.32
W12G1	0.3	0.27	0.157	0.153	0.245	0.244	0.432	0.416	0.29	0.29
W12G2	0.3	0.33	0.19	0.196	0.27	0.276	0.424	0.425	0.33	0.33
W12G3	0.3	0.28	0.21	0.233	0.282	0.3	0.423	0.432	0.29	0.29
W12H1	0.3	0.25	0.207	0.19	0.29	0.272	0.407	0.423	0.33	0.33
W12H2	0.3	0.41	0.192	0.189	0.275	0.272	0.418	0.427	0.36	0.36
W12H3	0.3	0.72	0.129	0.138	0.217	0.234	0.458	0.45	0.51	0.51
W12F1	0.3	0.46	0.185	0.198	0.266	0.276	0.423	0.424	0.35	0.35
W12F2	0.3	0.55	0.152	0.154	0.241	0.245	0.441	0.434	0.42	0.42
W12F3	0.25	0.69	0.106	0.134	0.194	0.225	0.462	0.446	0.5	0.5
W12J1	0.3	0.88	0.081	0.093	0.177	0.201	0.479	0.466	0.59	0.59
W12J2	0.3	0.88	0.079	0.091	0.175	0.198	0.476	0.467	0.57	0.57
W12J3	0.26	0.75	0.076	0.089	0.157	0.178	0.41	0.401	0.49	0.49

Where:

DEPAHO = Thickness (m) of topsoil of the soil profile

DEPBHO = Thickness (m) of subsoil of the soil profile

WP1 = Soil water content ($m.m^{-1}$) at permanent wilting point for the topsoil

WP2 = Soil water content ($m.m^{-1}$) at permanent wilting point for the subsoil

FC1 = Soil water content ($m.m^{-1}$) at drained upper limit (DUL) for the topsoil

FC2 = Soil water content ($m.m^{-1}$) at drained upper limit for the subsoil

PO1 = Soil water content ($m.m^{-1}$) at saturation (i.e. porosity) for the topsoil

PO2 = Soil water content ($m.m^{-1}$) at saturation (i.e. porosity) for the subsoil

ABRESP = fraction of soil water above DUL to be redistributed daily from the topsoil to the subsoil

BFRESP = fraction of soil water above DUL to be redistributed daily from the subsoil to the groundwater store.

4.3.4. Dams and irrigation scheduling

Farm dams and other reservoirs within the Mhlathuze catchment were identified through reference to literature, the WARMS (2013) database and Google Earth. Surface areas were obtained from both Google Earth and from a 1:50 000 topographic map sheet dating from 1996-2002, and then compared in terms of changes over time (historical and current). Storage capacities of each farm dam in the catchment were calculated using an algorithm developed by Tarborton and Schulze (1992) which is based on the surface area of a dam. Surface areas and capacities of these farm dams were aggregated for each Quinary catchment. Monthly adjustment coefficients to A-pan equivalent evaporation to obtain reservoir equivalents were obtained from Schulze (1995) for the appropriate climate zone in South Africa. Domestic abstractions were not accounted for at this stage and dead storage percentages of dams were set at 10% of the full storage capacities.

The NLC (2001) land use layer in conjunction with Google Earth, as well as literature values from previous studies and correspondence with a local extension officer within the catchment were used to identify areas under irrigation. Extensive irrigation areas exist within the catchment, especially just below the Goedertrouw Dam. These irrigation activities are managed by various Water User Associations who have fixed water allocations. The Mhlathuze catchment is constituted of five irrigation entities that utilise and facilitate the distribution and use of water below Goedertrouw Dam. These five irrigation entities are mainly utilised for irrigation of sugarcane and, to a lesser extent, citrus. The irrigator schemes are listed in order of distance from the dam.

- Nkwaleni Scheme
- Umfuli
- Heatonville
- Inkasa Irrigation Scheme
- Lower Mhlathuze Scheme

The Inkasa Irrigation Scheme (IIS) is constituted predominantly of small scale irrigators for sugarcane productivity. Within IIS the most developed areas with noticeable sugarcane productivity are at Biyela, Kwadlama and Mzimela. The irrigation scheduling assumptions applied by SASRI in their sugarcane crop forecasting system (industry-wide) were reviewed to guide the selection of a strategy for this project. SASRI assumes a maximum net application of 35 mm over a minimum 7-day cycle. Maximum weekly applications are set to 42 mm. Irrigation is only applied when the soil water deficit reaches the prescribed level (50% of Total Available Moisture) and the current irrigation cycle has been completed. The irrigation amount equals the least of the maximum application, the current soil water deficit, or the weekly water supply if it exceeds 17 mm. To simplify this in the ACRU model, the irrigation schedule was set to 35 mm in a fixed 7-day cycle, with the cycle only interrupted after 10 mm of rainfall on a given day. Conveyance and farm dam losses were set to 19 and 10%, respectively, with spray evaporation and wind losses set to 15%.

4.3.5. Water user allocations and the supply and distribution system

The main water supply system in the Mhlathuze catchment consists of the Goedertrouw Dam, with a capacity of approximately 300 million m^3 at a full supply level. The dam can be supplemented by water from the Mhlathuze weir and from the Thukela-Mhlathuze Emergency Transfer Scheme, which can pump water from the Thukela River to the Goedertrouw Dam at a rate of approximately 37 million m^3/annum. The Goedertrouw Dam was constructed in 1980 to provide water for irrigation downstream. Upstream of the Goedertrouw Dam is the Mvuzane River inflow where the Thukela Transfer Scheme discharges into the Mvuzane River. The Thukela Emergency Transfer System is used to augment the dam level when it drops as a result of high water demand. Since the commissioning of the emergency scheme, it has not been in service because the dam level has consistently been high enough. During the drought of 1994 an emergency augmentation scheme was put in place (commissioned in 1997) that has the capacity to deliver 38 million m^3/annum (equivalent to 1.2 m^3/s) to the Mvuzane stream. Only second time use of the scheme was necessary was during the second half of the 2014 calendar year, as a result of very low summer rainfall received and low raw water resources, at which time it was necessary to officially declare that the province of KwaZulu-Natal was in a drought situation. This drought had an adverse effect on the Mhlathuze water systems, with the Goedertrouw Dam dropping to below 65% for the first time since it was commissioned in 1980

The natural lakes within the catchment also contribute to the yield of the system. The latest yield estimate of this system, including the lakes, is 270 million m^3/annum at a 1:100 year assurance of supply after allowing for the ecological water requirements below the Goedertrouw Dam and including a transfer of 34 million m^3/annum from the Thukela River. Three coastal lakes are sources for abstraction in this strategic area: Lake Mzingazi, which supplies Bayside Aluminium and the Mzingazi Wastewater Treatment Works (WTWs), Lake Nsezi, which supplies the Nsezi WTWs and supplements Richard Bay Mineral's supply from other sources, and Lake Cubhu, which supplies the eSikhaleni WTWs. Values of allocated water amounts for various land uses together with the sources of water based on a study conducted in 2013 (DWS, 2015) are shown in Table 4-7 and were used to approximate abstractions from the Goedertrouw Dam for the verification study.

4.4. Verification

The performance of the ACRU model was assessed for the upper reaches of the Mhlathuze catchment by comparing modelled and observed streamflow volumes for weir W1H005 for an historical time period. Objectives were set beforehand for an acceptable simulation in terms of fit and were based on recommended objectives by Smithers and Schulze (2004). These included a coefficient of determination (R^2) value of 0.7 and above for daily values, and 0.9 and above for monthly values. These values were based on suggested R^2 values for a high rainfall, highly seasonal, summer rainfall hydrological regime. Other objectives included a less than a 15% difference between the sum of simulated (ΣQs) and observed flows (ΣQ o), as well as a less than 15% difference between standard deviations. There are observable discrepancies in some portions of the hydrograph, particularly the year 2004 where the model predominantly over-simulates streamflow amounts. Overall, the model under-simulates streamflow for the beginning of the time series and then over-simulates post 2004 (Figure 4-8). The statistical measures are shown in Table 4-8. Considering that two out of three of the objectives set for the verification of the model were met, the simulation for the Mhlathuze catchment was considered reasonable. The above results therefore suggest

Table 4-7 Allocated water abstraction values for various land uses and sources of water within the Mhlathuze catchment

Abstractions from Goedertrouw Dam			
Water User		Source	Water Allocated (million m^3/annum)
Domestic	**Urban and Light Industry**		
	Eshowe	Mhlathuze Water Supply System	14.1
	Richards Bay	Lake Mzingazi and Mhlathuze Water Supply System	0.5
	Esikhaweni	Lake Chubu and Mhlathuze Water Supply System	5.9
	Nseleni	Mhlathuze Water Supply System	2
	Vulindlela	Lake Mzingazi and Mhlathuze Water Supply System	1.5
	Empangeni Ngwelezane	Lake Nsezi and Mhlathuze Water Supply System	8.4
	Rural Water Use		
	Below Dam	Mhlathuze Water Supply System	2884 m^3/day
	Stock Watering	Mhlathuze Water Supply System	1.18
Industry	Richards Bay Minerals	Lake Nhlabane and Mfolozi River and Mhlathuze Water Supply System	40
	Mondi Richards Bay	Mhlathuze Water Supply System	28.5
	Mondi Felixton	Mhlathuze Water Supply System	2.9
	Tongaat Hulett	Mhlathuze Water Supply System	1.8
Reserve	Maintenance Flows-Goedertrouw Dam	Mhlathuze Water Supply System	54
	Drought Flows	Mhlathuze Water Supply System	14
	Estuarine	Mhlathuze Water Supply System	12
Irrigation	Water Boards	Mhlathuze Water Supply System	88.5

that the ACRU model can be used to simulate streamflow for the upper reaches of the Mhlathuze catchment with a reasonable degree of confidence. This part of the catchment is similar in characteristics to the section that feeds into the Goedertrouw Dam.

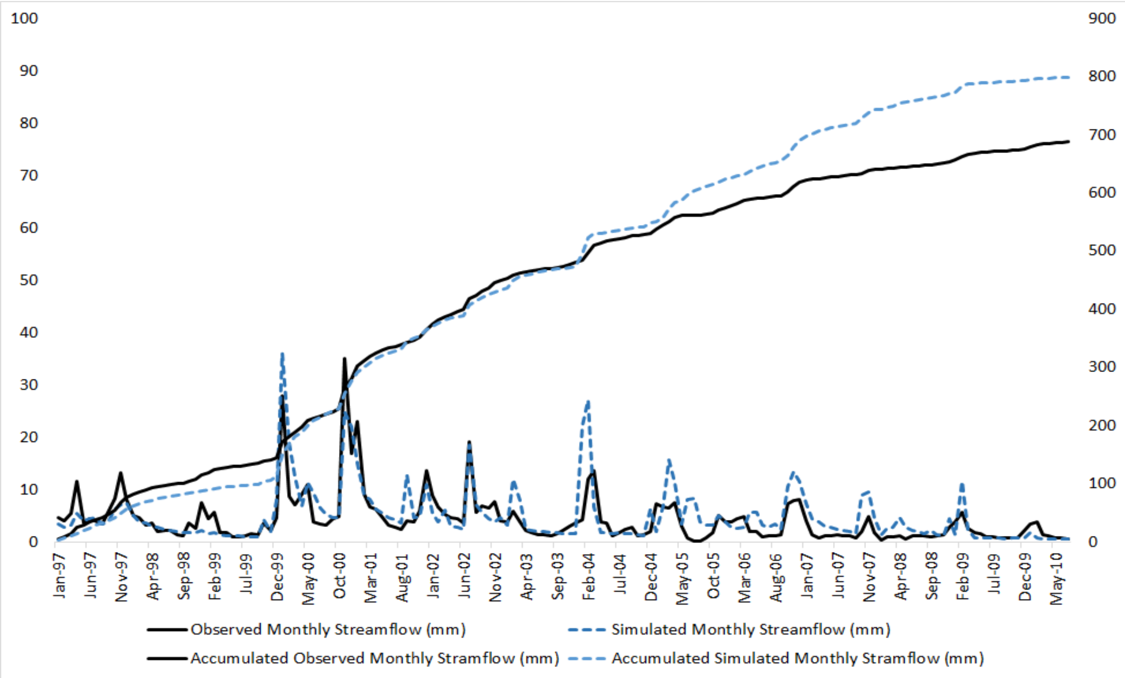

Figure 4-8 Total and accumulated monthly observed and simulated streamflow volumes for weir WIH005 for the period January 1997 to May 2010

Table 4-8 Statistics of performance upstream of Goedertrouw Dam

Mhlathuze (1997-2010)	
Total Observed Flows (mm)	687.72
Total Simulated Flows (mm)	799.22
%Difference between Totals	14.95
Average Error in Flow (mm/day)	-0.02
Mean Observed flows (mm/day)	0.16
Mean Simulated Flows (mm/day)	0.18
%Difference Mean	11.76
Standard Deviation of Observed Flows (mm/day)	0.362
Standard Deviation of Simulated Flows (mm/day)	0.356
% Difference between Standard Deviation	1.67
Correlation Coefficient: Pearsons r	0.68
Regression Coefficient (Slope)	0.8918
Regression Intercept	0.0188
Coefficient of agreement	0.767
Coefficient of determination (R^2)	0.59
Nash Sutcliffe Efficiency Index	0.48

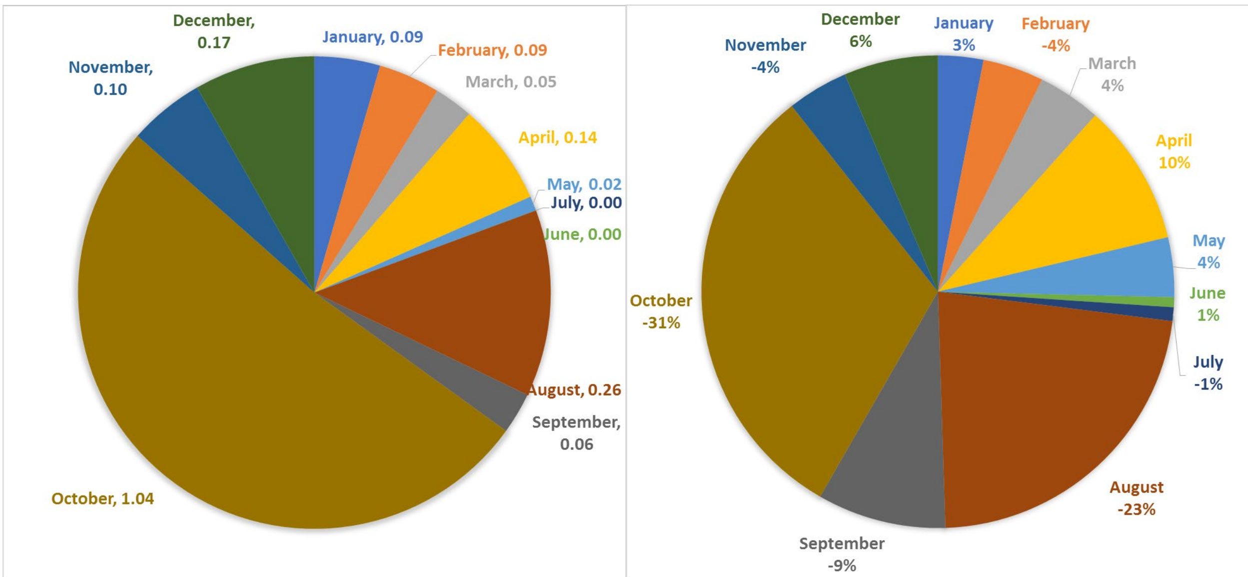

Figure 4-9 Coefficient of variations and percentage errors between observed and simulated streamflow volumes for weir W1H005 from January 2000 to January 2010

Monthly coefficients of variations for the simulated time series and percentage differences between observed and simulated streamflow volumes for weir W1H005 are shown in Figure 4-9. According to the calculated statistics, the total monthly streamflow's for the study period varied most from the average for the low flow month of October (CV 1.04). The model under-simulates the overall streamflow volumes for the month by 31% followed by 23% in August. The model shows more accurate estimations for low flow winter months of June and July with the lowest over- and under-simulations of 1% respectively. Overall, the largest errors fall within the months of August, September and October, where the highest under-simulations by the model occur.

4.4.1. Verification of Goedertrouw Dam Levels

The performance of the ACRU model in simulating observed water levels at various stage heights of the Goedertrouw Dam was assessed in terms of its ability to simulate observed monthly volumes (Mega Litres (ML)) during drawdown and recovery phases in the study period. It was noted at the outset that the observed volume levels were not consistent over the study period, with seasonal (Table 4-9) and inter-annual (Figure 4-10) variations evident in the data.

From Figure 4-10, it can be observed that the model is able to replicate periods of recovery and drawdown in water levels which correlate with periods of abstractions for land use activities downstream (releases), spillages or periods of drought. In terms of actual volumes, the model shows an overall under-estimation for the study period, particularly during the year 2005. The statistical evaluation criteria used for evaluating the study period overall is shown in Table 4-10. Under-estimations in mean volume and variability are indicated by the RMSE of 20167.54 ML, the 7.14% difference in mean observed and simulated water levels and the 1.67% difference in standard deviations. The measure of prediction accuracy represented by the Mean Absolute Percentage Error (MAPE) was 5.54%, while the relative quality of the

Table 4-9 Observed meteorological and reservoir characteristics for the Goedertrouw Dam

Month	Rain (ML)	Goedertrouw Dam Levels (ML)	Irrigation Abstractions	Below Dam (ML)	Evaporation (ML)
January	1031.3	205353.8	221.0	10080.7	787.4
February	930.8	214884.9	232.0	10105.9	896.0
March	490.7	222469.1	275.7	6883.4	1038.6
April	401.1	227884.1	245.9	7312.3	1153.1
May	62.1	235578.4	246.9	7670.9	1282.8
June	220.7	246487.1	211.6	5956.4	1583.7
July	366.6	249678.5	236.9	9295.5	1544.5
August	228.8	244777.0	249.9	6392.5	1419.9
September	452.4	234749.7	240.7	6403.2	1417.7
October	691.0	226555.4	230.3	4918.1	1059.6
November	1251.5	219915.4	218.2	14270.8	933.0
December	851.0	210810.8	256.3	15388.7	740.4

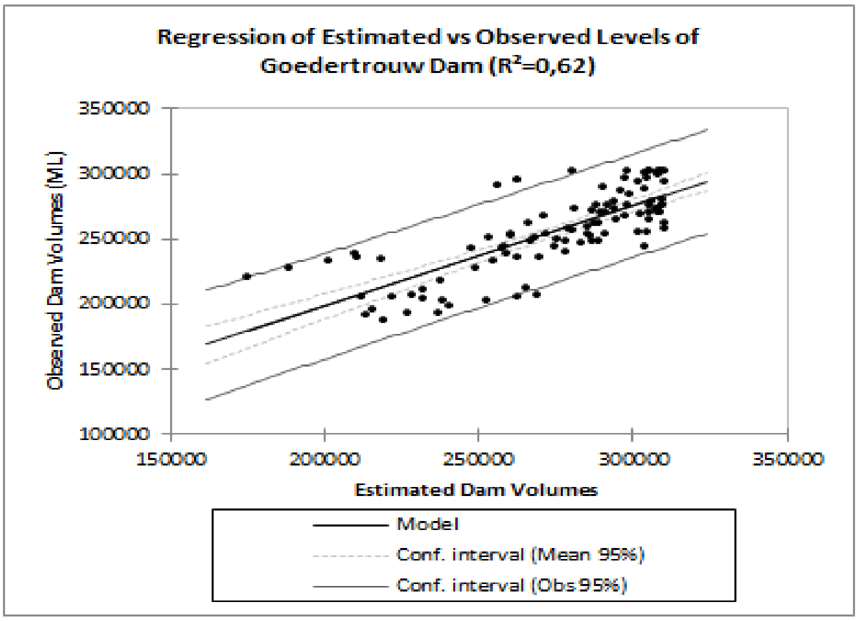

Figure 4-10 Correlation between observed and estimated Goedertrouw dam levels for the period (2000-2010) and 95% confidence intervals

model according to the AIC was 2103.29. The Coefficient of variation (R^2) and Pearson correlation coefficient (PCE) values were 0.62, and 0.79, respectively. According to Figure 4-10, all data points for the study period fell within the 95% confidence interval, with estimations being closer to observed values for volumes greater than 200 000 ML.

The performance of the model on a monthly basis was also analysed via box plots (Figure 4-11). Examination of Figure 4-11 shows that there is higher variability in the observed water levels in the summer months (November to March) as compared to winter months (April to October). Simulations follow the pattern of observed variability relatively closely, however, under-estimations of water volume variability are greater for summer months than for winter months. Based on the medians, the month of June shows the lowest variability in simulations. The graph of cumulative frequency shows higher observed frequencies for lower dam levels of 5000 to 25 000 ML for the study period when compared to simulated water levels, whilst simulations show higher frequencies of full storage capacities when compared to the observations (Figure 4-12).

Table 4-10 Statistics of performance for the Goedertrouw Dam levels (2000-2010)

Goodness of fit statistics	
R^2	0.62
Adjusted R^2	0.62
RMSE	20167.54
MAPE	5.549
AIC	2103.29
Pearson Correlation Coefficient	0.79
Mean Observed	257040
Mean Estimated	276074
% Difference between Means	7.14
Standard Deviation Observed	31796.08
Standard Deviation Estimated	32332.37
% Difference between Standard Deviations	1.67

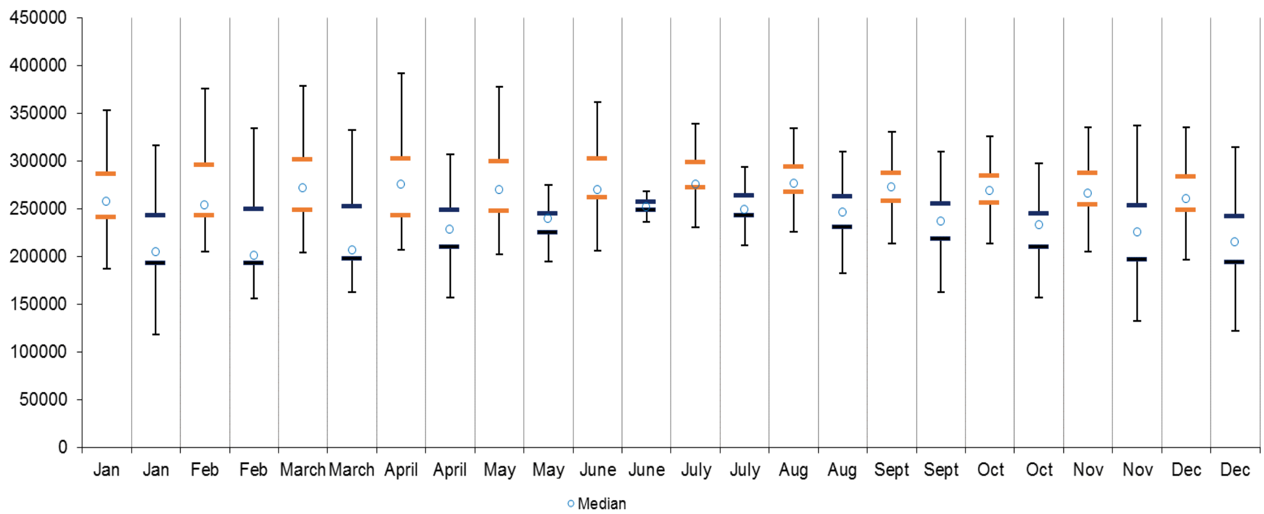

Figure 4-11 Box plots of monthly dam levels for the period 2000 to 2010, observed (orange) and simulated (blue)

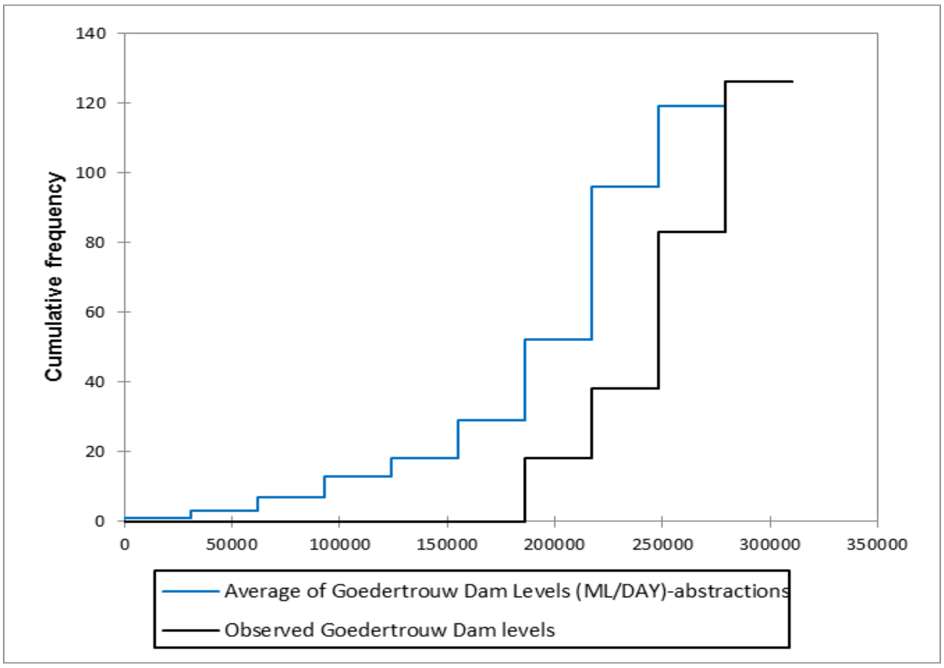

Figure 4-12 Cumulative frequency of simulated and observed Goedertrouw dam levels

4.4.2. Conclusion

This chapter aimed to verify historical simulations produced by the ACRU agrohydrological model. This was in anticipation of the model being used in a forecasting framework for the development of agrohydrological forecasts at short to medium range time scales, to support irrigated sugarcane production in the Mhlathuze catchment. Based on the above simulations, it is believed that the application of the ACRU model for forecasting inflows into the Goedertrouw Dam, as well as the levels in the dam, to support irrigation water availability estimates for sugarcane, is deemed viable. Land uses in the upper reaches of the Mhlathuze catchment vary considerably from those below the Goedertrouw dam and near the coast in Richards Bay. Contributions of streamflow to weir W1H005 through the Mfalazane River were from the dominant land uses of commercial forestry, subsistence agriculture and natural vegetation, as compared to the highly cultivated lands below the dam for citrus and sugarcane farming.

The ACRU model performed reasonably well in the upper reaches of the catchment with a minimal daily under-simulation error in streamflow of 0.01046 mm per day. On monthly time scales, upstream of the dam, a higher confidence is associated with the model's performance for the months of May, June and July, which showed the lowest coefficients of variations and percentage differences between simulations and observations. In July, simulations resulted in a 1% under-estimation of streamflow upstream of the dam.

Simulations of dam level volumes, including periods of drawdown and recovery, were found to be viable, with a quantified average monthly error of 20167.5 ML. The ACRU model under-estimated dam storage volumes. In the previous water balance study conducted for the Richards Bay area within the catchment, it was stated that allocated water requirements for each water user in the catchment were set much higher than actual water usages (DWA, 2015). This was to accommodate future climate and economic growth scenarios developed for the area. The absolute differences between simulated volumes and observations are lowest in the month of June and highest in the summer months of November to March.

In general the ACRU model simulated higher frequencies of volumes lower than the Dam's full storage capacities, but is able to explain 62% of the variation in dam level storage volumes for the study period. At a 95% confidence interval the ACRU model showed to be useful for estimating monthly dam levels. The ability to estimate inflows into the dam as well as dam levels after the consideration of allocated water abstractions for various water users below the dam allows for a level of confidence to be associated with the available water for irrigation scheduling.

There are various limitations in the study. For example, the study period was relatively short owing to the inaccuracies associated with the historical streamflow data especially post-2007. These inaccuracies may be related to changes in weir maintenance, in rating table calculations for weir measurements or to changes in land uses with time upstream of the dam. Records therefore may have not included potential low and high streamflows. Additionally, inherent errors in the climate record were observed. General limitations associated with the use of hydrological models, such as in insufficient representation of key hydrological and operational processes within the catchment, are also another potential source of error. As with previous verifications of the ACRU model for various hydrological applications under a range of climatic conditions, it is important to highlight the necessity for site-specific verifications of the model for reservoir level estimations. Information on quantified errors and improved understandings of uncertainties associated with the modelling component within an agrohydrological forecasting framework for dam level volumes, is crucial for water managers who must make decisions about drought declaration and water use restrictions.

4.5. References

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CHAPTER 5. DEVELOPMENT OF THE ACRU AGROHYDROLOGICAL FORECASTING TOOL

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5.1. Background

Generating agrohydrological forecasts requires performing a number of data intensive tasks. To streamline this process, a tool was developed to automate many of the steps involved. A literature review of hydrological and agricultural forecasting systems was performed to inform the development of the forecasting tool. This review had an emphasis on southern Africa and is presented in the beginning of this chapter. Following this, a brief overview of the forecasting tool for the Mhlathuze case study is presented. A generic framework for hydrological forecasting developed in the Netherlands (Delft-FEWS) was identified as the vehicle for developing the tool. A review of Delft-FEWS is presented in this chapter, and includes an overview and main outcomes of a Forecast Early Warning System Master course attended at the eThekwini Municipality. The configuration of the system for the Mhlathuze catchment is then presented at the end of the chapter.

5.2. Review of hydrological and agricultural forecasting systems

5.2.1. Introduction

Southern Africa is inherently characterised by a highly variable climate both spatially and temporally, and is considered a highly vulnerable region in Africa (Reason et al., 2005; Washington and Preston, 2006; Ghile and Schulze, 2008). Apart from the highly variable climate, reasons for the high vulnerability across the region include the extremely agrarian economies (rainfed and irrigated) (IPCC, 2007; Manyeruke et al., 2013; Alemaw and Simalenga, 2015), severe water challenges (quantity, quality and distribution), high exposure (Shongwe at al., 2006; Malherbe et al., 2014) and low adaptive capacity, particularly among rural communities (Manyeruke et al., 2013; Turpie and Visser, 2013).

Changes in the intensity, frequency and duration of weather extremes result in recurrent droughts, floods, tropical cyclones and other phenomena over the region (IPCC, 2012; Thornton et al., 2014; Malherbe et al., 2014; Engelbrecht and Engelbrecht, 2016). Projected increases in the frequencies and magnitudes of such events through to 2050, coupled with rising populations in the region, suggests that the vulnerability of weather sensitive sectors, particularly water resources and agricultural production (Waongo et al., 2015; Ghile and Schulze, 2008), are expected to rise in the future (Zhang et al., 2013; Kusangaya et al., 2013; Thiemig et al., 2014).

Water resource managers and agriculturalists therefore need to be advised of likely climatic and hydrological conditions well in advance (Ghile and Schulze, 2008). With prior knowledge of likely precipitation patterns, rainfall totals, onsets and cessation dates, mean, minimum and maximum temperatures, distributions of wet/dry/cold/ warm spells and extreme events, as well as subsequent estimations of future hydrological states and fluxes for the region, the risk of economic losses can be reduced, profits increased, and improved short to medium and long-term planning and decision making on security-related issues can be achieved (Klutse et al.,2015; Reason et al.,2005; Shukla and Lettenmaier, 2011; Mudombi and Nhamo, 2014).

The climate science arena has shown remarkable advancements in weather and climate forecasting for the region which can be largely attributed to model sophistication and research orientated at improving the understanding of dynamic ocean atmosphere processes (Landman and Goddard, 2002; Engelbrecht and Engelbrecht, 2016; Malherbe et al., 2014; Beraki et al., 2015; Lazenby et al., 2014). A number of institutions and platforms in the region produce and provide forecasts for various forecast horizons. These include national meteorological services, university research groups as well as various global ensemble forecasting centres (Johnston et al., 2004).

Both statistical and dynamic methods of hydrological and agricultural forecasting are undertaken in the region. Statistical forecasts work by extrapolating direct relationships between climate indices and hydro-climatic variables while dynamic methods involve the use of weather and climate measurements from stations, radar and satellites, combined with high resolution NWP model forecasts to drive hydrological and crop models of varying complexities and spatial dimensions (lumped, semi-distributed or distributed) to produce estimates of future agricultural and hydrological variable states. Studies dealing with floods and droughts are at the forefront of hydrological forecasting for the region and are focused on medium to large-size transnational river basins such as the Okavango (Bauer-Gottwein et al., 2015; Milzow et al., 2009 Zhang et al., 2013), the Limpopo (Botswana, Mozambique, South Africa and Zimbabwe) (Trambauer et al., 2015) and the Orange and Zambezi (Meiere et al., 2011). However there is also a need to estimate the consequences of weather and climate variability with respect to agrohydrological variables such as streamflow amounts, reservoir levels, soil moisture contents and water availability for irrigation scheduling purposes. Such operational forecasts are either limited for the region or have been discontinued for reasons such as a lack of funding or local and institutional support, amongst others.

Many agrohydrological forecasting systems are developed through international initiatives which aim for simplicity and robustness making optimal use of freely available global datasets for poorly gauged river basins. Additionally, most of the forecasting endeavours target either short (<3 days) or long-range (>2 weeks) forecasts, with increasing efforts focused on seamless data assimilation techniques using freely available global remote sensing derived products and ensemble predictions for improved hydrological and agricultural forecasts at all lead times. Moreover, only a handful of agricultural or hydrological forecasts are typically made available for the target end users, with most studies simplifying field conditions by not considering actual water users and abstractions in the catchments. Other focused areas of research include the interface between the production of weather and climate forecasts and the access, communication, translation and interpretations of the forecasts for key stakeholders (for example, water managers, smallholder and commercial farmers) (Archer, 2003; Usman et al., 2005; Archer et al., 2007; Unganai et al., 2013). These studies have highlighted the need for an integrated approach between climate scientists, system scientists and the end users who provide vital feedback to improve the entire end-to-end forecast production.

5.2.2. General structure of forecasting systems

Whether statistical (e.g. black-box model) or dynamic methods of varying complexities (conceptual or process-based models) and spatial dimensions (lumped, semi-distributed or distributed) are used for agrohydrological forecasting, all methods involve inputs (e.g. precipitation, surface air temperature, potential evapotranspiration) and outputs (e.g. streamflow, actual evapotranspiration, crop yields) (Tang et al., 2016; Devia et al., 2015). For statistical methods, climate indices are frequently used to directly forecast agrohydrological variables (Muchuru et al., 2015; Malherbe et al., 2014). For dynamical approaches, either an iterative or static approach is used, where the former allows for feedback between climate and application models but requires equal spatial resolutions between them, and the latter operates in a successive manner where climate forecasts are first produced, processed and translated for use in application models of differing spatial and temporal resolutions (Block et al., 2009).

Within the southern African region dynamic methods of agrohydrological forecasting are being increasingly used and involve an initial reference or historical simulation, followed by a nowcast/real time phase and finally a forecast phase, with uncertainties being associated with each phase of the system (Thiboult et al., 2016) (Figure 5-1).These uncertainties relate to meteorological forcings used as input, assumed initial hydrological conditions (e.g. soil moisture content, reservoir levels), other model inputs, process representation in models and observational data used in calibration and validation (Block et al., 2009; Thiboult et al., 2016). Both the quantification and reduction of these uncertainties are necessary for the generation of accurate and actionable forecast information for effective risk-based decision making (Ramos et al., 2013; Sene and Darch, 2011; Thiboult et al., 2016).

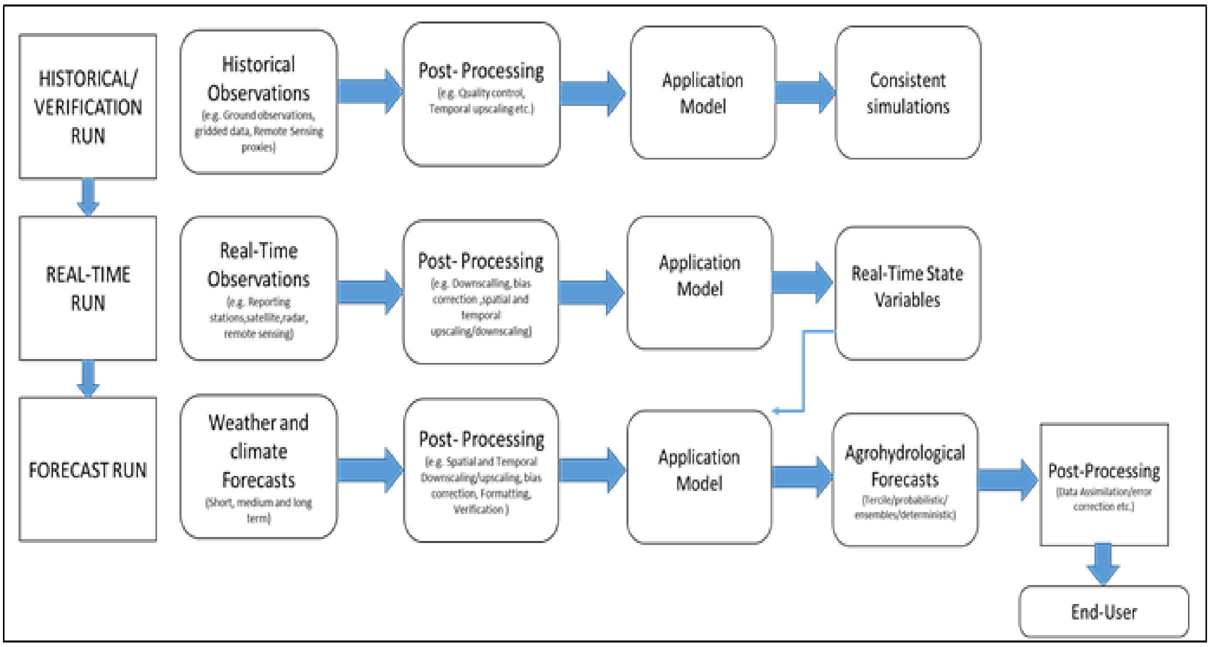

Figure 5-1 Structure of a typical agrohydrological forecasting system

Data assimilation (DA) methods are typically applied in forecasting systems to help reduce uncertainties and have proven to be promising for the ultimate improvement of forecast accuracy and the quantification of uncertainty. Within a forecasting system, DA methods are applied for; model state updating, calibration purposes for model parameter estimation or optimization, and error updating to revise the forecast outputs (Liu et al., 2012). Typical DA methods include, for example, variational algorithms and extended or ensemble Kalman filtering. Additionally, these uncertainties may vary with catchment characteristics and the lead time of the forecast, however, it is commonly accepted that the greatest uncertainty stems from the forcing input data (Emerton et al., 2016; Liu et al., 2012; Fekete et al., 2007).

According to Dutra (2012) there are two challenging criteria necessary for a forecasting system. These include statically homogenous long term observational data sets of more than 30 years, and near real time updates of these data sets. For the region, these criteria are particularly challenging to achieve considering the numerous studies that highlight the uneven, sparse and declining observational station networks resulting in a dearth of climatological (rainfall and temperature) and observed discharge data (Alfeiri et al., 2012; Bauer-Gottwein et al., 2015; Ghile et al., 2010). There is a marked cluster of climate observation networks over South Africa (Malherbe et al., 2015; Coning, 2013). However, these direct methods of measurements suffer from inconsistencies at both spatial and temporal scales throughout the region (Tang et al., 2016; Di Baldassarre and Montanari, 2009). Weather related input data have been identified above as a critical component of forecasting systems and are reviewed in more detail in the following subsections.

5.2.3. Historical and near real-time observational data

In view of the sparse available gauging network, efforts are directed to combining data available from ground observations, remote sensing measurements and NWP model outputs within forecasting systems (Milzow et al., 2011).

Remote sensing derived rainfall estimates from radar and satellite are being increasingly used over the region. Satellite estimates are more commonly used considering the lack or poor maintenance of available advanced high resolution radar systems over the region due to lack of local capacity, support and funding. The SAWS has the most advanced radar systems in the continent with a total of 14 operational systems across the country. The majority of the forecasting initiatives within the region are developed to make optimal use of global satellite and merged satellite/gauge public domain datasets. The advantage of such estimates is the capability of providing full spatial coverage over the region which can be used for validation, calibration and data assimilation within forecasting systems (Theimig et al., 2011). In addition to rainfall, these satellite derived data sources include evaporation, terrestrial water storage changes and soil moisture. These products are also now commonly investigated, especially for data assimilation and calibration purposes. While historical and near real time observations are used for calibration, validation or verification purposes, the forecasting component of the system requires reliable and skilful forecasts of the same forcing data at various

5.2.4. Weather and climate forecast products

Nowcasts are location specific and provide forecasts of the initiation, growth and dissipation of weather phenomena, such as heavy rainfall, hail, frost and lightning, and rely heavily upon satellite and/or radar systems (De Coning, 2015). Such warnings are the mandate of all operational weather services. For the region, initiatives such as the Severe Weather Forecasting Demonstration Projects (SWFDP) by the WMO, delivers improved forecasts and warnings of severe weather and also engages with programmes that concern the real-time prediction of hydro-meteorological hazards such as the Hydrology and Water Resources Programme (HWRP) for developing synergies and linkages with Flash Flood Guidance System (FFGS). For the South African domain, real time satellite-based rainfall estimation tools operational at SAWS developed through the Nowcasting Satellite Application Facility (SAF) software include the Convective Rainfall Rate (CRR) which uses three Meteostat second generation (MSG) channels, together with input from NWP models to create a near-real-time rainfall product, the Hydro Estimator (HE) which provides satellite precipitation estimations forecasts every 15 minutes using the MSG IR108 and the Unified Model (UM) as inputs (De Coning et al., 2015) with accumulation products of 1h, 3h, 6h, 24h, 10 days and 1 month, operationally on a rolling time average basis.

Weather forecasts for the Region are issued by the SAWS and the CSIR. CSIR use a variable resolution Conformal-Cubic Atmospheric Model (CCAM) for ensemble member forecasting (16 members), the highest spatial resolution being at 8 km (Landman et al., 2001, Bezuidenhout and Schulze, 2006; Ghile and Schulze, 2008). These include 7 day forecasts of rainfall, winds, thickness fields, instability indices, maximum and minimum temperature, and are issued daily through the Atmospheric Modelling Strategic Initiative (AMSI) of the CSIR's Natural Resources and the Environment (NRE) for South Africa. Short-range (4 day) forecasts of the same variables are also produced for the region. Weekly reports on drought, incorporating rainfall and temperature (minimum, maximum, heat waves and drought index), are also provided through SAWS.

Long range (monthly and seasonal) forecasts for the region are produced by CSAG, SAWS and CSIR, and are incorporated into a multi-model forecast product. CSAG produces provincial ensemble mean seasonal forecasts using a non-standard version of HadAM3, the atmosphere component of the Hadley Centre Coupled Model (HadCM) developed at the Hadley Centre for Climate Prediction and Research in the United Kingdom. Other commonly used and freely available weather and climate forecasts for the region include those of ECMWF (SYS4), ECMWF-ENS, IRI, the Potsdam Institute for Climate Impact Research and the Australian Bureau of Meteorology. The SAWS ECHAM4.5-Modular Oceanic Model version 3 (MOM3-SA) is the first OAGCM to be developed in Africa for seasonal climate prediction.

5.2.5. Uncertainties in observational and forecast data sets

It is crucial to evaluate the precision of observational and forecast data, products as well as the associated uncertainty before opting for specific applications (Ghile et al., 2010). Several studies have been conducted over the region with the aim of evaluating satellite derived products against local observations or proxies, as well as studies of inter comparison between the datasets (Cohen et al., 2012). Most studies conclude that these products are able to display useful information on rainfall patterns, especially at higher temporal scales, however, substantial errors in rainfall amounts which ultimately propagate through to derived forecasts are often observed. For example, Ghile et al. (2010) aimed at evaluating the performance of the discontinued SIMAR products developed by SAWS on a 1-7 km spatial coverage and daily temporal scale which included rain gauges, radar, satellite and merged rain fields from a hydrological perspective. This was conducted for a Water Research Commission project which aimed to use rainfall forecasts for agricultural decision making in selected catchments in South Africa. An analysis was conducted of the skill of these datasets for two high rainfall events and over a continuous period of 90 days in the Mngeni catchment (South Africa) in terms of the positional accuracy of the rainfall distribution estimates, as well as the direct evaluation of the discrepancy between daily estimates and reference data. Results showed, in general, that the relationship between all data sources and the reference data was low, with R^2 values between 0.0-0.58 for rainfall totals, and 0.0-0.96 for streamflow simulations using the ACRU agrohydrological model. Raw satellite data showed over-estimates of 3.57 mm, which resulted in streamflow over-estimations of 5.01-5.18 mm. The overall finding was that the raw radar and satellite products cannot be used directly for operational hydrological forecasting applications.

Most studies have justified further investigations into the use of these products for forecasting applications and have concluded that the satellite data cannot be used without modification and further processing beforehand (Ghile and Schulze, 2010). In addition, an evaluation of such products is required from a hydrological perspective, as well as the ability to produce estimates relevant to crop forecasting, for example dry spells and extreme events such as frost, hail, etc.

While historical and near real time observations are used for calibration, validation or verification purposes, the forecasting component of the system requires reliable and skilful forecasts of the same forcing data at various time horizons. Just like the satellite derived products over the region, weather and climate forecasts for the region have been shown to present their own challenges and uncertainties for use in application models for operational purposes.

Forecasts are commonly validated against observed records in terms of sharpness, reliability and skill. However, studies have shown issues of temporal variability with deterministic NWP forecasts, and therefore need to be evaluated from a hydrological perspective. Ghile and Schulze (2008) evaluated the ability of three experimental NWP models (CCAM, UM and NCEP MRF) from a hydrological perspective to capture four selected rainfall events, as well as a continuous 92 day period record. Occurrences of rainfall were represented correctly over most of the study period, especially by the CCAM and the UM models, but with a tendency to respectively under- and over- estimate observations. Suggestions for improvement were made for the models, especially in terms of making the model spatial scales more compatible with the requirements of hydrological models for applications in small and medium sized catchments.

Studies focused on developing operational forecasting systems have also focused on developing systems that have the ability to translate tercile-based seasonal forecasts into a form that can be used in application models. Common methods include those based on the analogue concept. For example, a GIS-based tool was developed to serve as an aid to process all the computations required to translate the seasonal climate forecasts into daily quantitative values suitable for application with hydrological or crop models (Ghile and Schulze, 2008). An important component of the tool was the translation of the categorical monthly and seasonal rainfall forecasts into daily quantitative values which was conducted using two methods viz, the Historical Sequence Method and the Ensemble Re-Ordering

Method. The first approach was designed to sample daily rainfall values from the same dates in selected analogue years, while the second approach randomly generates ensembles of 10 members from selected analogue years for each forecast day, and uses the Ensemble Re-Ordering Method as a post-processing step to reconstruct the temporal persistence of the synthetically generated daily rainfall data. These methods, however, assume that hydrological processes are stationary over time, and that they are realizations of an ergodic stochastic process. Despite the level of uncertainty associated with the hydrological and agricultural forecasting systems, various decision makers and end users require climate information for ground applications and decision making.

5.2.6. Uncertainties in the application models

The limitations of statistical methods of agrohydrological forecasting, have been long linked to the inability to realistically represent the complexity of a catchment particularly the lagged responses and dynamic hydrological processes. Robertson et al. (2013) explains this limitation when considering the issue of initial conditions in streamflow forecasting through the use of antecedent streamflow and rainfall. He mentions that antecedent streamflows do not immediately respond to antecedent rainfall but soil moisture and groundwater stores are first replenished which may lead to low forecasts due to the underestimation of initial soil moisture conditions. Simulation models such as Rainfall-runoff and crop models are considered particularly more effective tools in attempting to represent a catchments multiple variables, multiple space-time scales and multiple interconnected systems is regarded as an invaluable tool in simulating information for use in decision making for water resources planning and management and agricultural production at various lead times in agrohydrological forecasting (Brown, 2014; Warburton et al., 2012; Schulze, 2005).

Apart from the observational and forecast weather and climate data, uncertainties in dynamic methods of agrohydrological forecasting include the assumed initial hydrological conditions (e.g. soil moisture content, streamflow, and reservoir inflows) from which the forecast is run, hydrological state variables as well as the model parameters and structure (Block et al., 2009; Thiboult et al., 2016).

The quantification, reduction and communication of these uncertainties are necessary for the generation of more accurate and actionable forecast information for effective risk-based decision making (Ramos et al., 2013; Sene and Darch, 2011; Thiboult et al., 2016).

5.3. Overview of the ACRU Forecasting Tool

The agrohydrological forecasting system of Ghile and Schulze (2008) alluded to in the above literature review was a product of a WRC project (Lumsden and Schulze, 2012) that was a precursor to the current project. Unfortunately, the forecasting system is no longer usable due to the ArcGIS software package no longer using the Visual Basic language in its programming environment. Other reasons why the system can no longer be used in its current form include changes in the available weather and climate forecasts, and the discontinuation of the SIMAR rainfall product. These problems were exacerbated by a lack of funding to maintain the system on an ongoing basis. Given this context, it was necessary to design a new forecasting system for ACRU for application in this project. The design of this new system drew on the previous system and sought to avoid a recurrence of the problems in continuity.

A theoretical framework for the new ACRU forecasting tool for the Mhlathuze case study is presented in Figure 5-2 in the form of a schematic diagram. The development of this schematic was informed by the above literature review, and includes the components typically found in an agrohydrological forecasting system. From an ACRU perspective, a key component requiring new development was the model initialization aspect. When performing a simulation with ACRU, stores inside the model (for example, the soil moisture store) start at default, or in some cases, user specified values. If the simulation is over a long enough period, the store values will equilibrate to realistic values, and the starting value used will become insignificant. However, in forecast simulations, it is unlikely that store values will have time to attain realistic values, therefore making it important to ensure that the starting value used for the stores is realistic. The process of selecting and specifying realistic starting values is referred to as model initialization. Correctly initializing an agrohydrological model is an important facet of restricting the error present in an agrohydrological forecast. In order to implement the forecasting system, it was decided to link ACRU to the Delft-FEWS forecasting framework. A review of Delft-FEWS and a description of the training that was undergone to use it, are described in the next few sections.

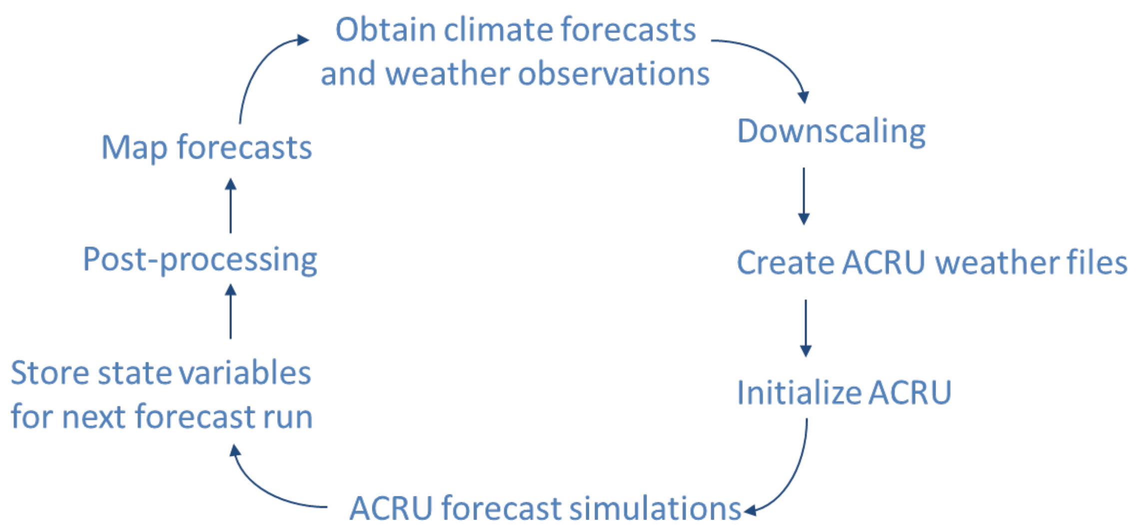

Figure 5-2 Schematic of the ACRU agrohydrological forecasting tool

5.4. Delft-FEWS Hydrological Forecasting Framework

Delft Flood Early Warning System (Delft-FEWS) is a hydrological forecasting framework developed in The Netherlands. This framework, which is not to be confused with FEWS-NET, has its origins in flood forecasting. However, this framework is now applied at a range of time scales, including up to climate change time scales. The framework is generic in that any hydrological model can be plugged into the system, and it is highly customizable. This framework was evaluated as a potential vehicle to develop the ACRU forecasting tool.

A review of the Delft-FEWS system is presented next in this chapter. This is followed by an overview of the main outcomes from a forecast master class on the Delft-FEWS system attended by members of the project team.

5.4.1. Review of Delft-FEWS

There are two main types of data required for hydrological forecasts (i) measured or estimated values describing the real-time state of the hydrological system at the start of a forecast period, such as dam levels and soil moisture, and (ii) forecast climate driver variables, such as rainfall, evaporative potential and temperature. It was anticipated that the most difficult part of being able to produce hydrological forecasts in this project, was not running the ACRU model, but rather the acquisition, processing and management of the forecast input variable and state variable datasets. The project team identified the Delft-FEWS software, developed by Deltares, as a potential tool to assist with the acquisition, processing and management of data and to manage the workflows required to produce hydrological forecasts.

This review of the Delft-FEWS flow forecasting system is based on a paper by Werner et al. (2013). Additional information about Delft-FEWS can be found on the Delft-FEWS website (Deltares, 2016a). Delft-FEWS is described as open platform through which data and models can be flexibly integrated to construct operational forecasting systems. The platform is open in the sense that it not based on hard-wired data sources, data formats and specific models; rather it provides a set of open interfaces that (i) enable integration of external models and algorithms and (ii) use of application specific data formats. Thus, each implementation of Delft-FEWS can use data sources and modelling tools that are specific to the area and purpose of application. In addition, the platform provides a data storage layer, a data access layer and tools to import, manipulate, view and export data. The architecture of the Delft-FEWS platform, where various different types of modules access the data storage layer through the data access later, is shown in Figure 5-3. An example of the Delft-FEWS user interface is shown in Figure 5-4.

The typical components and data flows of a Delft-FEWS forecasting system are shown in Figure 5-5. Data and information sources, such as in-situ measurements, remotely sensed estimates and forecasts, are imported by Delft-FEWS. Standard or customised tools within Delft-FEWS are used to validate, transform, and interpolate these imported datasets to provide suitable datasets for modelling. In some instances several measured and forecast datasets may need to be superimposed

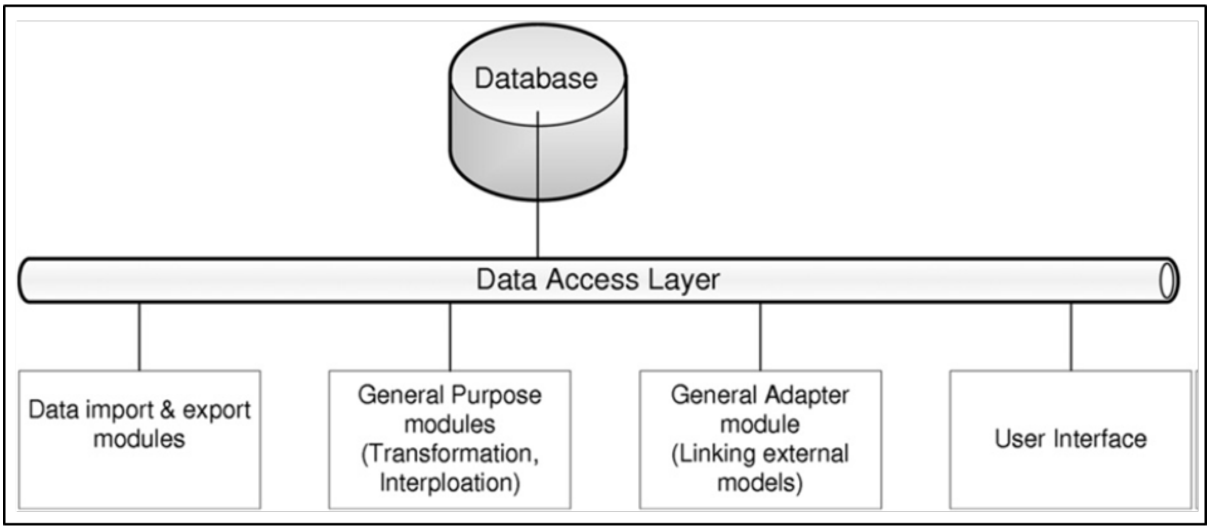

Figure 5-3 Delft-FEWS architecture (Werner et al., 2013)

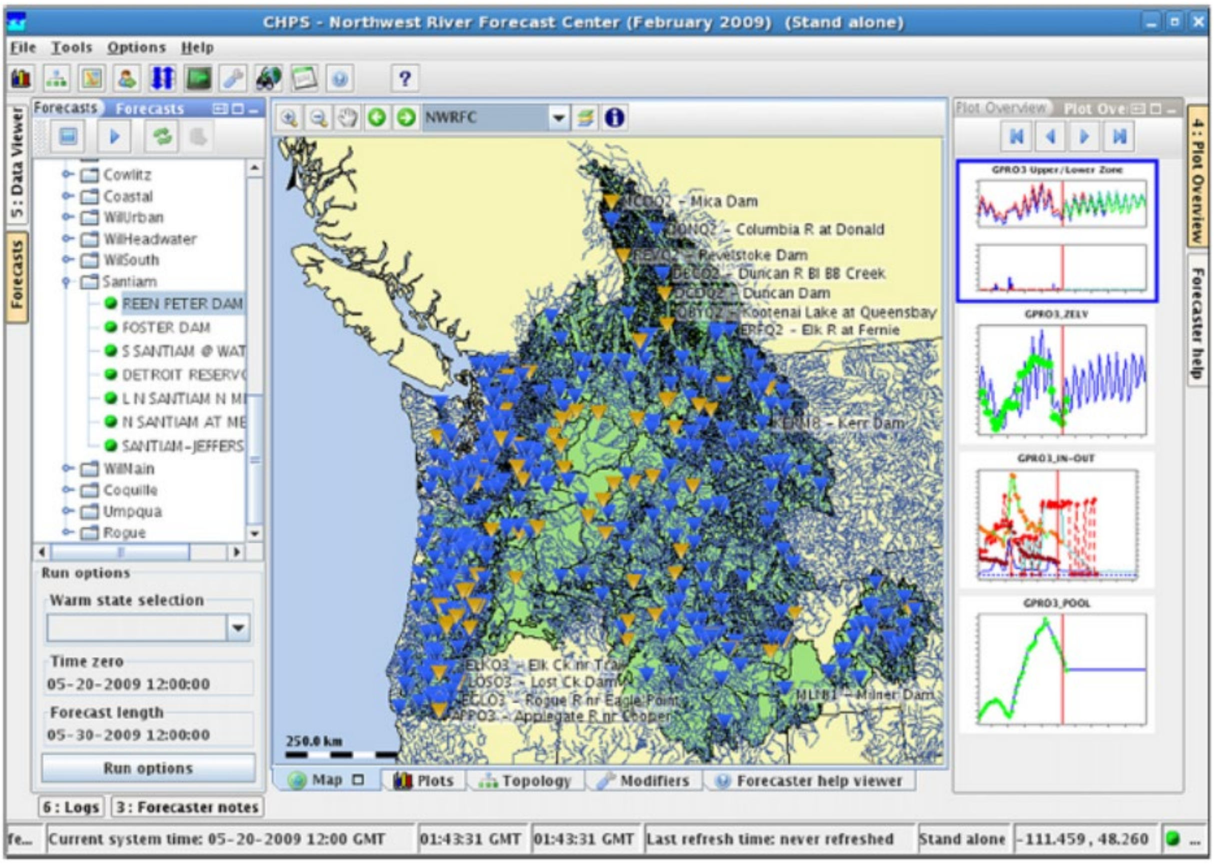

Figure 5-4 An implementation of Delft-FEWS showing the user interface (Werner et al., 2013)

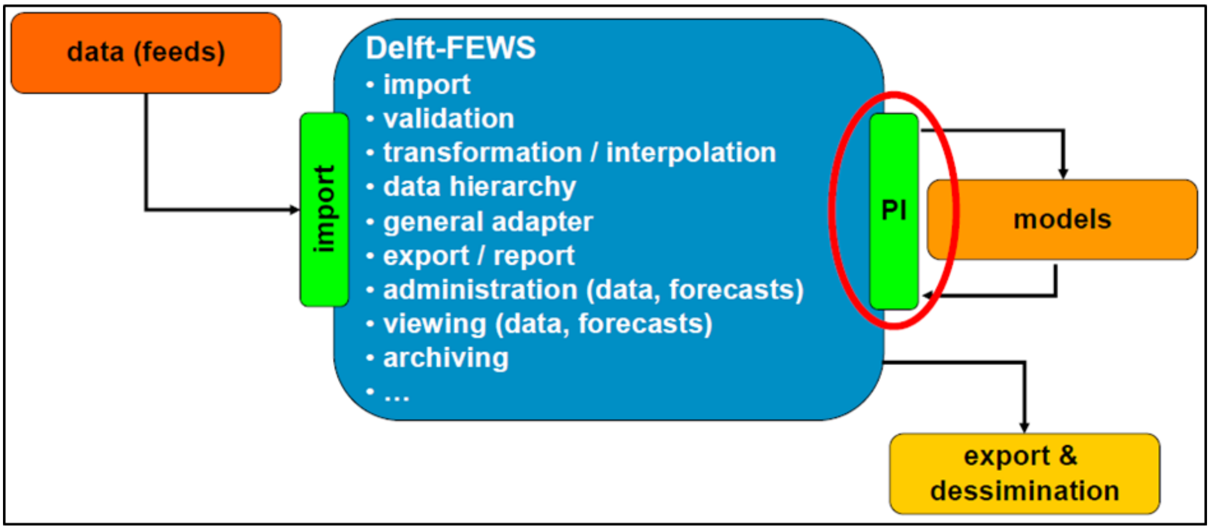

Figure 5-5 Typical components of a Delft-FEWS forecasting system (Deltares, 2016b)

Delft-FEWS has been developed using the Java programming language, making it platform independent, and thus able to run on both Windows and Linux operating systems. It also makes extensive use of eXtensible Markup Language (XML) files for defining the model and data interfaces. Delft-FEWS forecasting systems can be set up as (i) a standalone application on a single computer from which forecasts are run and analysed manually, or (ii) as a largely automated client-server application where data storage and processing takes place on one or more central servers which are accessed by forecasting staff from client computers.

A demonstration version of the Delft-FEWS software is available on the website (Deltares, 2016a). The software is free for research and demonstration purposes, however, use in an operational context requires a support and maintenance agreement and it is not clear what the costs associated with this agreement would be. A support and maintenance agreement entitles the user to the latest version of the software. There is documentation describing the software and how to set up a Delft-FEWS forecasting system available on the website (Deltares, 2016a).

Delft-FEWS seems to have been widely applied and Werner et al. (2013) state that since 2002/2003 it has been applied in more than 40 operational forecasting centres internationally. Model adapters have been created for numerous models and data adapters exist for a large variety of data formats.

The review of Delft-FEWS revealed it to be a promising tool for implementing an agrohydrological forecasting system and would: (i) potentially save the project team from unnecessarily developing software tools for the acquisition, processing and management of data, (ii) assist the project team in understanding the process of producing hydrological forecasts based on a variety of overlapping temporal historical and forecast datasets, and (iii) provide a foundation from which such an agrohydrological forecasting system could potentially be made operational subsequent to the project being completed. Despite the perceived advantages of potentially using the Delft-FEWS software, learning how to use the software and implementing it was not anticipated to be a simple process. As a first step, a model adapter would be needed to enable the ACRU model to run within Delft-FEWS. A practical evaluation of the software was conducted next to confirm the suitability of the software.

5.4.2. Evaluation of Delft-FEWS

The introductory configuration course exercises that are made available with the Delft-FEWS software were completed as part of the evaluation of Delft-FEWS. The topics covered in the course include:

- Understanding XML files
- Setting up the locations of gauging stations
- Changing controls on the FEWS Explorer (user interface)
- Importing station time series and adding associated validation rules and thresholds
- Adding pre-configured map displays
- Interpolating station time series
- Adding rating curves
- Spatial averaging of station data
- Importing NWP data
- Plugging in a new hydrological model with pre-developed adapters and generating a flood forecast

Some observations arising from undertaking these course exercises include the following:

- The highly customizable nature of the software comes at a price, this being that it is not simple to configure. The configuration is done via numerous XML files which require effort to understand in terms of their structure, function and linking. The user interface controls the execution of workflow tasks once the system is configured, and does not play a major role in the configuration itself.
- Being introductory in nature, the exercises focused mostly on applying default or pre-determined options in the framework, with only minor customization being demonstrated.
- The above point raised some questions regarding the customization of the software. Specific examples include:
  - Would it be possible to introduce downscaling methods that are not currently available in the software and how easy would this be to accomplish?
  - Can the ‘warm state’ option to initialize the hydrological model (based on model output from the previous forecast run) be modified to incorporate observations if these are available?

During the evaluation of the Delft-FEWS framework it came to light that it is applied for flood forecasting purposes by the water and sanitation department at eThekwini Municipality. A workshop presentation on this application was attended and revealed that it has been applied very successfully in this context.

The final decision on whether to apply Delft-FEWS involved a trade-off between the effort required to configure it and the effort required to develop new software with similar capabilities. Despite its lack of user-friendliness in terms of configuration, it is very powerful in terms of its functionality. Another long term consideration was that applying the software in an operational context requires a support and maintenance contract. This would become important if the experimental forecasts developed in this research project were deemed suitable for operational implementation beyond this project.

5.4.3. Forecast Early Warning System Master Class

The Coastal Stormwater and Catchment Management Department (CSCM) at eThekwini Municipality have piloted the use of the Delft-FEWS software to set up and operate a flood warning and coastal management system for the municipality. CSCM worked closely with Deltares to set up the system, but as far as possible opted to build capacity in their own staff in setting up and operating the system. This approach has put eThekwini Municipality in the position of being able to encourage and assist other municipalities in South Africa with setting up their own disaster management systems.

Two members of the project team, Mr Trevor Lumsden and Mr David Clark, were fortunate to be provided with an opportunity to attend a 3-day Delft-FEWS training course titled “Forecast Early Warning System Master Class”. The course, held from 1-3 August 2017 at Moses Mabhida Stadium in Durban, was organized and facilitated by the CSCM and the Municipal Institute of Learning (MILE). Technical expertise was also provided by two Delft-FEWS experts from Deltares. The course provided an ideal opportunity for the project team to gain a better understanding of how Delft-FEWS could be applied and an introduction to how to actually configure Delft-FEWS, import data and run models. A brief overview of what was covered in the course is shown in Table 5-1. Despite the course title, this was an introductory level course aimed at informing delegates of the capabilities of Delft-FEWS and providing a starting point for those delegates who might be wanting to setup Delft-FEWS systems themselves. Delft-FEWS, together with the models run within it, is a powerful and versatile tool, but requires a high level of technical knowledge to implement and operate.

After attending the Delft-FEWS master class, it was decided that the software would be applied in the project. The first step in doing this was to integrate the ACRU model into the software. This is described next.

5.5. Integration of the ACRU Model into the Delft-FEWS Forecasting System

Delft-FEWS is not a model, it is a system that facilitates data handling and model integration enabling users to build their own custom modelling systems. For each application of Delft-FEWS, users decide which model or models need to implemented and the datasets required to run these models. External models are usually linked into and executed from DELFT-FEWS using the General Adapter module as shown in Figure 5-6.

Table 5-1 Overview of Delft-FEWS course

Day 1	● Background to the decision to use Delft-FEWS as part of the Municipality's disaster management system. ● Description of the advantages to other municipalities of applying Delft-FEWS and how eThekwini Municipality could assist. ● Introduction to the development of the Delft-FEWS software, its main features and examples of how and where the software has been applied internationally. ● Sources of forecast meteorological data and identifying other data requirements. ● Setup of the Delft-FEWS software on delegates laptops. ● Hands-on introduction to the operation of Delft-FEWS using eThekwini Municipality's configuration for the Palmiet River.
Day 2	● Introduction to the basic configuration of Delft-FEWS. ● Introduction to configuring data imports. ● Presentation on numerical weather predictions and the use of these. ● Hands-on practice in running models in Delft-FEWS. ● Understanding the limitations of numerical models and model verification. ● Hands-on practice in running models using Global Forecast System (GFS) data in Delft-FEWS. ● Overview of thresholds in Delft-FEWS.
Day 3	● Identifying what is required from a Delft-FEWS implementation. ● Setting thresholds for models in Delft-FEWS. ● Introduction to field instrumentation and its use in modelling and for validation. ● Hands-on practice in using hindcast or historical data to initialise models run in Delft-FEWS. ● Dissemination of results from Delft-FEWS for disaster management.

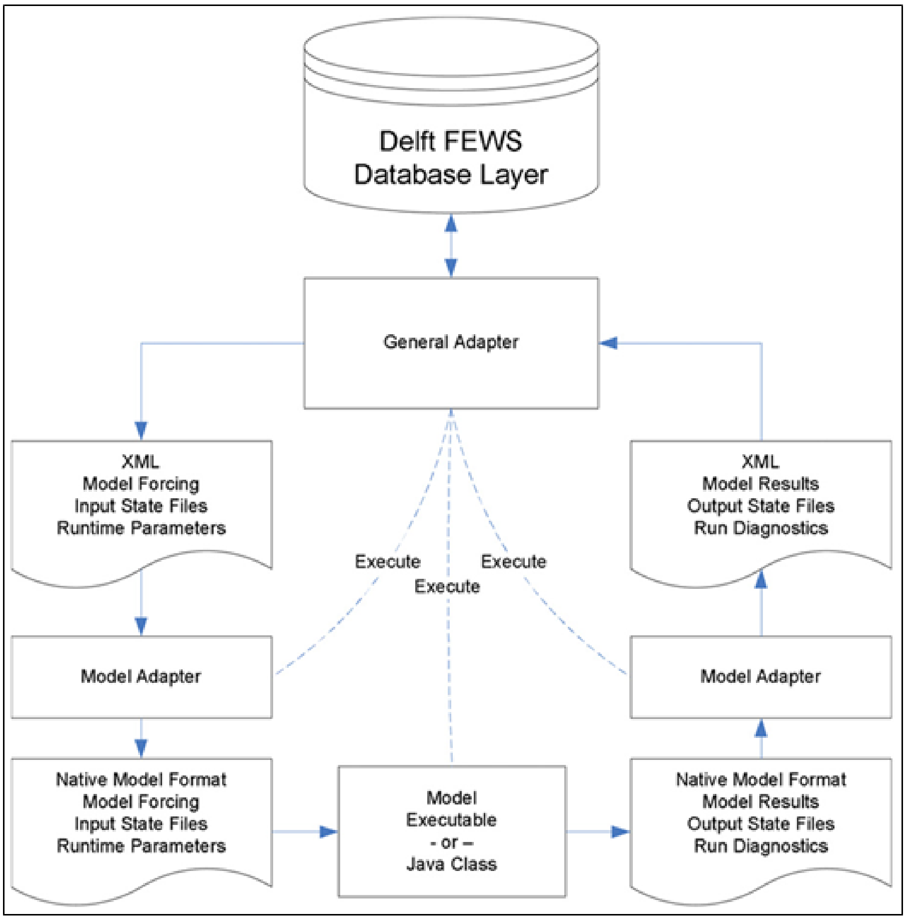

Figure 5-6 Linking and execution of external models in Delft-FEWS (Werner et al., 2013)

For each model several files, in Extensible Markup Language (XML) format, need to be configured. One of these files is the ModuleConfigFile which specifies (i) which input variables are required by the model, the commands to be used by Delft-FEWS to execute the model, and (iii) which output variables from the model should be imported back into Delft-FEWS. Prior to running a model the user would execute one or more Delft FEWS Workflows to import the data required for modelling into a Delft-FEWS database. For each model implementation a Workflow in Delft-FEWS would be used to execute an instance of the General Adapter for the model and the following sequence of events would typically occur.

1. First the General Adapter would retrieve data from the Delft-FEWS database.
2. The General Adapter would then write the data required by the model out to an intermediate file in the Delft-FEWS Published Interface (PI) XML format.
3. The General Adapter would then execute a pre-adapter, previously created by the model user, to translate model input data from the PI XML format to the model's native input format.
4. The General Adapter would then execute the model, which would typically (i) read the pre-adapted input file and possibly other model input files, (ii) perform a simulation for a specified period, and (iii) write out model result files.

5. The General Adapter would then execute a post-adapter, previously created by the model user, to translate user specified model results from the model's native output format to the PI XML format.
6. The General Adapter would then read the model results in from an intermediate file in PI XML format and store them in the Delft-FEWS database where they would be available for viewing, analysis, reporting or use as input to another model.

Delft-FEWS already contains pre-built adapters for a variety of models and also adapters to read and write a variety of commonly used data formats. One important point to note is that, although two or more models may be run from Delft-FEWS such that the output from one model is used as input to another model, these models are run in series. The implication of this is that any feedbacks, between different components of the modelled system represented by different models, cannot be modelled unless each model is run one time step at a time.

Typically models users would not have access to source code for the model and thus a pre-adapter and post-adapter is required to enable the transfer of data between Delft-FEWS and the model. However given that a member of the project team is involved in developing and maintaining the ACRU model, it was possible to omit the pre-adaption and post-adaption phases of linking and executing the model by adding functionality to the ACRU model to read from and write to the PI XML files directly. Two new classes were developed and incorporated into the ACRU4 version of the model: (i) the ADelftFewsPiXmlFileReader class which reads a PI XML file containing daily time series input data into ACRU and, (ii) the ADelftFewsPiXmlFileWriter which writes daily time series of ACRU simulation results to a PI XML file. These two new classes are shown in the Unified Modelling Language (UML) class diagram in Figure 5-7. The linking and execution of the ACRU model in Delft-FEWS in shown in Figure 5-8. A simple hypothetical configuration of Delft-FEWS and ACRU was used for testing and a Delft-FEWS Workflow was used to successfully run the ACRU model using historical time series of rainfall data imported into Delft-FEWS. A simulated streamflow time series was then imported back into Delft-FEWS. The successful development of classes within the ACRU model to read and write PI XML files, enabled the ACRU model be used as a model within Delft-FEWS

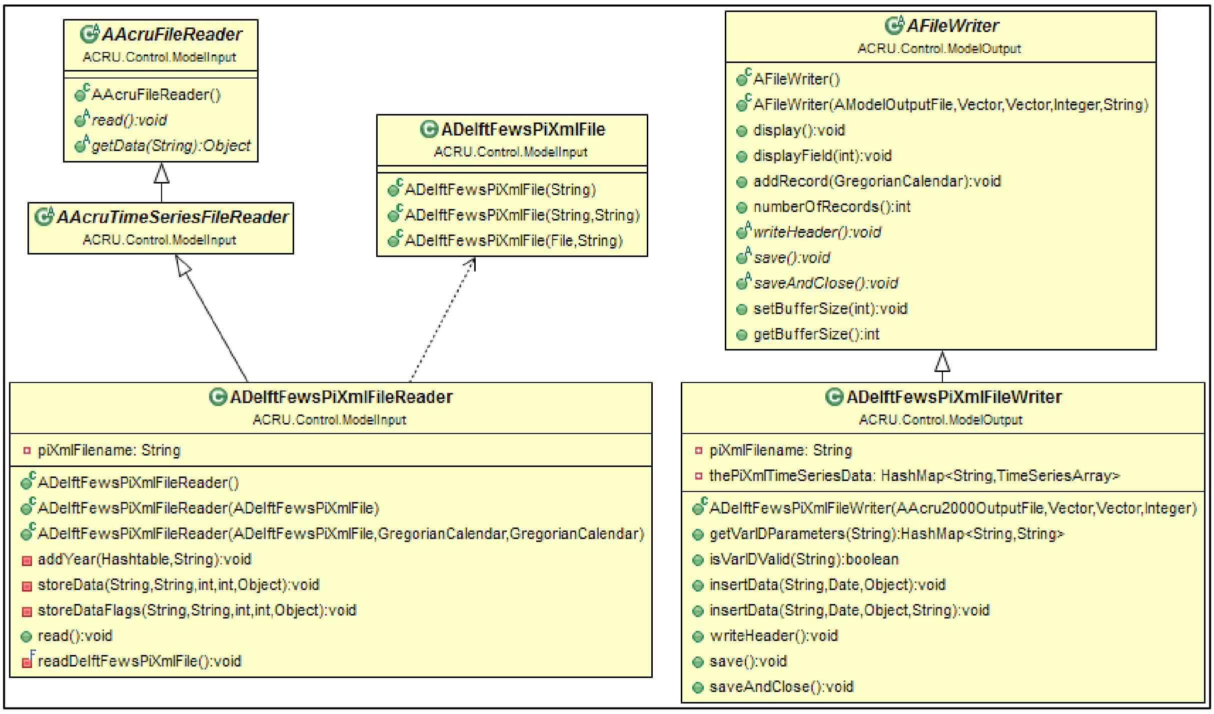

Figure 5-7 UML diagram of new ACRU classes developed to read and write PI XML files

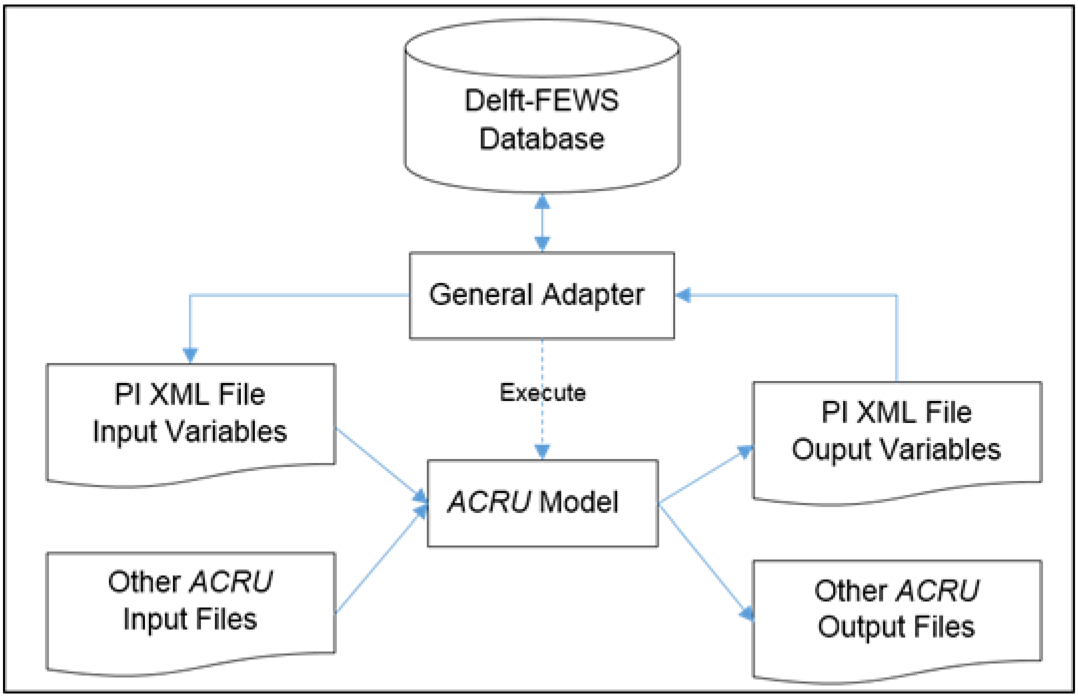

Figure 5-8 Linking and execution of the ACRU model in Delft-FEWS

5.6. Application of Delft-FEWS to the Mhlathuze Catchment

5.6.1. Introduction

This sub-section details the application of ACRU in Delft-FEWS in the Mhlathuze Catchment. Initially the focus was on producing a 20 year daily streamflow simulation using observed historical climate data. A screenshot view of the ACRU/Delft-FEWS configuration developed for this purpose, is presented. This configuration of ACRU in Delft-FEWS formed the foundation for applying the modelling system to produce agrohydrological forecasts. Additional configuration to enable forecast simulations is described.

5.6.2. Configuration of Delft-FEWS in the Mhlathuze catchment

Most of the configuration of Delft-FEWS is achieved through modifying a series of XML files in the directory structure of the software. Relatively little configuration is done through the graphical user interface (GUI) which is mainly used for operating a forecasting system once it is configured. The aspects of the configuration and the relevant XML files modified are outlined in Table 5-2. Some aspects of the configuration have been alluded to in the section on integrating ACRU into Delft-FEWS. The description of the configuration is not exhaustive.

5.6.3. Screenshot view of Delft-FEWS configured for the Mhlathuze catchment

The simulation of historical streamflow was focused on the catchment area of the Goedertrouw Dam in the upper section of the Mhlathuze catchment. There are three meteorological gauges in the area which is divided into 6 subcatchments for hydrological modelling purposes. The map display of the Mhlathuze catchment in Delft-FEWS is shown in Figure 5-9. The map shows the quaternary catchments in the Mhlathuze, the primary and secondary rivers, the meteorological stations and dams and lakes (including the Goedertrouw Dam). In the left hand side of the map display, there is a list box of the meteorological gauges and a single streamflow node, where the latter is a site immediately downstream of the Goedertrouw Dam. If items in this list box are highlighted, then the corresponding items are highlighted in the map (icons are surrounded by a box). In Figure 5-9 the meteorological gauges and the streamflow node (relevant to Goedertrouw Dam) have been highlighted.

In the data display view of Delft-FEWS (not shown), the meteorological gauges and streamflow node can once again be highlighted in the list box on the left hand side of the display. Selecting these points of interest results in the corresponding point data being plotted on the right hand side of the display, with separate plots being produced for each parameter type (one for precipitation and one for streamflow). When positioning the cursor over these plots it is possible to zoom in and out of the time series (X) axis to view particular periods in more detail. When zooming in and out, the data visible in the tables to the left of the plots change accordingly. There are basic statistics presented at the top of the table that are re-calculated when zooming into a different period.

Table 5-2 Aspects of Delft-FEWS configured for the historical streamflow simulation

Aspect	Description	XML File/s
Location of points of interest	Information about points of interest associated with observed and/or modelled data (e.g. meteorological stations, streamflow nodes) including their geographical coordinates. These can be specified individually or in sets. The information can be imported from CSV or shape files.	Locations.xml LocationSets.xml
Map display	Configures the display of relevant geographical features, for example, catchment boundaries, rivers, dams, roads, towns. Also configures the scale bar, north arrow, map projection, zoom extents, etc.	Explorer.xml
GUI display	Configures shortcuts, toolbars, options, web URLs, date/time format, time zone, sizing of panels, etc.	Explorer.xml
Parameters	Describes the parameters that are associated with observed and/or modelled data (e.g. rainfall, streamflow). Description includes units, time interval, type (accumulative or instantaneous), precision.	Parameters.xml
Grouping of points of interest	Specifies how points of interest (e.g. meteorological stations, streamflow nodes) are grouped for display (map view) or analysis (table, graph views)	Filters.xml DisplayGroups.xml
Location of ACRU files	Subfolders are created where ACRU's input and output files are stored. These subfolders are referred to in relevant modules of Delft-FEWS	

Table 5-2 Continued

Aspect	Description	XML File/s
Location of imported and exported data	Subfolders are created where external data are stored, either for importing to Delft-FEWS or for exporting from Delft_FEWS. These subfolders are referred to in relevant modules of the software	
Importing of external rainfall data	A module was configured to import observed rainfall data from external sources (e.g. SASRI, SAWS) into the Delft-FEWS database. The module contains information on the relevant parameters, locations and data file structure. The mapping of parameters and locations between the external data files and the internal Delft-FEWS database is also specified.	ImportCsvRainfall.xml idImportRainfall.xml ModuleInstanceDescriptors.xml
Running of ACRU	The *General Adapter* module described previously in the section on integrating ACRU into Delft-FEWS, was configured for use in the Mhlathuze catchment (it was named RunACRU4 in this instance). The mapping of parameters and locations between the Delft_FEWS database and the PI XML input and output files that ACRU reads and writes is also specified here.	RunACRU4.xml IdACRU4.xml ModuleInstanceDescriptors.xml
Workflows	The modules that are configured in Delft-FEWS (for importing external rainfall data and running ACRU) are called from within workflows. While workflows can call multiple modules, separate workflows were created for each module for testing purposes. Since workflows can be embedded within other workflows, it will ultimately be possible to execute all modules and workflows in one seamless process	ImportExternal.xml RunACRU4.xml WorkflowDescriptors.xml

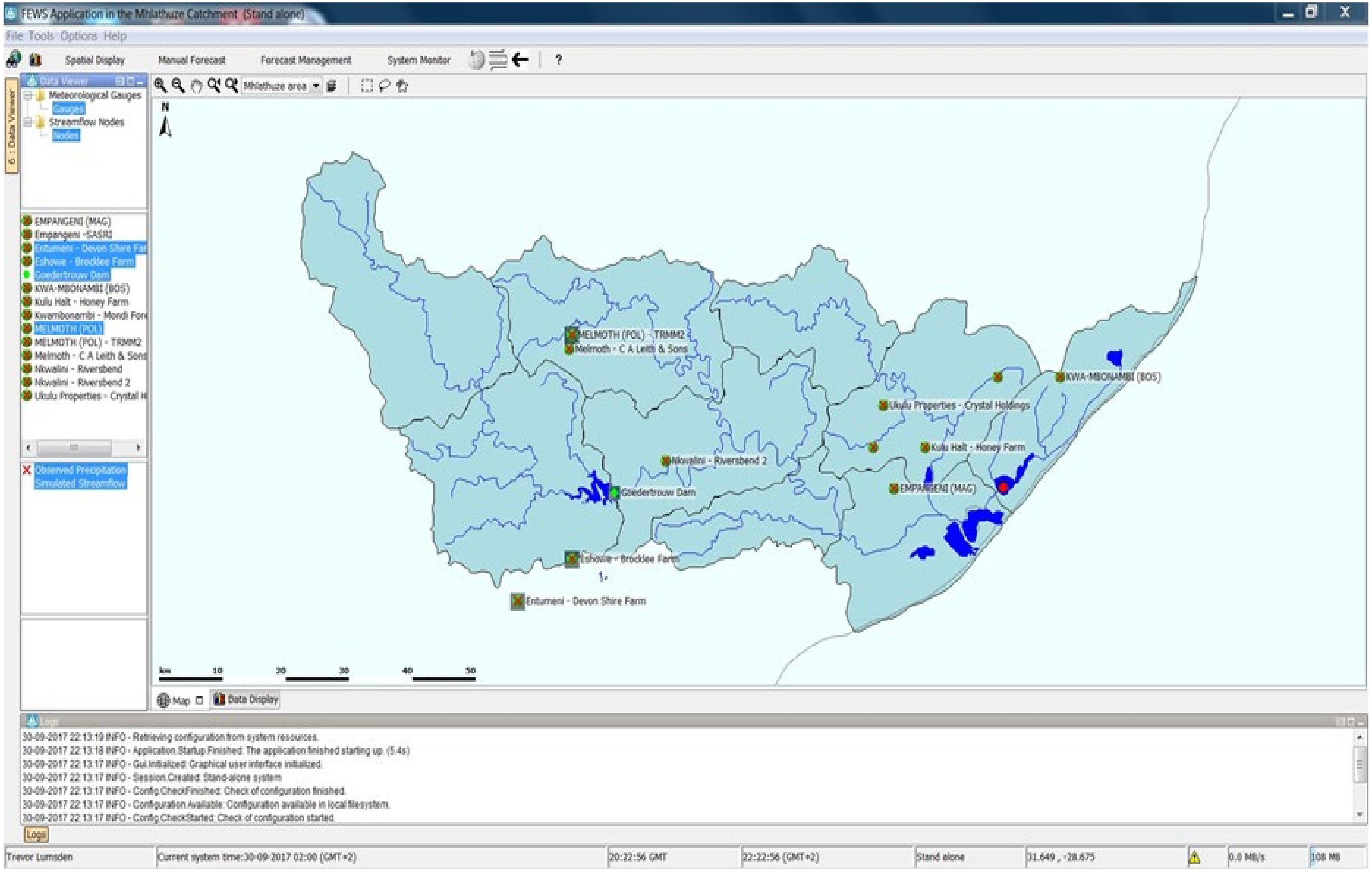

Figure 5-9 The map display in Delft-FEWS, as configured for the Mhlathuze catchment. Points of interest have been highlighted in the list box on the left hand side and are therefore displayed with a box around them in the map. The points of interest (3 meteorological gauges and a streamflow node) are relevant to the Goedertrouw Dam in the upper section of the catchment.

5.6.4. Additional configuration to enable forecast simulations

To enable forecast simulations to be performed the following additional configuration was performed:

- Modules to import weather forecast data including rainfall and temperature
- Modules to perform ACRU simulations for a forecast run (involving exporting of the weather forecast data in appropriate format and for the correct period, calling ACRU and importing model output for further analysis). Modules for different model scenarios were created.
- Modules to sum forecast output over the period of simulation (e.g. 7 days) to allow for comparisons with observations or other simulations.
- Display filters to generate data tables and plot graphs
- Modules to export results for reporting purposes
- Workflows to execute the above modules in an appropriate sequence

There is a whole array of features in Delft-FEWS that can be configured. The features configured here were those considered to be important for the context of the project.

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CHAPTER 6. SHORT TO MEDIUM RANGE AGROHYDROLOGICAL FORECASTS

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6.1. Background

Short to medium term agrohydrological forecasting in the Mhlathuze catchment was focused on the inflows to Goedertrouw Dam, and on crop water and irrigation requirements for sugarcane in selected sub-catchments deriving their water from the Dam. It was decided to focus the dam-related forecasts on the inflows to the dam, rather than on storage in the dam. The reason for this was that the historical withdrawals from the dam are variable in nature and would be difficult for the forecast producer to predict in an operational context. In addition, ACRU is only able to accommodate mean monthly withdrawal amounts for non-irrigation related abstractions, and would not be able to represent withdrawals that are specific to a particular 7 day forecast period. In this situation it would be better for users of the forecasts (e.g. water managers) to account for the expected dam withdrawals for the forecast period in question. From the interactions with sugarcane stakeholders, the main need for forecast information in the catchment relates to water availability for irrigation (cf. Chapter 2).

The specifics of the forecast methodology are described in the next sub-section and following this the results are presented. The analysis of results focuses on evaluating how good the forecasts are, and on assessing the impact of improved model initialization on the forecasts. These improvements are also discussed in the later chapter (9) on reducing uncertainty and error in forecasting.

6.2. Methodology

6.2.1. Locations and forecast variables

The sub-catchments feeding the Goedertrouw Dam include quaternary catchments W12A and W12B. Forecasts of dam inflows therefore depend on accurate representation of conditions in these catchments. The sub-catchments in which forecasts of crop water and irrigation requirements were developed include quinary catchments W12D3 (inland) and W12F3 (coastal). W12D3 is representative of the Nkwalini, Umfuli and Heatonville irrigation districts, while W12F3 is representative of the lower Mhlathuze / Empangeni irrigation districts. Both regions rely on water releases from the Goedertrouw Dam to supply their irrigation water. In the context of the forecasts developed in this chapter, crop water requirements are defined as the potential evapotranspiration of the crop. If a crop has access to an equivalent amount of water (through rainfall and irrigation), it will not be subject to water stress and maximum yields will be obtained. The irrigation requirement relates to the amount of water that must be added, in addition to rainfall, in order to meet the crop water requirement. In this context, net irrigation requirements were considered. In other words, this represents the water that must be made available to the plant roots, and excludes the additional water that is required to satisfy losses due to wind drift, leaking pipes, etc. (the additional water is not available to the plant).

6.2.2. Weather forecasts

The weather forecasts used to develop the above agrohydrological forecasts were the 7 day rainfall and temperature forecasts produced at a 15 km resolution (cf. Chapter 3). Although, these forecasts were at a lower resolution than the 8 km forecasts produced subsequently, they had the advantage of including temperature forecasts (unlike the later set), and also extended throughout the year for the 2013-2016 period. The 8 km forecasts were produced for the same 4 year period, but only for the summer (Dec-Jan-Feb) rainfall seasons. The availability of forecasts throughout the year, and the inclusion of temperature variables, were considered to be more important in a sugarcane production context than having a very high spatial resolution.

6.2.3. ACRU configuration

The following changes were made to the configuration of ACRU relative to the detailed description given in Chapter 4 which focused on the verification of the model for historical conditions:

- The method of estimating reference potential evaporation was changed to the Hargreaves and Samani (1985) equation based on daily temperature input. This allowed for temperature-driven evaporation estimates to be produced and for the benefit of the availability of temperature forecasts to be realized. Reference potential evaporation is a key driver in the estimation of crop evapotranspiration, and thus crop water requirements and irrigation demand.
- Simulations based on observed climate were still required in the development of agrohydrological forecasts, as these represented a baseline against which forecasts could be compared if observations of the forecast quantities were not available. Furthermore, they were also used in providing initial values of key storages in the model at the commencement of forecast simulations. The rainfall stations previously used in representing rainfall in the catchment during the model verification process (cf. Chapter 4) were still used Exceptions to this were for W12D3 and W12F3, where different stations that had available data for the period of interest (2013-2016), were selected. These station data were obtained from SASRI and included Nkwalini and Heatonville stations for W12D3, while Empangeni station was selected to represent W12F3. Temperature records from these stations were also used to represent conditions in the catchments. Temperatures in quaternary catchments W12A and W12B (and their component quinary catchments), were represented by SASRI station Entumeni. Temperature lapse rates were applied to these data to better represent the higher quinary catchments given that a fairly steep altitude gradient exists between the station and the upper catchments.
- No adjustments were made to rainfall or temperature forecasts to better represent the relevant catchment areas, since unique CCAM grid points were located inside most of the sub-catchments.

- For the forecasts of crop water and irrigation requirements a hypothetical soil was assumed to represent the cultivated areas of the relevant catchments. Key characteristics of this soil included the depth in which the majority of roots are found (1.0 m), the potential maximum rooting depth (1.5 m), the wilting point (0.16 m/m), drained upper limit (0.26 m/m) and porosity (0.5 m/m). Assumptions made regarding the values of key plant related variables included the crop coefficient (0.83) and daily interception loss (2 mm).
- Irrigation was assumed to be applied throughout the year in a 7 day cycle, and was applied until the soil reached drained upper limit on the day of irrigation. Test simulations revealed that the maximum 7 day total of crop water requirement was approximately 60 mm. The capacity of the irrigation system was set such that it would be able to satisfy this maximum requirement. In ACRU, it is assumed that irrigation is only applied if the requirement is more than a third of the system capacity.

6.2.4. ACRU model initialization

When performing a simulation with ACRU, storages inside the model (for example, the soil moisture store) start at default, or in some cases, user specified values. If the simulation is over a long enough period, the store values will equilibrate to realistic values, and the starting value used will become insignificant. However, in shorter range forecast simulations (such as those developed in this chapter), it is unlikely that store values will have time to attain realistic values, therefore making it important to ensure that the starting value used for the stores is realistic. The process of selecting and specifying realistic starting values is referred to as model initialization. Initializing an agrohydrological model with the best available information is an important facet of restricting the uncertainty and error associated with an agrohydrological forecast. Stores in the ACRU model that could potentially be initialized include the following:

- Baseflow store (accumulates water draining from the lower soil horizon and slowly releases it in the river as baseflow)
- Soil moisture store
- Dam store
- Stormflow store (releases delayed subsurface flow into the river in the days following a storm)
- Interception store

Initial values for these stores could be estimated from (in decreasing order of preference):

- Observations (if they are available)
- Simulated store values based on observed weather (if up to date observed weather is available prior to generating a forecast)
- Simulated store values based on forecast weather (i.e. store values output following a previous forecast run)

In the context of the variables forecast in this chapter, the stores that are most critical to initialize include the baseflow store (for the catchments feeding the Goedertrouw Dam – relevant to inflow forecasts) and the soil moisture store (for the catchments feeding the

Goedertrouw Dam and the catchments selected for forecasting crop water requirements and irrigation demand). Owing to time constraints it was not possible to initialize all stores that could potentially influence the variables being forecast.

Since observations of the critical stores were not available, values of the stores were estimated from a simulation based on observed climate (alluded to in 6.2.3). This simulation was conducted for the period 2009 to 2016. The period of simulation from 2009 to the start of the first forecasts (in 2013) allowed the model to warm up, and for the stores in the model to attain realistic values.

The hotstarting feature of ACRU simplifies the process of initializing the model. When the feature is turned on, the model automatically takes its starting store values from a specified file (in this case a file output from the historical observed climate simulation run). It searches for the day prior to the first day of forecast simulation and reads in the values of the relevant stores. From that starting point, the forecast simulation proceeds.

To investigate the impact of model initialization, forecasts were generated with and without initializing the store values. When the store values are not initialized, ACRU assumes the following for every forecast simulation:

- Baseflow store = 0 m
- Soil moisture of catchments = 50% of plant available water (can be altered by the user)
- Soil moisture of irrigated fields = 50% of plant available water

6.2.5. Delft-FEWS configuration

The configuration of the Delft-FEWS system that ACRU was linked to for the purpose of generating agrohydrological forecasts, was previously described in Chapter 5.

6.2.6. Observed data used to assess agrohydrological forecasts

As the sugarcane crops represented in the forecast simulations were not based on actual crops where measurements of the relevant variables are available (crop water requirements and irrigation demand), it was not possible to assess the forecasts against observations. In this situation, the next best data set against which the forecasts can be assessed is the model simulation run based on observed climate.

For the inflows to the Goedertrouw Dam, it is possible to derive a calculated times series of inflows based on the dam water balance and available measurements of the components of the balance. The dam water balance may be expressed as:

final dam volume = initial dam volume + rainfall + inflows - evaporation - outflows

Measurements of all the components of the water balance (with the exception of the inflows) are available from the Department of Water and Sanitation. Thus by rearranging the water balance equation it is possible to calculate the inflows. The necessary component data were obtained from DWS and the inflows calculated for the period of interest. The calculated inflows, plus the inflows derived from the historical simulation, were then available for comparison with the forecast flows.

6.2.7. Approach to evaluating the agrohydrological forecasts

As alluded to in the above paragraphs, the approach to evaluating the agrohydrological forecasts involved comparing the forecasts to observations, and to the historical simulation run. These comparisons were made for 7-day totals of the respective forecast variables. The impact of initializing ACRU when generating a forecast was also assessed by comparing the forecast runs produced with and without initialization.

6.3. Results

6.3.1. Forecasts of Goedertrouw Dam inflows

Forecasts of 7-day inflows to Goedertrouw Dam were assessed by comparing the observed inflows to forecast inflows produced using historical initial store values (hereafter referred to as initialized forecasts), as well as default initial store values (hereafter referred to as non-initialized forecasts). The simulated inflows based on observed historical weather data were also compared to the observed inflows (Figure 6-1). The historical simulated inflows tended to over-simulate the observed high flows. There was also a large 7-day flow event in April 2015 that the simulated time series did not capture. Baseflows tended to be under-simulated for much of the time period considered.

Initialized (Figure 6-2) and non-initialized (Figure 6-3) forecasts were able to simulate high and low flow trends of the observed inflows, however, there were some observable discrepancies with regards to the magnitudes of inflow forecasts. Focusing on the 7-day inflows below 10 million m^3 (Figures 6-4a to c), allows for the differences in magnitudes to be more clearly seen for events in this range (i.e. the majority of events). Historical simulations and the initialized forecasts followed trends of high and low flows better than forecasts that were not initialized. Non-initialized forecasts are likely to only consist of stormflows since baseflow will not be simulated over a 7 day period without initialization of the baseflow store. This is reflected in the large number of 7-day inflows with zero flow. Overall, forecasts that were not initialized underestimated observed inflows while forecasts that were initialized overestimated most high flows.

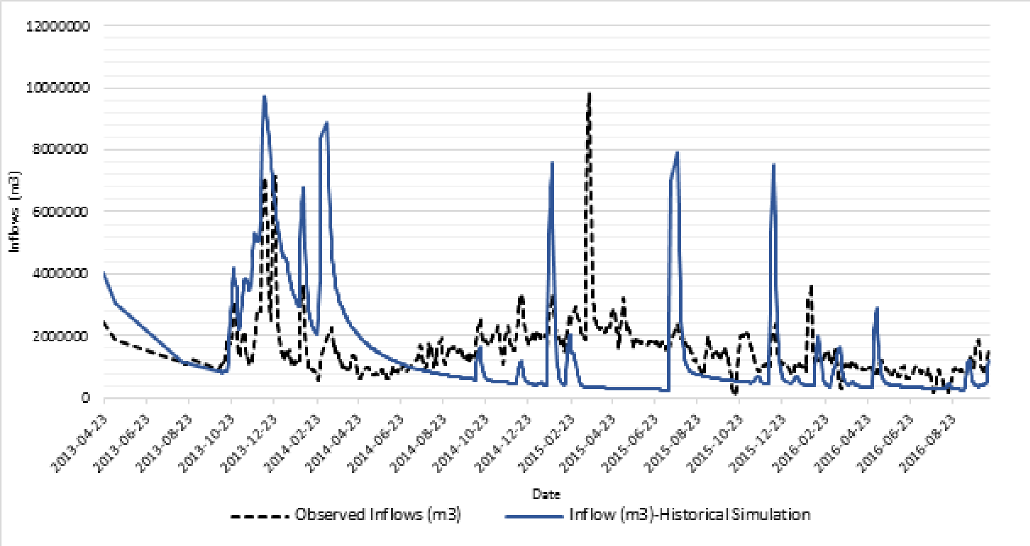

Figure 6-1 Observed and simulated (historical) inflow volumes (m^3) for the Goedertrouw Dam for 2013/04/23 to 2016/10/14

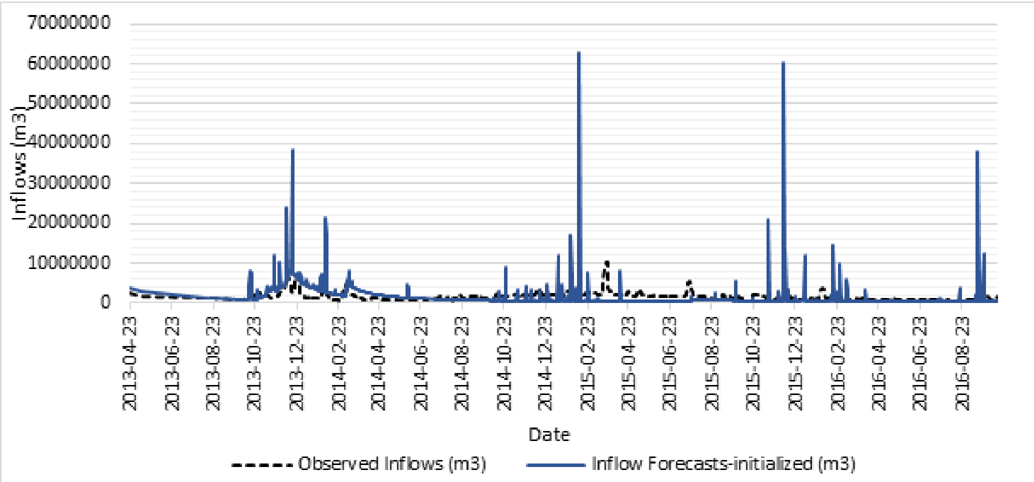

Figure 6-2 Observed and forecast (initialized) inflow volumes (m^3) for the Goedertrouw Dam for 2013/04/23 to 2016/10/14

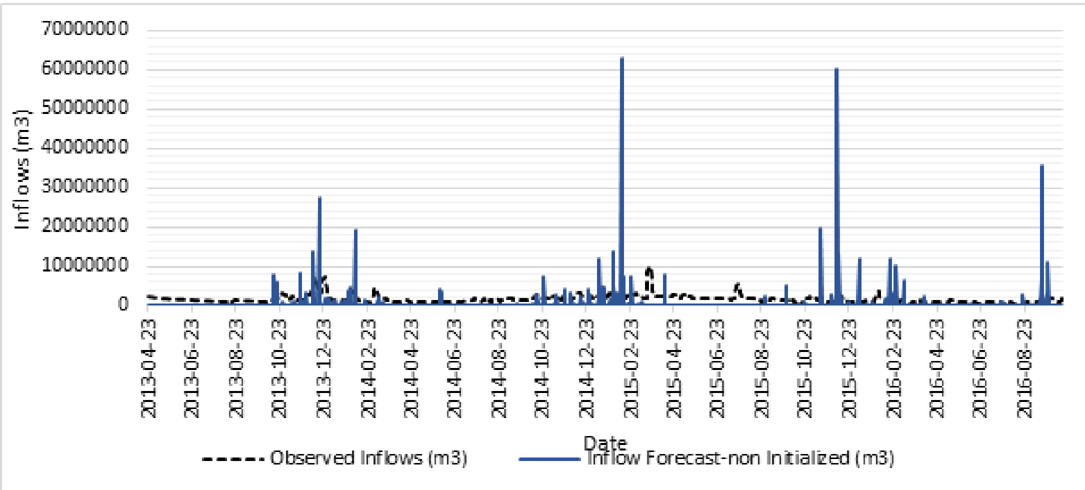

Figure 6-3 Observed and forecast (non-initialized) inflow volumes (m^3) for the Goedertrouw Dam for 2013/04/23 to 2016/10/14

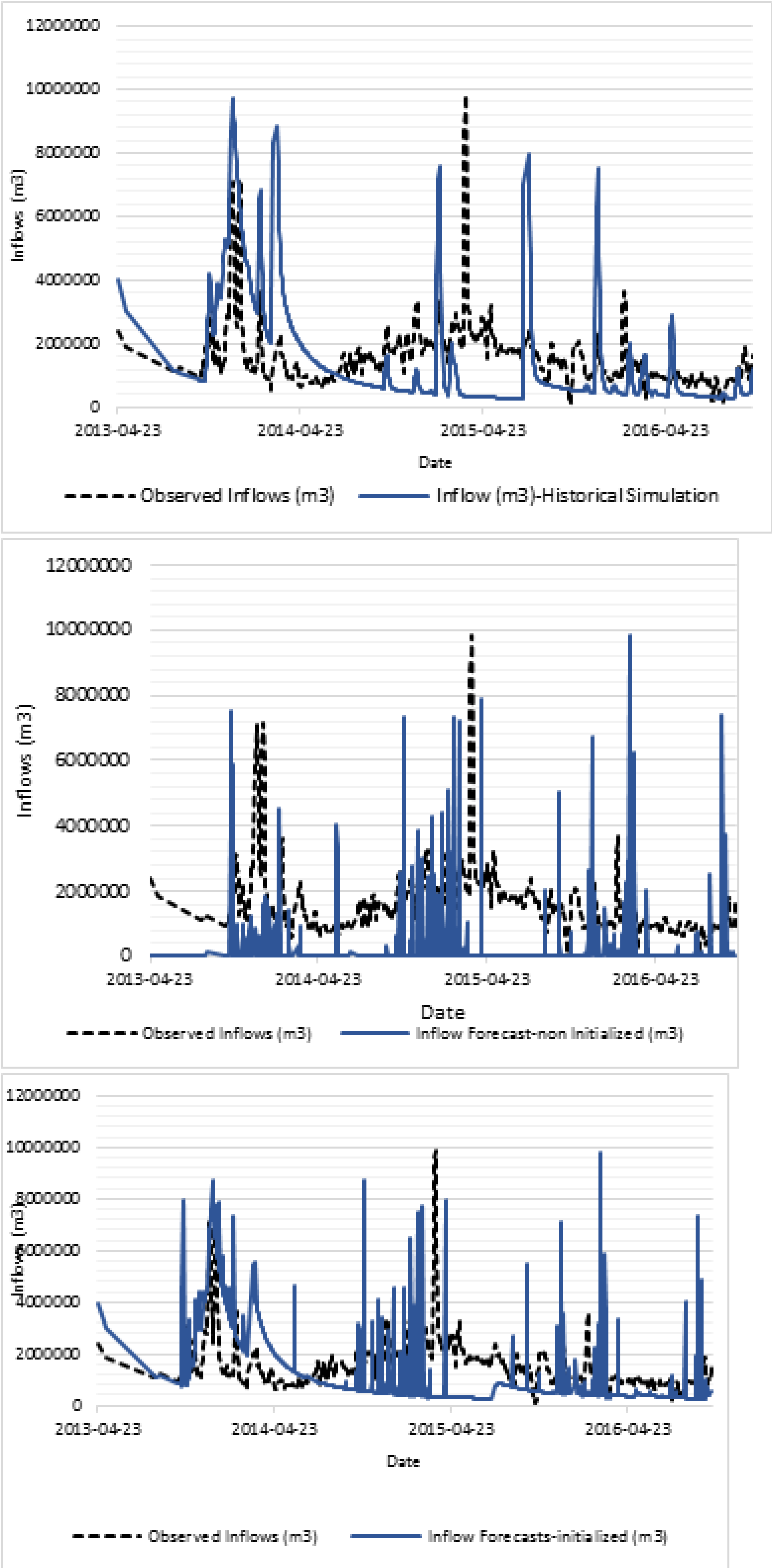

Figure 6-4 Observed inflows and a) historical simulations, b) non-initialized forecasts and c) initialized forecasts (7-day events below 10 million m^3)

Statistical measures of the forecast performances (relative to observations) are presented in Table 6-1. Average inflow errors showed that initialized and non-initialized forecasts underestimated observed inflows overall. Non-initialized forecasts produced larger average inflow errors of 1097541.37 m^3, while initialized forecasts produced lower errors of 37262.24 m^3. A maximum percentage difference between mean observed and forecast inflows of 67.20 were found for forecasts that are not initialized, while initialized forecasts showed a lower percentage difference of 2.28. Pearson correlation coefficients were found to be relatively low overall with a higher correlation of 0.2 for initialized forecasts, and a lower correlation of 0.1 for non-initialized forecasts.

Table 6-1 Statistics of performance (relative to observations) for inflows into the Goedertrouw Dam

Inflows (m^3)	
Total observed inflows	1729543715.65
Total forecast (non-initialized) inflows	567247403.20
Total forecast (initialized) inflows	1690083002.90
Total simulated (historical) inflows	1773579879.10
Mean observed inflows	1633185.76
Mean forecast (non-initialized) inflows	535644.38
Mean forecast (initialized) inflows	1595923.52
Mean simulated (historical) inflows	1674768.54
Average Inflow Errors: forecast (non-initialized)	-1097541.37
Average Inflow Errors: forecast (initialized)	-37262.24
Average Inflow Errors: simulated (historical)	41582.78
% Difference Mean: forecast (non-initialized)	67.20
% Difference Mean: forecast (initialized)	2.28
% Difference Mean: simulated (historical)	-2.55
Pearson Correlation: forecast (non-initialized)	0.10
Pearson Correlation: forecast (initialized)	0.20
Pearson Correlation: simulated (historical)	0.42

The Pearson correlation between simulated (historical) inflows and observed inflows was also relatively low at 0.42. This correlation with observations is lower than the streamflow simulation performed at weir W1H005 (correlation = 0.68) on a different tributary of the Mhlathuze River (Chapter 4). It is also lower than the correlation obtained for the simulated historical levels (correlation = 0.62) of Goedertrouw Dam (Chapter 4). The lower correlation obtained in this chapter might be attributable to a different catchment area (when comparing to W1H005), or to the more variable nature of streamflow (compared to dam levels). The relatively low correlation between simulated (historical) and observed dam inflows obtained in this chapter is also likely to be partly responsible for the low correlations between the forecast and observed inflows, as it reflects deficiencies in the model representation of the dam catchment area. These conclusions are based on the assumption that the observed inflow record is accurate. As described previously, this record was derived from the dam water balance and observations of the components of the balance. It was noted during the compilation of this record that there were days where the calculated inflows were negative in value. Although the 7-day periods considered in the statistical comparisons excluded any periods containing days with negative calculated inflows, it nevertheless casts a measure of doubt on the accuracy of the calculated inflows. It is possible that there are components of the dam water balance that are poorly represented.

6.3.2. Forecasts of crop water requirements

Forecasts of 7-day Crop Water Requirements (CWRs) for the two selected quinaries are presented in Figures 6-5 and 6-6. There is no distinction made between initialized and non-initialized forecasts since the variable initialized for the simulations in these catchments (soil moisture) does not influence CWR. As alluded to previously the forecasts are compared to historical simulations since there are no observations of the CWR available. Forecasts for both catchments follow closely to the trends and magnitudes in the historical simulations. Statistical performances for both catchments are presented in Table 6-2. Both catchments show an average overestimation of CWR's, with the coastal catchment WI2F3 showing the lowest error of 0.84 mm. Both catchments showed a high agreement between forecasts and historical simulations with correlation coefficients of 0.81 and 0.88 for W12D3 and W12F3, respectively (Figure 6-7).

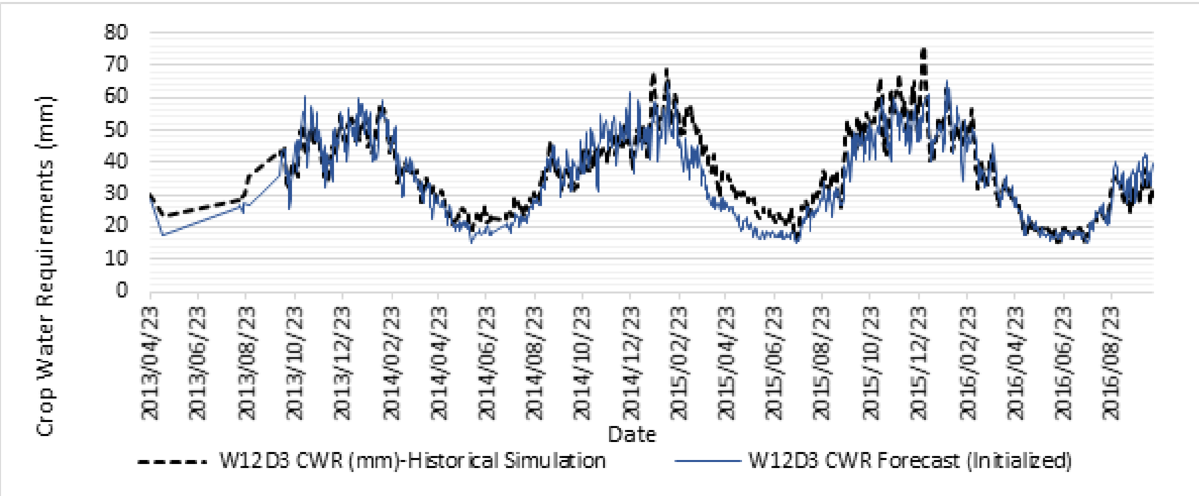

Figure 6-5 Forecast and simulated (historical) crop water requirements for quinary catchment W12D3

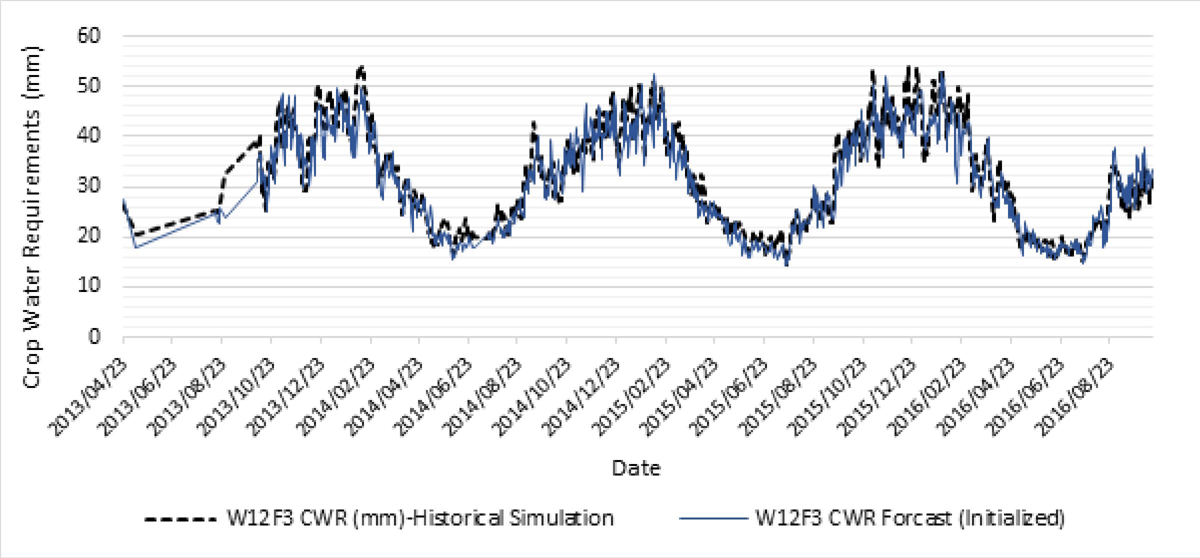

Figure 6-6 Forecast and simulated (historical) crop water requirements for quinary catchment W12F3

Table 6-2 Statistics of performance for crop water requirement forecasts in quinary catchments W12D3 and W12F3 (relative to the simulated historical time series)

	Crop Water Requirements (mm)	
	W12D3-Forecast	W12F3-Forecast
Mean Errors	-2.04	-0.84
RMSE	5.92	3.61
Agreement	0.94	0.97

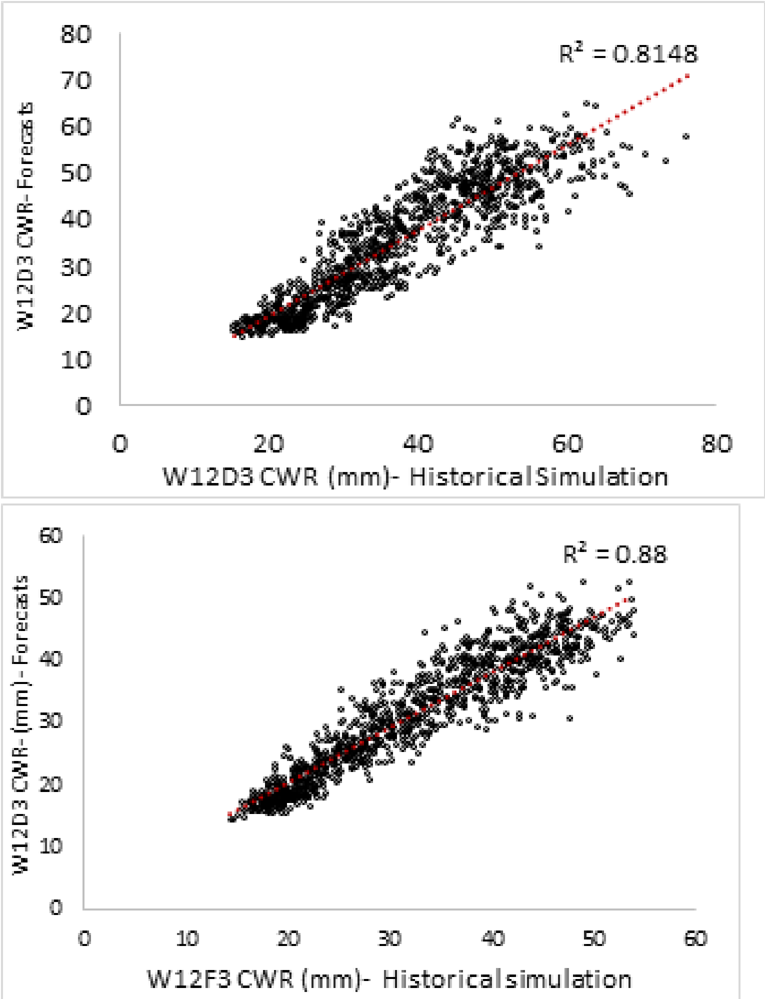

Figure 6-7 Plots of forecast versus simulated (historical) crop water requirements for W12D3 (top) and W12F3 (bottom)

6.3.3. Forecasts of net irrigation requirements

Forecast and simulated (historical) 7-day Net Irrigation Requirements (NIR) are presented in Figures 6-8 and 6-9 for catchments W12D3 and W12F3, respectively.

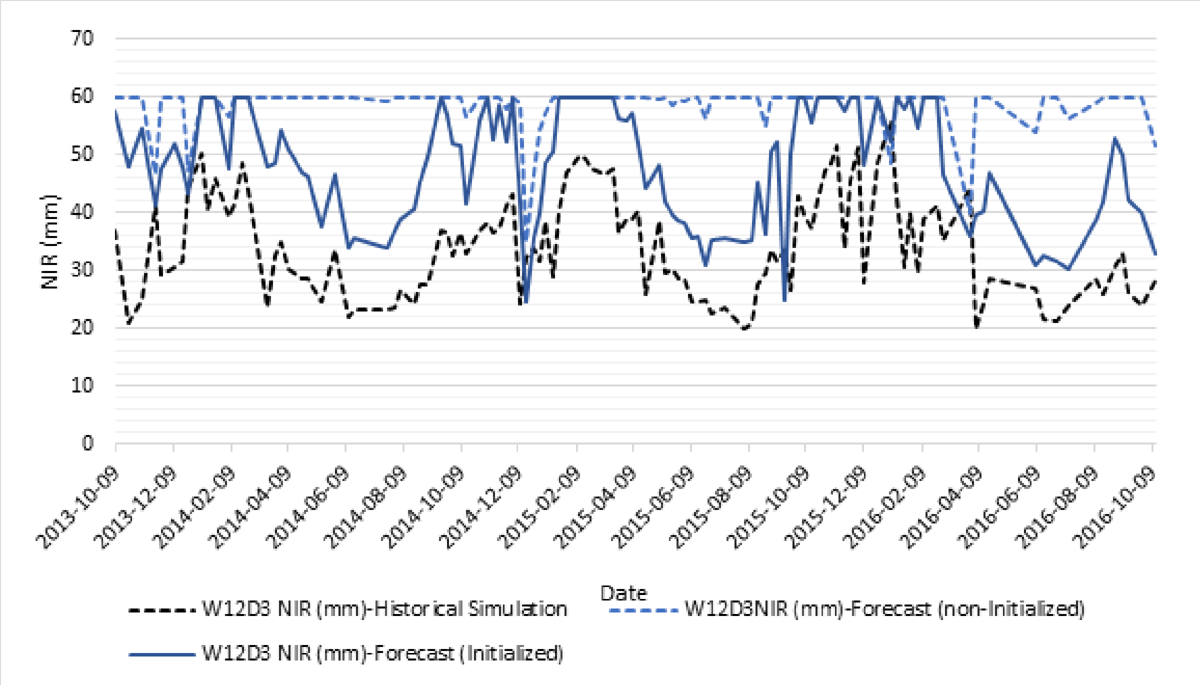

Figure 6-8 Forecast (initialized and non-initialized) and simulated (historical) net irrigation requirements for quinary catchment W12D3

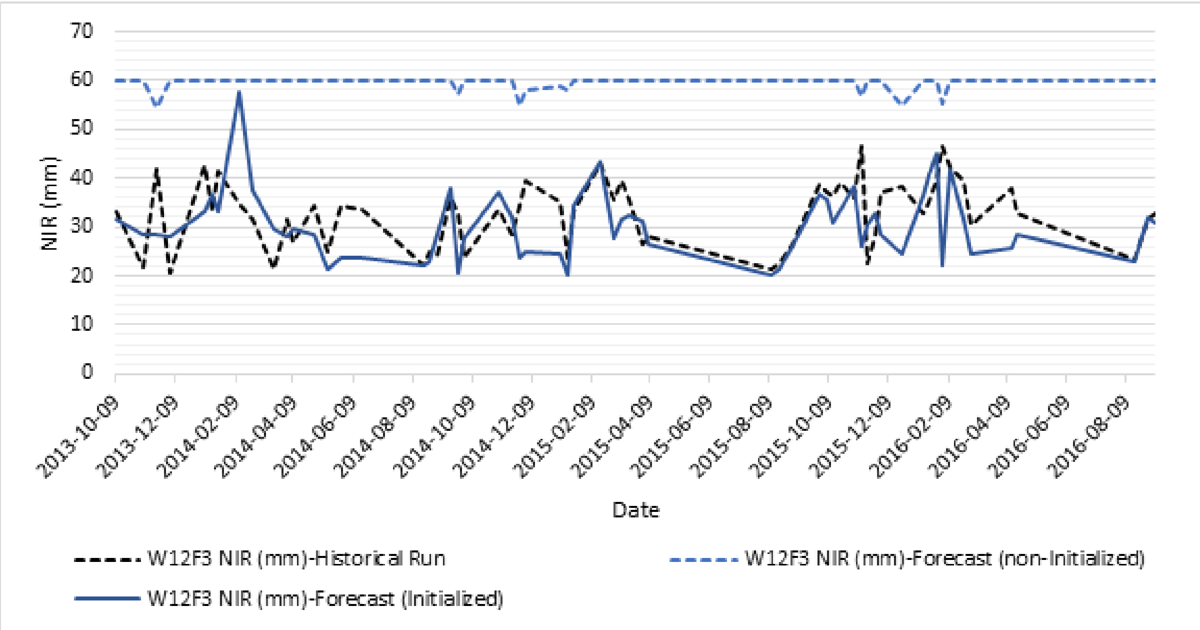

Figure 6-9 Forecast (initialized and non-initialized) and simulated (historical) net irrigation requirements for quinary catchment W12F3

Overall, initialized forecasts were found to follow historical simulations closely in terms of trends and magnitudes. Forecasts for the coastal catchment W12F3 showed closer associations in terms of magnitudes as compared to the inland catchment. Overall, non-initialized forecasts for both catchments performed poorly. The non-initialized forecasts start at 50% Plant Available Water (PAW) which, combined with evaporation, results in low soil moisture contents and creates irrigation requirements greater than 60 mm. Since a maximum irrigation system capacity of 60 mm in 7 days was used (see 6.2.3), this resulted in many irrigation applications being capped at 60 mm, thus producing a straight line on the graphs at this level.

Statistical performances for NIR forecasts are presented in Table 6-3. The lowest mean errors were observed for initialized forecasts, with the coastal catchment showing an overall underestimation of 4.14 mm and the inland catchment W12D3 showing an overall overestimation of 10.3 mm. Initialized forecasts for both catchments showed good agreements and correlations with the simulated historical time series.

Table 6-3 Statistics of performance for NIR forecasts in quinary catchments W12D3 and W12F3 (relative to the simulated historical time series)

	Net Irrigation Requirements (mm)	
	W12D3-Forecast (non-Initialized)	**W12D3-Forecast (initialized)**
Mean Errors	**-24.6**	**10.3**
RMSE	**26.24**	**16.89**
Agreement	**0.45**	**0.58**
Correlation	**0**	**0.53**
	W12F3-Forecast (non-Initialized)	**W12F3-Forecast (initialized)**
Mean Errors	**26.17**	**-4.14**
RMSE	**27.55**	**11.03**
Agreement	**0.31**	**0.55**
Correlation	**0.12**	**0.59**

6.4. Conclusion

Performances of forecasts for the Goedertrouw Dam inflows and the coastal and inland catchment CWR's and NIR's were analysed. Overall, initialized forecasts showed the best performances. Large errors were seen in the non-initialized dam inflow forecasts, which can be attributed to little or no baseflow being generated (the baseflow store starts with a value of zero). These errors would be masked in times of large stormflows, as the latter would dominate the total streamflow. Forecasts of CWR's and NIR's performed well for both catchments for initialized forecasts when compared to historical simulations. This was particularly for CWR, where the highest correlations and lowest average errors were observed. This suggests that the CCAM daily maximum and minimum temperatures perform well for the Mhlathuze catchment.

6.5. References

HARGREAVES, G.H. and SAMANI, Z.A. (1985). Reference crop evapotranspiration from temperature. Transactions of the American Society of Agricultural Engineers, 1, 96-99.

CHAPTER 7. SEASONAL FORECASTS OF THE STORAGE IN GOEDERTROUW DAM

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7.1. Background

Stakeholders in the sugar industry have indicated that obtaining accurate seasonal and longer term forecasts of water availability would be of great benefit in the Mhlathuze catchment, and elsewhere. In this regard, a statistical approach was adopted to developing seasonal forecasts of storage in the Goedertrouw Dam. Unlike the dynamical, simulation-based approach adopted for shorter time scales in the Mhlathuze case study, the statistical approach does not require daily input data in the development of forecasts. This avoids the need to apply downscaling techniques to obtain the necessary data at a daily time scale. In addition, the statistical approach does not require abstractions from the dam to be explicitly accounted for. Abstractions from the dam are variable, thus introducing uncertainty around their estimation. Further details of the statistical forecast methodology are given in the following subsection, after which the results are presented.

7.2. Methodology and Results

The observed data required to construct and test the seasonal forecasting model included monthly time series' of rainfall and dam storage volumes. These data were obtained from DWS for the period 1981/82 to 2009/10. From these data, seasonal cycles of the rainfall in the catchment and of the water volumes in the dam were calculated (Figure 7-1).

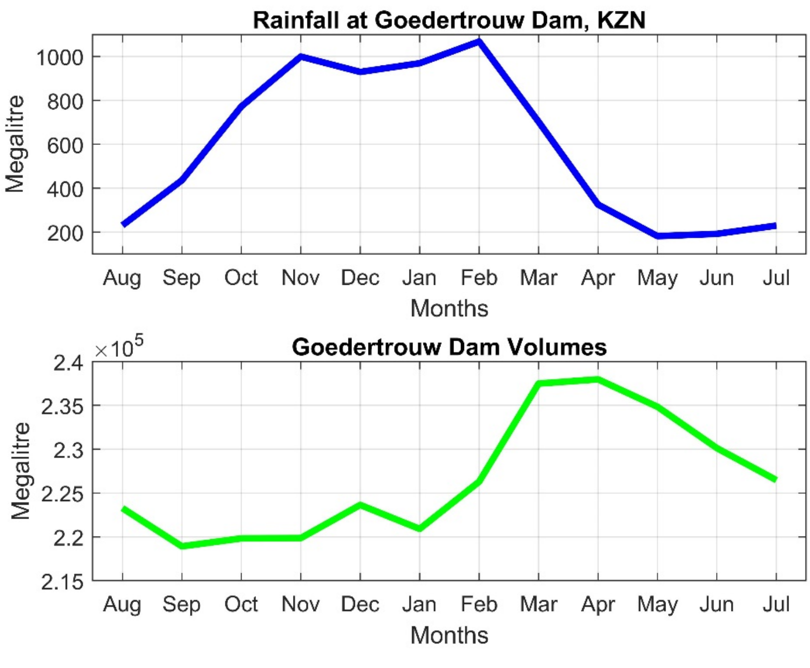

Figure 7-1 Annual cycles of the monthly rainfall (top) at Goedertrouw Dam and the monthly storage volumes (bottom) of the dam

From the graphs in Figure 7-1, one can see that the 3-month season of highest volume (bottom graph) occurs during March-April-May (MAM). This season was, as a result, chosen as the target season for which prediction models were to be constructed. Owing to the observation that the maximum volume season immediately follows the maximum rainfall season (top graph), one may be able to conclude that rainfall is the main driver of the dam volumes, and might be useful as a predictor of those volumes. This notion was tested next.

Since MAM was the target season for which dam volumes were to be predicted, nine run-on seasonal rainfall totals over the given period were correlated with the MAM volumes. Table 7-1 shows the rainfall seasons correlated with MAM volumes on the left, the Kendall's tau correlations in the middle and associated levels of statistical significance on the right.

Table 7-1 Rank correlations between seasonal rainfall totals over the given period and MAM dam volumes

Season	Kendall's tau	Significance (%)
MAM	0.242	96.01
FMA	0.333	99.27
JFM	0.322	99.08
DJF	0.379	99.74
NDJ	0.499	99.99
OND	0.385	99.78
SON	0.339	99.36
ASO	0.271	97.53
JAS	0.293	98.37

The NDJ rainfall season was best correlated with the MAM dam volumes. Normalized values for NDJ rainfall and MAM dam volumes are given in Figure 7-2. The finding that NDJ rainfall correlates best with MAM volumes (marked with orange in the table) was then used to build three different prediction models.

The first model used a simple linear equation ("y=mx+c") that relates NDJ rainfall totals as predictor with MAM normalized volumes (top right graph of Figure 7-3). Following the work of Muchuru et al. (2016), global climate models' output were also used as predictors of the MAM volumes. The first of these used the ECHAM4.5-DC2 coupled model's 850 hPa geopotential heights (Muchuru et al., 2016), a useful proxy for rainfall totals, of the NDJ season as predictor in a multiple linear regression model (graph bottom left of Figure 7-3). The second of this type of model used the GFDL's (GFDL-CM2p5-FLOR-B01 of the North American Multi-Model Ensemble) precipitation fields as predictor in a multiple linear regression model (graph bottom right of Figure 7-3). However, neither of these two models were able to outperform the simple linear model. It is noted that the lead-times of the latter

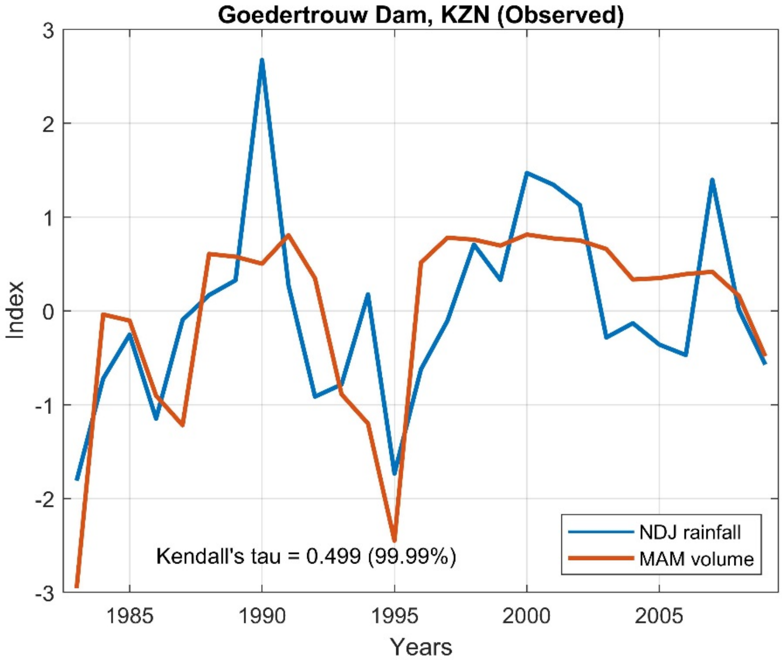

Figure 7-2 Normalised time series of NDJ rainfall and MAM dam volumes

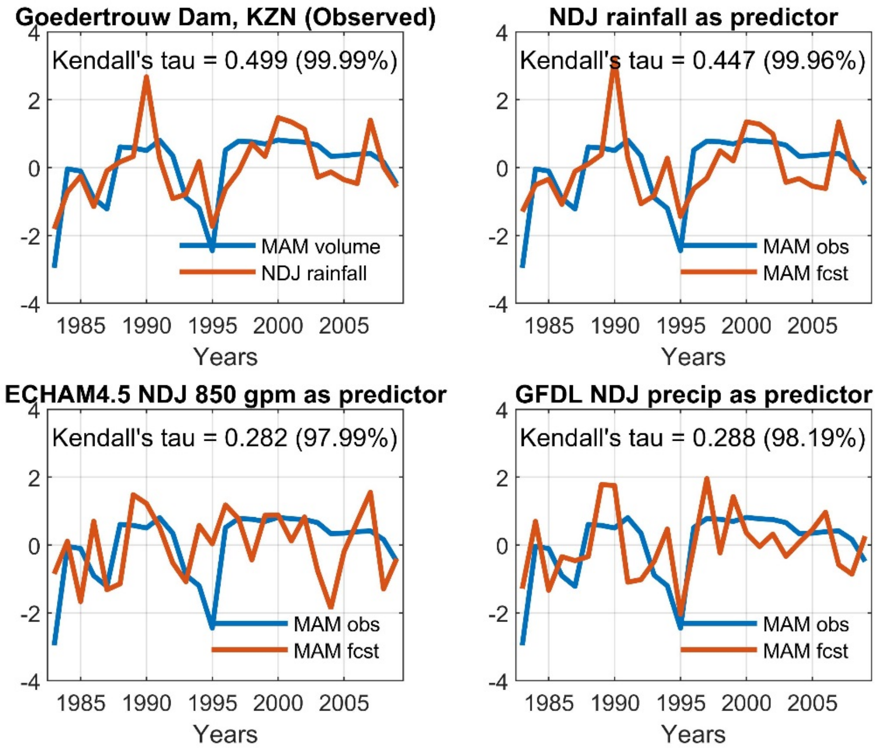

Figure 7-3 Cross-validation results from the three models predicting MAM dam volumes. Also included is the observed rainfall and dam volumes for easy comparison (top left graph). The rank correlation and its statistical significance between the two time series on each graph is shown near the top of each graph.

two models (predictions in October) were quite a bit longer than the lead-time of the simple model (predictions in February). For all three models, a 3-year-out cross-validation design was used for model testing.

The simple linear model was subsequently used to demonstrate an operational utility of such a forecast system that could potentially be used by a manager of a dam. Probability of exceedance (PoE) forecasts were produced for the last five MAM seasons after training the linear model with data up to 2004. These MAM volume forecasts would only be produced in February after the NDJ rainfall totals have been recorded.

A demonstration of how to use the PoE forecasts is given as follows: The climatological (long term) probability (represented by the thick black curve in Figure 7-4) for a storage volume of 2.5 x 10^5 Ml is 45%. However for the 2007 MAM season (orange curve), that probability increases to almost 80%. In contrast, for the 2009 season (green curve), the probability decreases to about 30%.

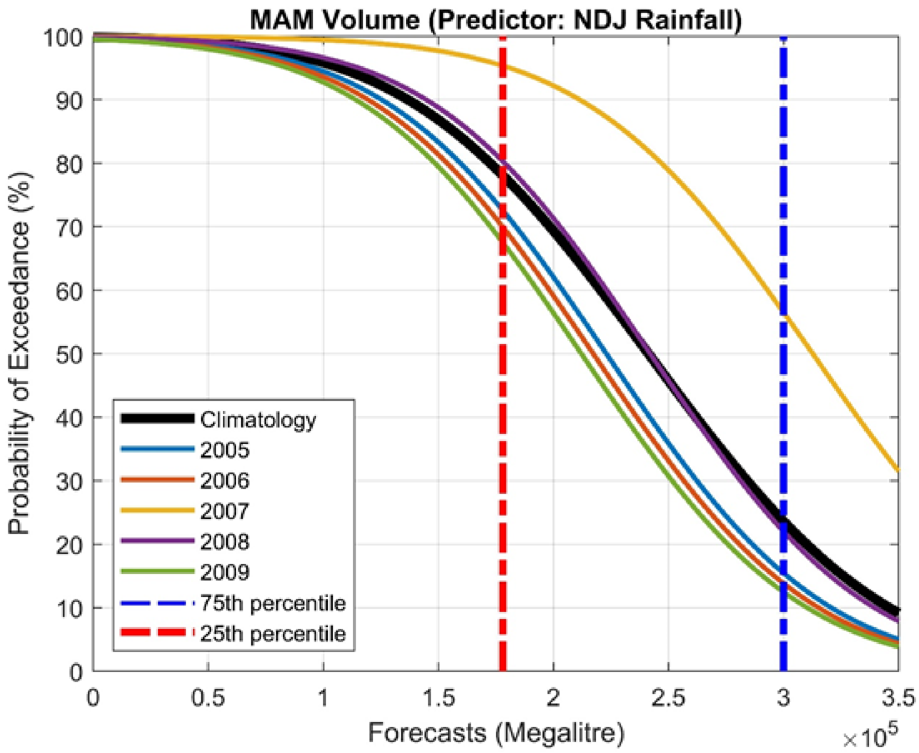

Figure 7-4 Probability of exceedance curves for five MAM seasons

7.3. Conclusion

A number of forecast models for peak-season dam volume predictions were constructed and tested for the Goedertrouw Dam in the Mhlathuze catchment. Predictability, albeit restricted, was demonstrated, especially with the use of a simple linear regression model that used NDJ observed rainfall over the catchment as a predictor of MAM storage volume. A scheme was also proposed to allow a dam manager to make use of seasonal forecasts to estimate probabilities for certain dam volumes being reached in a coming peak season.

7.4. References

MUCHURU, S., LANDMAN, W.A. AND DEWITT, D. (2016). Prediction of inflows into Lake Kariba using a combination of physical and empirical models. International Journal of Climatology, 36, 2570-2581, doi:10.1002/joc.4513.

CHAPTER 8. EXPLORING THE POTENTIAL TO PRODUCE SEASONAL FORECASTS OF CROP YIELD AND WATER PRODUCTIVITY: A CASE STUDY INVOLVING THE AQUACROP MODEL AT EMPANGENI

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8.1. Description of the Empangeni site

The Empangeni site is located at 28°45'10.9"S 31°53'39.1"E within the Mhlathuze catchment, and is characterised as having a sub-tropical climate. It contains 8200 ha of rainfed land and 1100 ha of irrigated land. It has the potential for production of a variety of alternative crops, including horticulture, organic sugar, bio-diesel, essential oils, tea production, herbs and spices, assorted vegetables and grains. A Google Earth image of Empangeni and its surroundings, including cultivated agricultural fields, is presented in Figure 8-1.

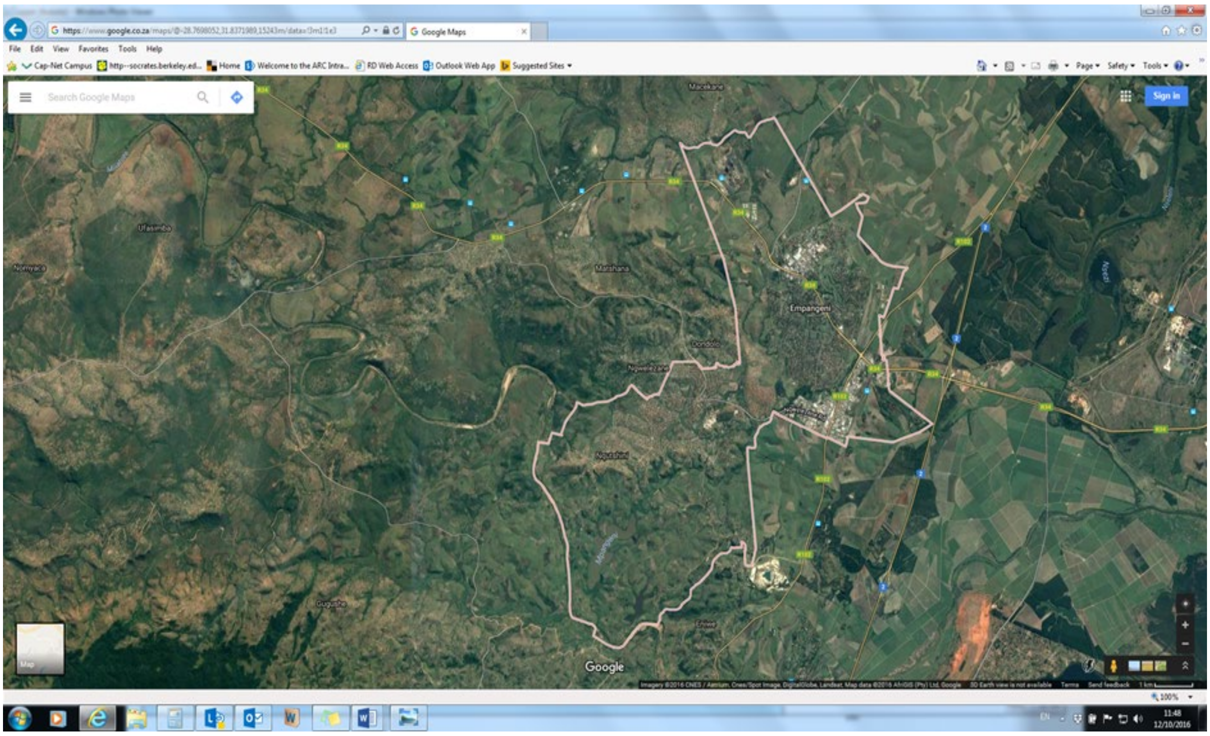

Figure 8-1 Google Earth image of Empangeni and its surrounding

8.2. Description of the Aquacrop model

A brief description of the Aquacrop model was included in Vol. 1 Chapter 4. The reader is referred to that chapter for details of the model.

8.3. Factors affecting sugarcane productivity at Empangeni

Sugarcane productivity and juice quality are highly influenced by weather conditions dominant prior and during the crop growth stages. Sugarcane has essentially four namely: germination and establishment phase, tillering phase, grand growth period and ripening phase. Better understanding of progressive stages is critical as it aids in efficient water and nutrient management toward optimal crop growth. Furthermore, knowledge of phenological growth phases is indispensable for ensuring maximum cane yields and sugar recovery.

Sugarcane productivity is highly suitable from sea level to almost 1000 m in altitude. It is categorised as a tropical plant, since it is a long duration crop occurring in the tropics and hot and humid climatic conditions throughout its life cycle. Like all plants, the critical climatic parameters that control sugarcane productivity are temperature, solar radiation and soil water availability. The goal of sugarcane producers is to maximize the production of good quality sugar.

The optimal production of sugarcane requires the following climatic conditions: a long, warm growing season with high solar radiation and rainfall; a frost free season for ripening and harvesting; a rainfall amount that ranges between 1100 and 1500 mm with a good distribution throughout the season; temperatures that may differ for different crop phases, such as, at sprouting of stem cuttings a threshold range between 32°C to 38°C, temperatures above 38°C reduce the rate of photosynthesis and increase respiration, at ripening a range of 12°C to 14°C are required for the enrichment of sucrose; relative humidity above 80% favours rapid cane elongation however, a moderate value of about 50% with controlled water supply is favourable during ripening phase; it thrives in areas receiving 18-36 MJ m^2, this C4 plant is capable of high photosynthetic rates and the stalk growth increases within the range of 10-14 hours daylight. It is estimated that around 6350 MJ m^2 mean total radiation received in 12 months of sugarcane growth, about 60% of intercepted radiation occurred during formative and grand growth periods (Ramanujam and Venkataramana, 1999).

Sugarcane is a perennial grass that is very efficient in harvesting radiation, that is, in converting the sun's energy into sugar and fibre. Climate at Empangeni is classified as warm and temperate with annual rainfall of about 1082 mm and an annual average temperature of 21.5°C and Köppen-Geiger climate classification of Cfa. The highest average monthly temperatures (Figure 8-2) are observed in January (25.2°C) while the lowest average temperatures occur in July (17.7°C). The minimum monthly rainfall occurs in July with an average of about 44 mm, and the maximum monthly rainfall occurs in the month of March with an average of 143 mm (Figure 8-3). Therefore, given the outline of Empangeni's climatic conditions and according to Köppen-Geiger climate classification, the Empangeni location is environmentally favourable for sugarcane production.

According to the climate data utilised for the purpose of this investigation (sourced from the ARC data bank), which was recorded from 2004 to 2013, the decadal maximum average temperature was 27.8°C and the average minimum temperature was 16.6°C. This decadal climate data was utilised to analyse sugarcane productivity scenarios using the AquaCrop simulation model. The relative humidity for Empangeni ranges from 80% to 98%, which provides sufficient atmospheric moisture for sugarcane production.

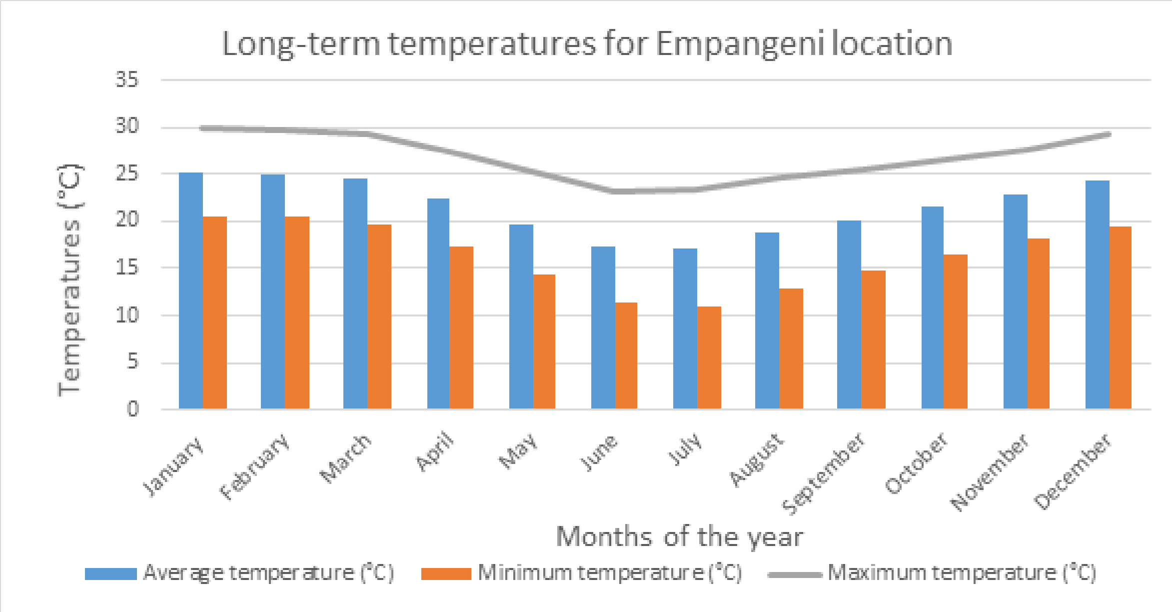

Figure 8-2 Long-term monthly average temperature for Empangeni (ARC-ISCW databank)

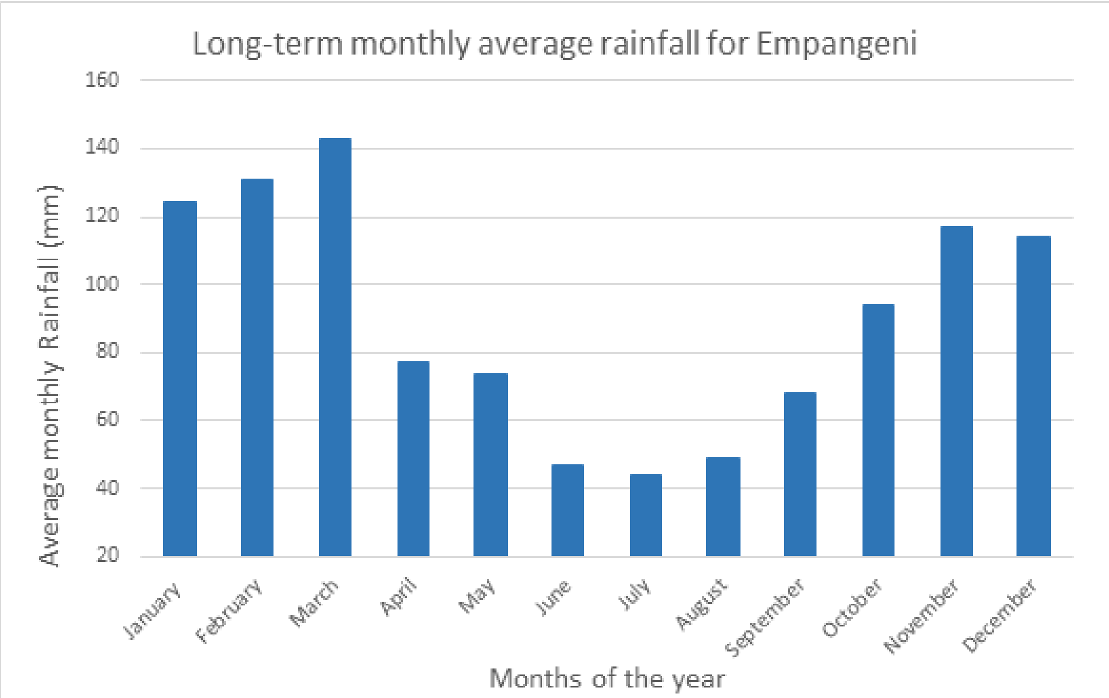

Figure 8-3 Long-term monthly rainfall for Empangeni (ARC-ISCW databank)

Soil is the most important medium that all plants require for growth. Sugarcane requires fertile, deep and well-drained soils. Humic soils which range from 100 to 150 cm deep with good drainage are most appropriate for sugarcane productivity. However, sugarcane can successfully grow on diverse soil types ranging from clay loams, heavy clay and sandy soils. Salinity in sugarcane induces water stress, which results in premature wilting, scorching of the leaves, limited growth, and death of plant.

The major role of soil as a medium is to provide anchorage, nutrients, water to the growing plant from sprouting to harvesting phase of the plant. In well-drained, deep, loamy soil, a bulk density has to be in the range from 1.1 to 1.2 g m^{-3} and in sandy soils it has to range from 1.3 to 1.4 g m^{-3}. Ideally, the porosity should be 50% or higher. The criteria to define soils which are appropriate for sugarcane productivity are listed in Table 8-1. Poor soil physical conditions may be caused by intense mechanisation which leads to soil compaction, and is difficult to ameliorate for proper plant growth.

Table 8-1 Criteria to Classify the Aptitude of Soils for Growing Sugarcane (Kofeler and Bonzelli, 1987)

Characteristics	Class			
	Good	Average	Restricted	Unfit
Effective depth	Deep	Medium	Shallow	Too shallow
Soil texture	Clayey	Medium to clayey	Sandy	Too sandy
Relief	Flat	Rolling	Too rolling	Hilly
Fertility	High	Medium or low	Too low	Too low
Drainage	Good	Medium to accentuated or incomplete	Incomplete	Excessive or deficient
Restraints to mechanization	Absent	Medium	Strong	Too strong
Susceptibility to erosion	Low	Medium	High	Too high

To amelioration the effects of soil compaction, it is imperative to consider the application of organic manure and/or growing green manure crops. Soil compaction causes reduction in porosity which impedes water infiltration and water storage, by increasing the bulk density and soil penetration resistance, thus resulting reduced nutrient intake and water uptake. Management of soil acidity is crucial, especially in high rainfall areas such as Empangeni. Soil acidity in sugarcane production affects the overall sugarcane growth, the quality of the produce, final yield and the sucrose content. It is crucial to select suitable cultivars for a specific area, since varieties differ in their reactions to soil acidity and salinity. When comparing growth phases, germination and early growth phases are more sensitive than later crop growth phases. Manipulation of the soil environment allowing soil recovery and proper soil drainage, together with growing salt tolerant varieties, provides amelioration measures for improved sugarcane productivity.

8.4. Configuration of AquaCrop and simulations based on observed climate

8.4.1. Climate

From climatic daily data retrieved from automatic weather station located at Empangeni which is geographically located at the latitude of -28, 7 longitude of 31, 89 and the altitude of 105 m. The retrieved data was for the period from 1st February 2004 to 24th March 2014. The highest recorded temperature during this period was 42°C while the lowest recorded minimum temperature was 16.5°C. The highest maximum relative humidity of 98.8% and the lowest minimum relative humidity of 63.8%. AquaCrop simulation model generates three critical files using loaded climatic data, which are rainfall data, temperature and reference evapotranspiration (Figure 8-4).

8.4.2. Plant growth

Crop parameters are strongly influenced by planting and management practices adopted or preferred by a specific farmers. Such may be identified as type of planting method, planting density that refers to direct sowing or transplanting which determines the initial canopy cover and maximum canopy cover as well as the rate of or the time to 90% seedling emergence. The ideal time for planting under rainfed conditions in Empangeni is April to May, in provision for supplementary irrigation it is the ideal planting time is from February to April. The initial canopy cover was estimated at 0.54% at transplanting planting type with the canopy size transplanted seedling at 15 cm^2 $plant^{-1}$ which resulted to about 35714 plants ha^{-1} which is equivalent to 3.6 plants cm^2. The row planting with row spacing of 1.40 m and plant spacing 0.20 m. The crop development at canopy maturity which is CCx was estimated at 95%. It took the crop 64 days to reach maximum canopy, 330 to reach senescence and 365 days to reach harvest phase of the crop (Figure 8-5). The root development maximum depth was reached at 81 days with an expansion of 1.8 cm day^{-1} which is the average root zone expansion. The harvest index varied from about 67% and above starting from recovered transplant to harvest. Crop development can be defined in calendar days or growing degree days (GDD) which is the average temperature take away base temperature (GDD = T_{avg} – T_{base}) which provides temperature in °C day, base temperature refers to the temperature below which crop development does not advance.

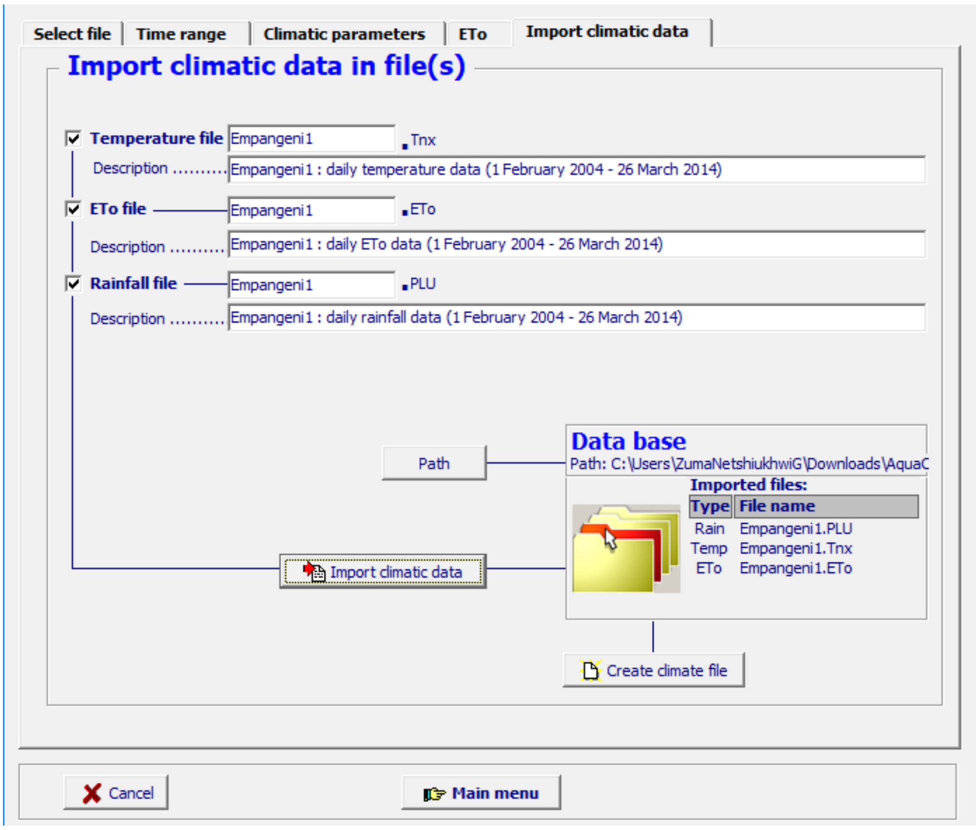

Figure 8-4 AquaCrop model imported climatic data for Empangeni

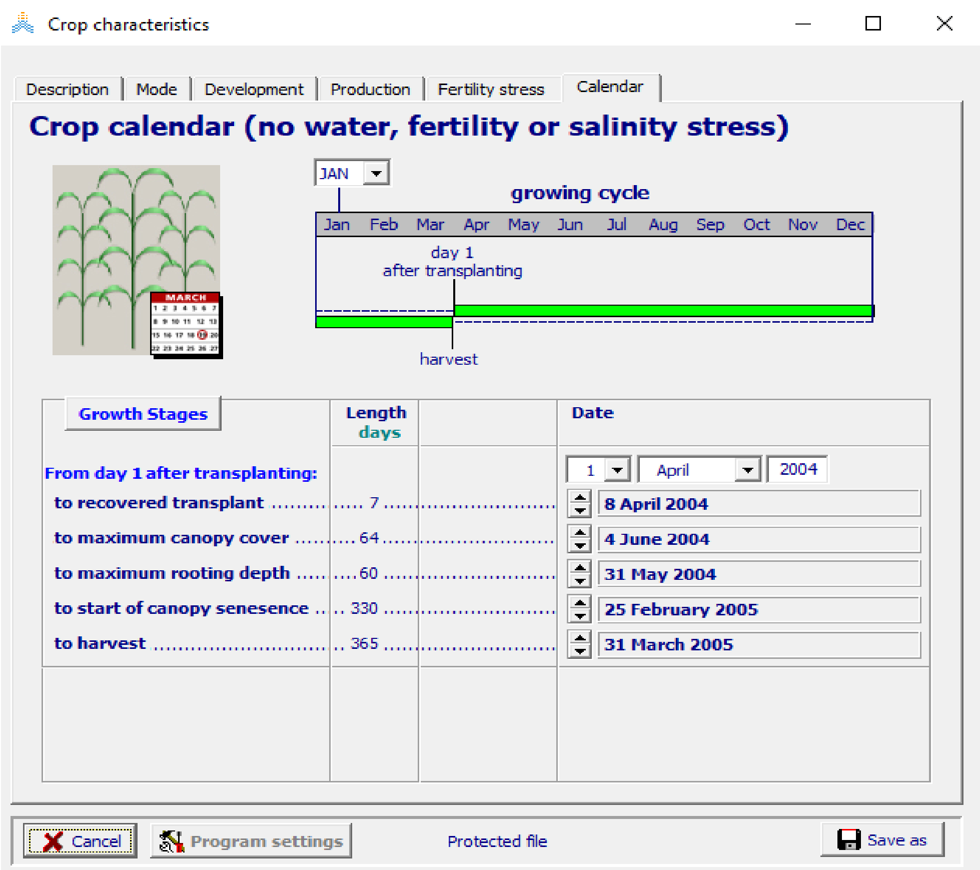

Figure 8-5 AquaCrop growth stages in terms of calendar days for Empangeni

AquaCrop runs for planting date starting from 1 April 2004 show at a rate of 7 mm day^{-1} at 10 days internal, at day 20 the water content is below the threshold for crop water requirement. Thus indicates that the soil water content is decreasing and has reached three coefficient phases. As the planting season progress the soil water content decreases even further and the crop canopy does not develop as it should due to water stress. Since water stress affect leaf expansion and triggers early canopy senescence. However, the simulation run for planting date 1 April 2004 to March 2005 indicated that climatic conditions were optimal for the crop to develop throughout the season, and the crop stress coefficient remained at 1. The crop canopy was at its optimum until the plantation reached its senescence phase. The biomass production reached 70.0 ton ha^{-1} with dry yield at 24.5 ton ha^{-1}. During the planting period no triggers were observed for stomatal closure and early senescence (Figure 8-6). The growing degree days for the planting season amounted to 4837.0°C day with the reference evapotranspiration that accumulated to 1545.9 mm and rains of 577 mm, thus the evapotranspirative water productivity was 2.37 kg (yield) per m^3 water evaporated. For the planting season 2005-2006, soil water stress was observed starting from day 275 until day 330 whereby a significant decline in the crop canopy occurred. This led to a decline in biomass and dry yield to 69.9 ton ha^{-1} and 24.5 ton ha^{-1}, respectively, and the evapotranspirative water productivity increased to 2.50 kg (yield) per m^3 water evaporated. The growing degree days for the planting season amounted to 4926.5°C day with the reference evapotranspiration that accumulated to 1540.6 mm and rains of 650 mm, (Figure 8-7).

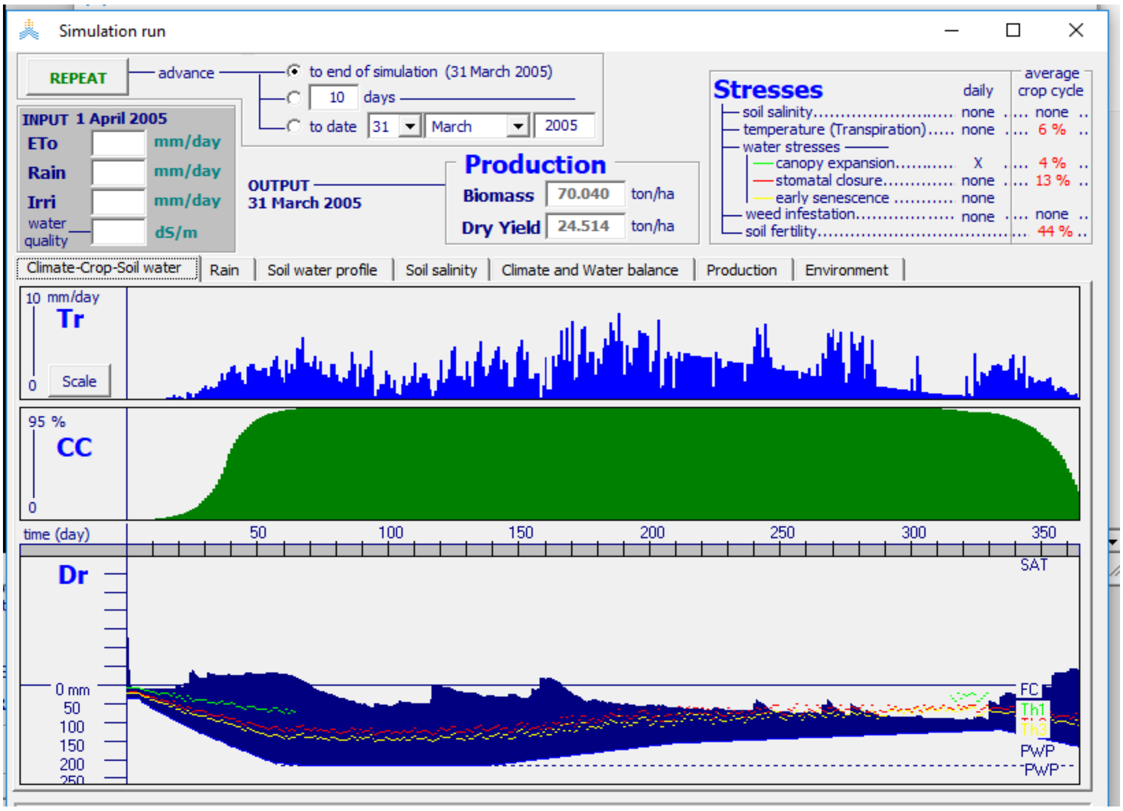

Figure 8-6 AquaCrop simulation run output for planting date April 2004 to March 2005 for Empangeni

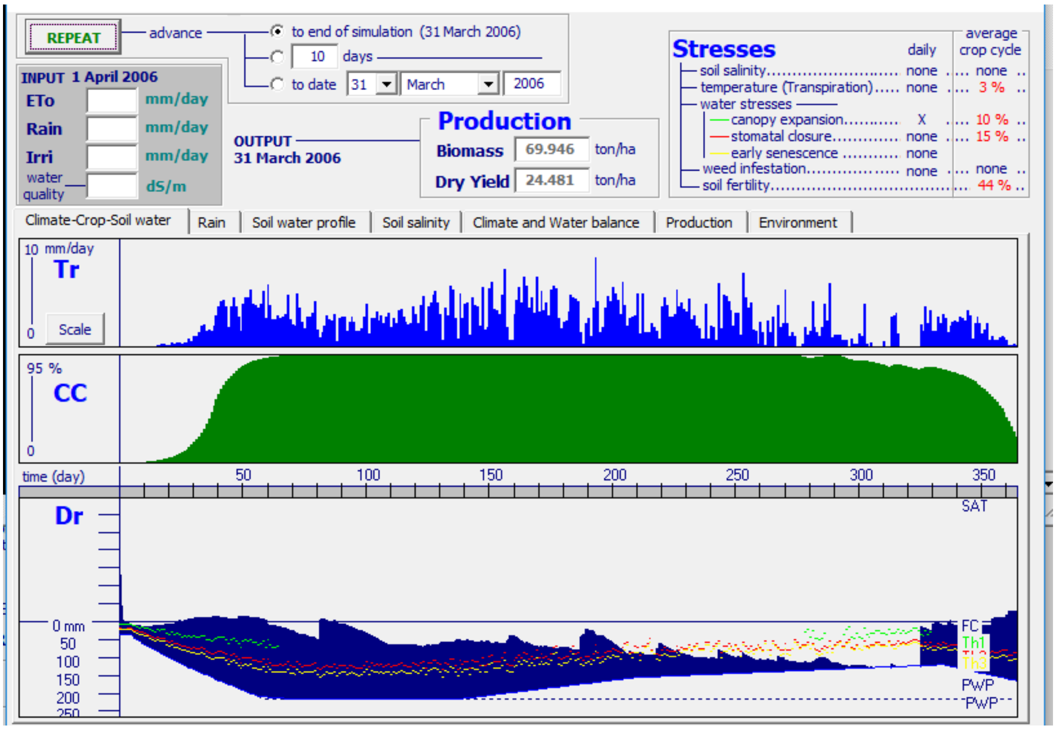

Figure 8-7 AquaCrop simulation run output for planting date April 2005 to March 2006 for Empangeni

The planting season 2006 to 2007 showed an improved biomass and dry yield of 79.8 ton ha^{-1} and 27.9 ton ha^{-1} respectively. The growing degree days for the planting season amounted to 4756°C day with the reference evapotranspiration that accumulated to 1534.8 mm and rains of 799 mm. The evapotranspirative water productivity was observed to be 2.37 kg (yield) per m^3 water evaporated. Due to even better and conducive climatic condition for planting season 2007 to 2008, the biomass increased to 80.7 ton ha^{-1} and the dry yield escalated to 28.3 ton ha^{-1}. The growing degree days for the planting season amounted to 4610.5°C day with the reference evapotranspiration that accumulated to 1445.4 mm and rains of 1267 mm. The evapotranspirative water productivity was observed to be 2.44 kg (yield) per m^3 water (Figure 8-8, 8-9 and 8-10).

During the 2008 to 2009 crop season, indications were that the biomass produced reached 70.5 ton ha^{-1} and the dry yield amounted to 24.7 ton ha^{-1}, the growing degree days for the planting season amounted to 4645.0°C day with the reference evapotranspiration that accumulated to 1477 mm and rains of 774 mm. The evapotranspirative water productivity was observed to be 2.55 kg (yield) per m^3 water, no significant daily stresses observed but about 13% stomatal closure occurred in average crop cycle. The crop productivity in crop cycle 2009 to 2010 remained at the biomass and dry mass of 76.9 ton ha^{-1} and 26.9 ton ha^{-1}, respectively, without indications of daily stresses and in average crop cycle, but in day 318 a slight decrease in rains resulted to a decrease in leaf expansion by 3% and a stomatal closure of 5% was detected. In 2009-2010 crop cycle the growing degree days for the planting season amounted to 4610°C day with the reference evapotranspiration that accumulated to 1453.2 mm and rains of 844 mm. The evapotranspirative water productivity was observed to be 2.49 kg (yield) per m^3 water (Figures 8-8, 8-9 and 8-10).

In 2010-2011 performed incredibly comparing to other years, since the crop cycle the growing degree days for the planting season aggregated to 4813.5°C day with the reference evapotranspiration that accumulated to 1416.7 mm and rains of 920 mm. The evapotranspirative water productivity was observed to be 2.56 kg (yield) per m^3 water. The calculated biomass increased to 82.0 ton ha^{-1} with the dry yield of 28.7 ton ha^{-1}, however according to AquaCrop the potential biomass is estimated at 83.0 ton ha^{-1}. During crop cycle 2011 to 2012, the calculated biomass production was 79.1 ton ha^{-1} with the dry yield of 27.7 ton ha^{-1} with no stresses encounter, the accumulated growing degrees amounted to 4479°C day, reference evapotranspiration at 1408.9 mm and the annual rains of 924 mm, the actual produced biomass was equivalent to the potential biomass, thus resulted to the evaporative water productivity of 2.46 kg (yield) per m^3 water (Figure 8-8, 8-9 and 8-10).

Under optimal climatic conditions crop productivity is expected to increase significantly, crop cycle 2012 to 2013 obtained an increased productivity since the biomass of 82.1 ton ha^{-1} and the dry yield of 28.7 ton ha^{-1} was observed, with the accumulated degree days amounted to 4547.5°C day, reference evaporation at 1440.6 mm and the annual rainfall of 1195 mm per annum. The optimal biomass produced was the same for the actual produced and the potential produce with the evaporative water productivity of 2.60 kg (yield) per m^3 water. The crop growing cycle 2013 to 2014 was the last crop cycle under investigation, whereby a slight decrease in biomass productivity was detected, the biomass and the dry yield was 75.4 ton ha^{-1} and 26.4 ton ha^{-1} with evaporative water productivity of 2.56 kg (yield) per m^3 water. Whereby the potential biomass was estimated to be 83.0 ton ha^{-1} to the actual biomass of 75.4 ton ha^{-1}, with the growing degrees reaching 4563°C day, reference evapotranspiration of 1437.7 mm and the annual rains reaching 681 mm (Figure 8-8, 8-9 and 8-10). AquaCrop has clear distinction between biomass water productivity and ET water productivity which also referred to as water use efficiency (Raes et al., 2009). Water use efficiency which is also referred to as transpiration efficiency which describes the essential exchange between carbon fixation and the process of water loss that occurs in crops produced under rainfed conditions, since water evaporates from open stomata for CO_2 attainment. The water use efficiency of crop is low as plants lose plenty of water than the comparable units of carbon fixed for photosynthesis process to occur within the green plants of the crops. There is a number of factors that affect the yield, such as, climatic parameters, soil properties, soil fertility status, irrigation, weeds, pests and diseases to mention a few. Biomass water productivity refers to the amount of biomass that is attained with a definite quantity of water transpired, expressed as kg m^{-3} of transpired water. As expressed in Figure 8-10, the relationship between crop yield and evapotranspiration provides ET water productivity. In comparison for two different planting dates, it shows that the water use efficiency was significantly higher for most crop cycles except for years 2004, 2006, 2007 and 2011. Therefore, planting date selection has a remarkable impact on the final biomass and dry yield produce (Figure 8-8).

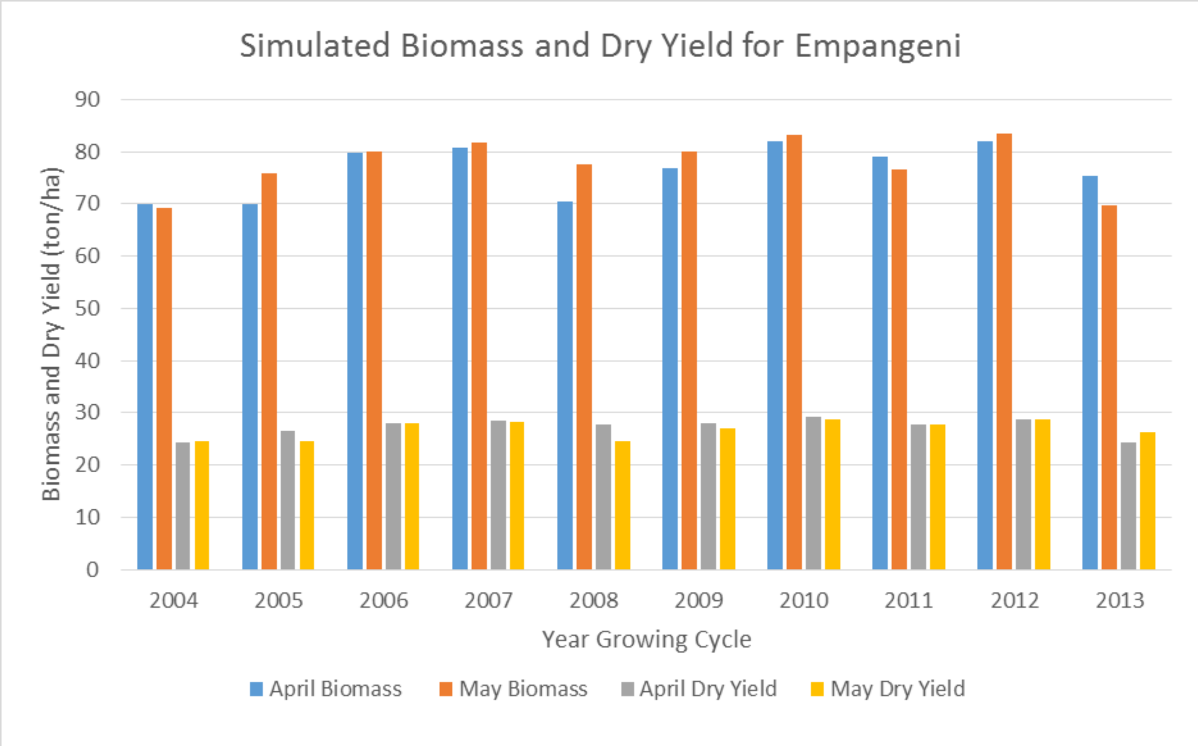

Figure 8-8 AquaCrop simulation run biomass and dry yield for two planting dates

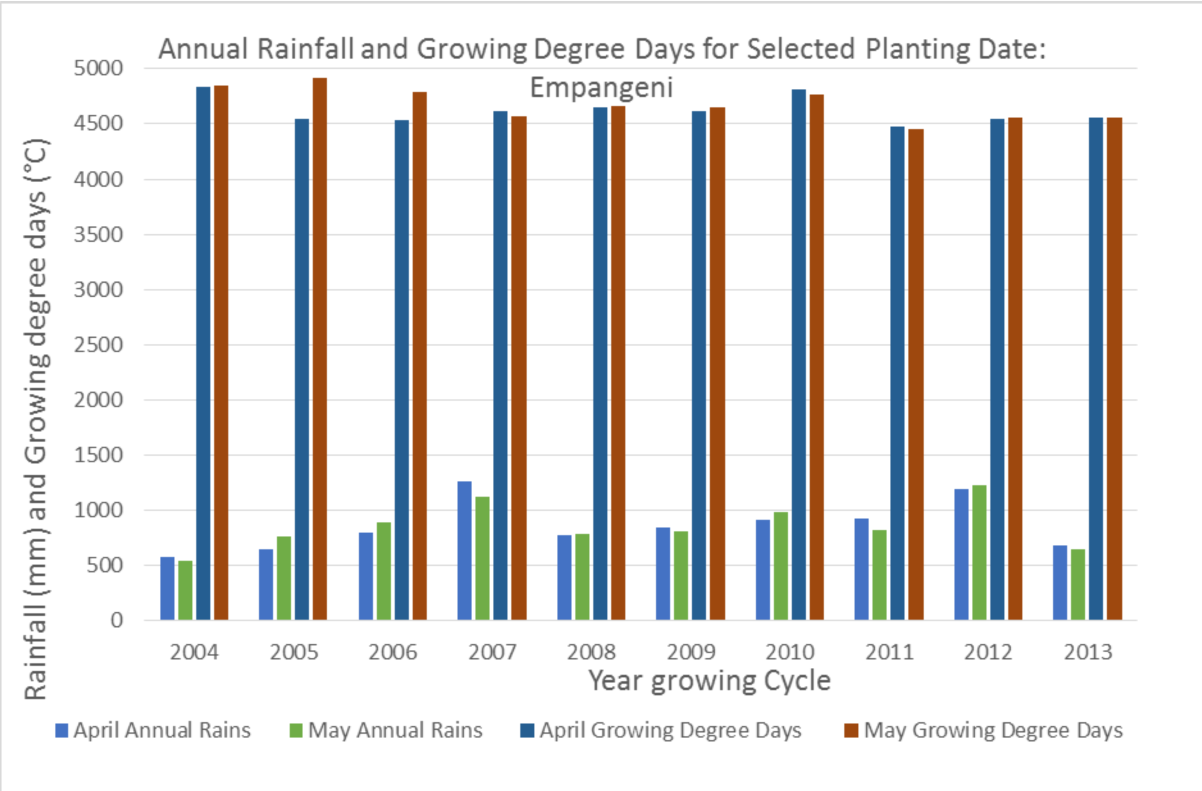

Figure 8-9 Growing cycle annual rains and accumulated growing degree days for two planting dates

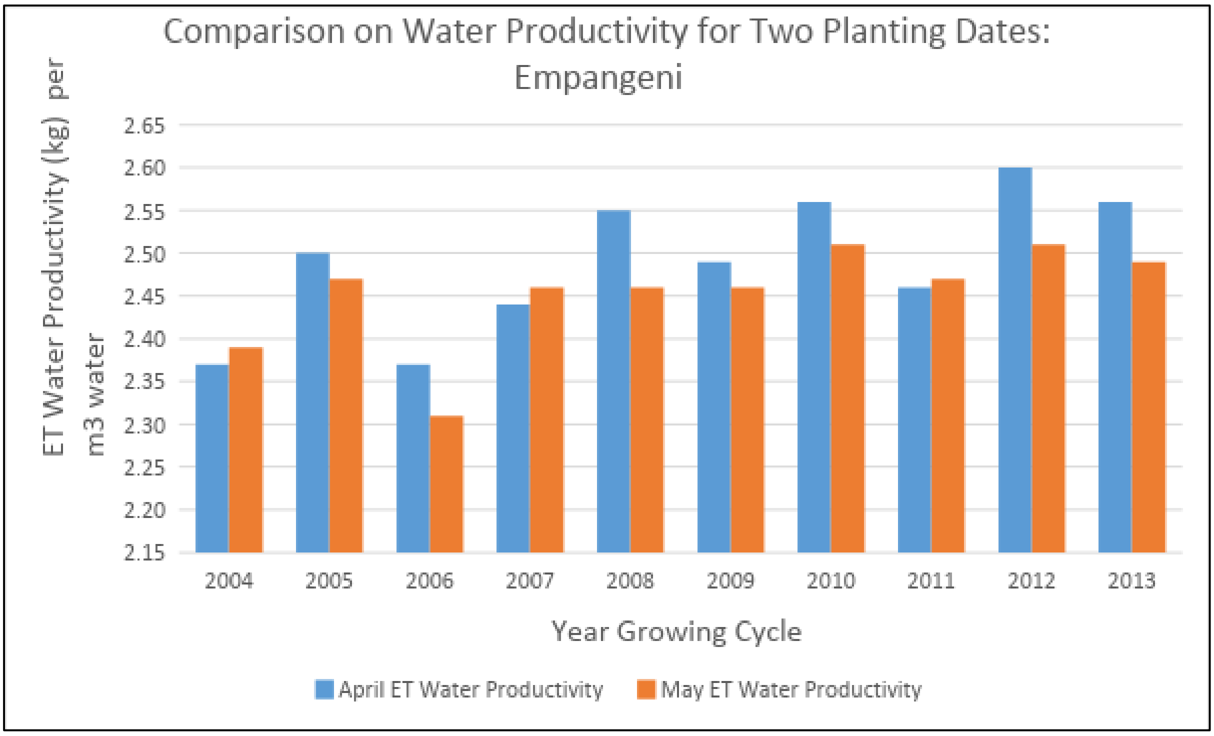

Figure 8-10 Comparison of biomass water productivity for two planting dates

Planting dates selection is determined by the farmer's farming conditions based on whether it is under rainfed or irrigated conditions. The farmers could opt for autumn or spring planting with consideration of sequential planting. For this investigation the simulation runs were based on the possibilities of early planting and to determine the impact of different planting dates. It is critical for sugarcane farmers to consider proper management activities for improved biomass productivity. Such management activities based on weed control, proper variety selection, green manure introduction, getting weather forecast and climatic predictions, insect and pests control, and testing of herbicides.

8.5. The potential for seasonal forecasts of crop yield and water productivity: challenges and recommendations

Agriculture has always been discernible by irregular variations in production because of the role played by factors such as weather and climate variability in determining crop yields. Therefore, understanding the significant needs, on crop requirements and dependable indications of coming crop production have substantial significance for commercial farming to be placed on more favourable bargaining position in the market. The need for advance knowledge of probable supplies remains a challenge, since farmers could utilise such information for financial advantage. Crop forecast relates to the magnitude of production based on known facts on a given date, assuming weather forecast and climate prediction conditions, and damage from insects or pests to be about the average of the previous years (Bezuidenhout and Singles, 2006). Crop forecasting remain the national value as likely supply situation for agricultural products exporting to other countries and as a means of assessing the level of competition to world market and allow anticipation of marketing difficulties.

Undeniably, it is worth mentioning that the significance of a crop forecasting information depends mainly on the importance of the role played agricultural commodity in the country's economy. The countries rural agricultural productivity are vitally interested in estimated production of competing large-scale producers. The mostly used technique for crop forecasting yield per hectare (ha) is calculated from the condition figure based on data from years, between the percentage condition figure and the actual yield per ha. The closer crop forecasting made to harvest time the easier it is to obtain definite indication of possible crop yield. Weather data plays a critical role in devising crop forecasting, thus weather-climate-crop relationships remains a crucial factor, regardless of its complexity.

Similarly, to other agricultural commodities, sugarcane industries are vulnerable to uncertainty associated with variable climate, which affects the value chain from cane growing to post-harvesting and marketing (Everingham et al., 2016). According to Spinks (1956), industrial crop such as sugarcane, when the raw product is processed, accurate production statistics are available almost immediately on the completion of harvest, and therefore yield forecasting on sugarcane is little to no significance. Everingham et al., 2008 emphasize to the fact that accurate yield forecasts are essential for planning prior selling of annual harvest. In South Africa, sugarcane crops are grown under a wide range of agronomic and socio-economic conditions, which suggests to the complications and sophistications of approaches required for crop forecasting.

AquaCrop 6 simulates the yield response to water on different types of crops as a function of water availability and consumption under rainfed, deficit and irrigation conditions. Plant production depends entirely on the soil water conditions and its interaction with the plant and management systems adopted. AquaCrop attempts to balance accuracy with regard to plant physiological processes and soil water budgeting processes, thus it is a water-driven. Parameters such as transpiration is calculated and converted into biomass water productivity.

Simulations are performed on calendar time, whereby the model uses canopy ground cover to calculate transpiration and to separate out soil evaporation from transpiration. Thus, the model has no provision for weather forecast and seasonal climate prediction toward further statistical analysis for crop forecasting. In the AquaCrop mode, crop responses to water deficits are simulated with four modifiers that are functions of fractional available soil water modulated by evaporative demand (Ket et al., 2018; Steduto et al., 2008). These modifiers are based on plant water stress sensitivity canopy expansion, stomatal control of transpiration, canopy senescence, and harvest index. AquaCrop focuses on the use of a relatively small number of parameters to balance simplicity, accuracy, and potency on simulations. The results generated from AquaCrop are designed to fit the need of extension agents, agricultural specialists, economists and policy specialists who use simple models for planning and scenario analysis.

Crop-weather relations in different studies have been studied as a means of crop yield forecasting. Like adopted by AquaCrop simulation model, this approach, is based on historic climatic data and the harvested yield of the same period. In such cases, the techniques is rather largely experiential and have no known measure of accuracy. However, zooming into sugarcane productivity, which is a unique multi-year crop, and can be harvested annually up to 6-7 years without replanting. After an annual harvest, the ratoons grow new stems that are cut the following year. There has been evidence on some farms, whereby, sugarcane is harvested continuously over 9 months (Legendre et al., 2000). Such high amount of production creates a tremendous need to provide regular crop yield estimates. Complexity becomes eminent, since the daily harvest of cut sugarcane must be efficiently transported to a sugar mill for processing and ensuring continuous supply to the mills. Another methodology used for crop forecasting within the is to leverage Normalized Difference Vegetation Index methods which address some of the concerns of scouting and sampling, suffer from reduced reliability, accuracy, and scalability. Changing climatic conditions, soil types, varieties and farming management practices make it extremely difficult to estimate, accurately, yield for sugarcane over very large areas. Nevertheless, NDVI-based metrics and sugarcane yield has R^2 values of 0.48-0.53 (Lofton et al., 2012).

Further research is desirable to develop specific guidelines for distinguishing different canopy structures considering the fact that sugarcane is a multi-year crop, since within AquaCrop simulates crop canopy for a single planting season. In this study, the authors assumed that sugarcane is a seasonal crop and ignored the fact that ratoons re-grow continuously. The authors utilized variety reports to determine differences in canopy structure; however, numerical guidelines that take into account physiological characteristics of each variety, such as leaf angle or length of leaf to the first bend, would provide a more precise method of separating sugarcane varieties. In addition, due to limitations associated with NDVI and the lack of provision to utilize seasonal rainfall probabilistic data on AquaCrop, further research is recommended to investigate other methodologies or techniques to develop guidelines on sugarcane crop forecasting.

The development of a comprehensive systems approach that is capable of running crop model simulations using historical climatic data, and capable of incorporating seasonal climate forecasts, to produce crop forecasts and improve risk management and decision-making capability across the sugarcane industry, is recommended. The challenge with incorporating seasonal climate forecasts is that they are frequently issued as a seasonal total (rainfall) and/or mean (temperature), whereas a model such as AquaCrop requires and daily climatic time series as input. This presented a challenge to this component of the project that could not be resolved within the time and resources available.

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CHAPTER 9. EFFORTS TO UNDERSTAND AND REDUCE UNCERTAINTIES AND ERRORS IN AGROHYDROLOGICAL FORECASTING

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9.1. Background

Aim 7 of the project had the objective of attempting to understand and possibly reduce uncertainties and errors in agrohydrological forecasts. The efforts to address this aim began with evaluating the 7 day rainfall and temperature forecasts (described in Chapter 3). Quantifying and appreciating the error in the weather forecasts is an important aspect of understanding the error in the resultant agrohydrological forecasts. The second effort in the theme of reducing error and uncertainty relates to model initialization. This is discussed next. Finally, the benefit of incorporating temperature forecasts into agrohydrological forecasting (in place of historical mean temperatures) is investigated as another effort to reduce forecasting errors.

9.2. Evaluation of medium range numerical weather prediction rainfall and temperature hindcasts for agrohydrological forecasting

Errors and uncertainties in agrohydrological forecasting originate from the meteorological forcings used as input to application models, other model input parameters, the assumed initial hydrological conditions (e.g. soil moisture content and reservoir levels) from which the forecast is run, model structure and processes represented as well as all related observational data used in calibration and validation (Block et al., 2009; Thiboult et al., 2016; Kusangaya et al., 2016). Additionally, these uncertainties may vary with catchment characteristics and forecast lead time, however, it is commonly accepted that the greatest uncertainty stems from the observed and forecast input values (Emerton et al., 2016; Liu et al., 2012; Fekete and Vörösmarty, 2002) which are used to drive agrohydrological models and generate quantitative information.

Evaluations of the forecasts are usually undertaken from a meteorological/climatological perspective which is different to a hydrological perspective in terms of how risks, uncertainties and errors are viewed (Pappenberger et al., 2008). For example, in terms of scale, meteorologists and climatologists focus on synoptic scales, while hydrologists are concerned with the scales at which decisions are taken and adaptation options should be made (Schulze et al., 2014; Pappenberger et al., 2008).

Owing to these differences, the extent to which weather forecasts are beneficial in hydrological forecasting depends considerably on the ability of the Numerical Weather Prediction (NWP) model used to produce the forecasts being able to resolve scales and processes relevant for hydrological applications, and whether or not the surface hydrology in the catchment is dominated by rainfall. For agrohydrological applications, the evaluation of weather forecasts is aimed at understanding the nature of the forecasts errors. For example, with rainfall, the ability of the forecasts to capture various threshold magnitudes (light vs heavy) as well as sequences of wet days and dry days above and below specific thresholds is important in terms of irrigation scheduling and in influencing antecedent soil moisture conditions. In terms of temperature, the ability of forecasts to correctly capture maximum and minimum temperatures and sequences thereof affects the estimations of second order derivatives such as potential evaporation and forecasts of temperature related warning indices, for example veld fire conditions, heat stress indices, heat waves and frost events.

Accurate weather forecasts have the potential to reduce the uncertainty in the inputs to agrohydrological models, and can greatly improve the quality of the generated forecasts (Shrestha et al., 2013). This study therefore aims to evaluate medium range (7 day) rainfall and maximum and minimum surface temperature hindcasts generated by the variable resolution CCAM model for the Mhlathuze catchment in KwaZulu-Natal, South Africa. The evaluation is conducted from a hydrological perspective, with a view to informing the generation of agrohydrological forecasts from the CCAM forecasts. With an understanding of the associated errors and uncertainties related to weather forecasts, there can be an improved understanding of the errors and uncertainties associated with the generated agrohydrological forecasts.

9.2.1. Observed data

A representative weather station was selected per quinary catchment to compare its record with the weather hindcasts. This comparison was conducted at quinary catchment scale as this is the scale at which agrohydrological modelling and forecasting is to be performed. Requirements for the selection of representative "driver" stations per quinary catchment were based on the need for; high quality and reliable records, reasonable historical record lengths (i.e. more than 20 years), currently active stations (for operational forecasting purposes) and stations representative of both the mean altitude and annual and monthly rainfall of the catchment. The representivity of the driver stations in terms of annual and monthly catchment rainfall was verified by making reference to the gridded historical rainfall surfaces developed for the country by Lynch (2004).

The observed daily rainfall and temperature (maximum and minimum) data for each quinary catchment were sourced from a total of 12 climate stations within and around the Mhlathuze catchment for the study period from 15/08/2013 to 15/10/2016. Driver stations included both automatic weather stations and raingauges from the South African Sugarcane Research Institute (SASRI) and the South African Weather Service (SAWS) (Table 9-1). Not all of the selected driver stations had daily temperature data. For these stations, daily maximum and minimum temperatures were estimated using data from nearby surrounding stations with the same altitude that were too far away to represent a quinaries rainfall. Published regional adiabatic lapse rates for monthly means of daily maximum and minimum temperatures (in °C/1000 m) were applied to the data from the surrounding stations to estimate temperatures at the driver stations (Schulze, 1995)

Table 9-1 Selected driver stations per quinary catchment

Station number	Station altitude (m.a.s.l.)	Quinary	Quinary Area (Km^2)	Quinary average Altitude (m.a.s.l.)
0337382 W	770	W12A1	149.51	1257.29
0303695 W	800	W12A2	381.96	1026.68
		W12C2	243.85	639.21
		W12C3	165.90	374.10
		W12D2	50.91	328.69
0303534 S	636	W12A3	94.25	748.03
		W12B1	20.81	862.52
		W12B2	295.02	601.97
		W12B3	173.72	366.75
		W12C1	162.61	906.87
		W12D1	67.91	584.34
		W12E1	54.36	341.95
		W12E2	69.17	211.89
0303711 S	581	W12B1	78.64	862.52
		W12B1	90.45	862.52
		W12D2	62.59	328.69
0304201 S	122	W12D3	349.47	138.56
		W12G1	47.75	395.56
		W12G3	175.03	149.34
0304015 S	118	W12D2	62.49	328.69
0304705 S	102	W12E3	126.26	91.26
		W12F1	26.63	107.90
		W12F2	56.24	63.80
0304680 S	24	W12F2	39.08	63.80
0305308 W	35	W12F3	279.12	20.80
		W12J1	39.40	80.47
		W12J2	38.64	57.83
		W12J2	125.10	57.83
		W12J3	56.96	28.16
		W12J3	73.74	28.16
0304073 S	201	W12G2	195.29	255.50
0304700 S	117	W12H1	31.72	178.20
		W12H3	260.24	56.58
0305037 W	77	W12H2	195.29	111.26

As the comparison of observed and forecast weather is to be conducted at quinary catchment scale, the observed rainfall station data were adjusted to better represent the areal rainfall over their respective quinary catchments. These adjustments were implemented as 12 monthly multiplicative factors applied to the daily rainfall station data. These factors were calculated as the ratio of the spatially averaged median monthly catchment rainfall to the equivalent median monthly rainfall at the station. The spatially averaged median monthly catchment rainfall was determined from the gridded historical rainfall surfaces (one arc minute of a degree resolution) developed for the country by Lynch (2004).

Archived hindcasts of medium range (0 to 7 day) rainfall and maximum and minimum temperatures, produced at the Council for Scientific and Industrial Research (CSIR) for the period 15/08/2013-15/10/2016, were used in the study. (See Chapter 3 for the detailed description of the CCAM model). Typically, a quinary catchment falls over two CCAM grid boxes (Figure 9-1).

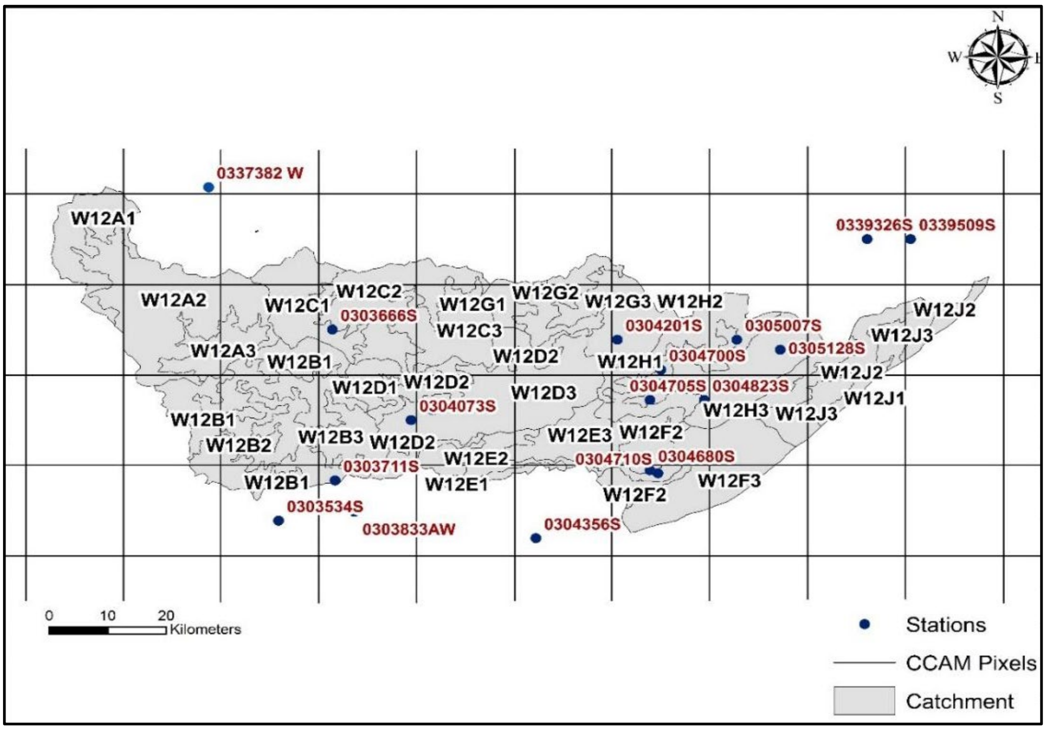

Figure 9-1 CCAM grid box resolution and selected representative weather stations

9.2.2. Method used to evaluate the skill of rainfall forecasts

It must be noted that the number of quinaries controlled by the same station is hydrologically significant as it implies that each of the quinaries will be given the same value on a given day (Schulze, 2014). This is specifically for multiple quinaries with only one representative station within the area, for example the high altitude quinaries. Due to the limited number of selected driver stations, one driver station was selected for more than one quinary based on the selection criteria specified above. Additionally, a station only covers an area of 0.0005 km^2 within a catchment (Schulze, 2014) which is highly variable climatically and are also subjected to numerous random and systematic measurement errors. Nevertheless, ground observations have long been accepted as the most realistic representation of actual rainfall available. With this in mind, an error envelope of 1 to 10% above or below the daily weather observations are assumed to be “correct” forecasts for this exercise.

Comparisons were conducted per station by comparing the station adjusted rainfall values and the average forecast values per quinary. Average rainfall forecasts for each quinary (Fc) is computed by weighting each rainfall forecast (Fi) at the grid cell I by the fraction of the quinary area within the grid cell i and given by:

$$\mathrm{Fc} = \frac{\sum_{i=1}^{N_g} A_i F_i}{\sum_{i=1}^{N_g} A_i}$$

Where Ai is the area of catchment within the grid cell i, Ng is the number of the grid cells covered partly or fully by the catchment. An initial evaluation of the 7 day CCAM rainfall forecasts was conducted for the Mhlathuze catchment as a whole. This evaluation was focused on determining the frequencies of daily forecast errors for different classes of error. A spatial analysis evaluating the quantitative errors per quinary catchment was then undertaken. An analysis of the differences between the observed and forecast time series' in terms of the frequency of occurrence of events of varying magnitudes, was undertaken. The selection of the event magnitudes was based on a preliminary evaluation of the observed rainfall data during the study period, and also considering the general agricultural and water resource management needs listed in Table 9-2. Differences in the total number of selected wet and dry day sequences between the observations and forecasts for the study period were also evaluated. A rainday in this study is defined as one in which more than 1 mm of rainfall is observed.

Table 9-2 Selected rainfall threshold magnitudes and associated agricultural and water resources management decisions (adapted from Lumsden and Schulze, 2012)

<table>
<tr><th>Threshold</th><th>Agricultural user need</th><th>Water Resources management decisions</th></tr>
<tr><td>No Rain - Light Rain (1 to 10 mm)</td><td>Land preparations
Crop production activities;
Livestock management and movement
Controlled burning</td><td>Irrigation water allocations and scheduling,
IFR low flow releases,
reservoir management,
water poverty release alleviations;
estimations of antecedent soil moisture conditions,</td></tr>
<tr><td>Moderate Rain (10 to 20 mm)</td><td>Crop production activities
Irrigation scheduling</td><td>Antecedent soil moisture conditions, irrigation scheduling</td></tr>
<tr><td>Heavy Rain (20 to 40 mm)</td><td rowspan="2">Crop protection from damage
Infield machinery removal
Livestock protection
Protection of topsoil from removal due to runoff or soil erosion.
Protection from lightning and hail.</td><td rowspan="2">Runoff and stormflow generation, Flood management; Reservoir inflows timings, Safety releases from reservoirs, landslides, Storm surge analysis in rivers</td></tr>
<tr><td>Extreme Rain (>40 mm)</td></tr>
</table>

9.2.3. Method used to evaluate the skill of temperature forecasts

Differences between the observed and forecast temperature values (daily maximum and minimums) were evaluated using the same method as the daily rainfall forecasts. An initial evaluation focused on determining the frequencies of daily temperature forecast errors for different classes of error for the catchment. This was followed by a spatial evaluation of quantitative errors per quinary catchment. For a maximum or minimum temperature forecast to be considered as “correct”, a maximum error allowance of 1°C (above and below) was assumed. An analysis of the differences between the observed and forecast time series’ in terms of the frequency of occurrence with which temperatures fall within defined threshold intervals, was then undertaken. The threshold intervals were selected based on perceived user needs and preliminary analysis of observed temperature data across the catchment (Table 9-3).

Table 9-3 Selected maximum and minimum thresholds

Maximum T Threshold (°C)	Minimum T Threshold (°C)
27 to 32	<0
32 to 35	0 to 5
>35	5 to 10 10 to 20

9.2.4. Verification scores

No single evaluation score is adequate to evaluate the accuracy of NWP model forecasts, and therefore forecast errors per for the study period were evaluated using a total of five commonly used continuous verification scores, as outlined in Table 9-4 below.

Table 9-4 Outline of selected verification scores

Verification score	Equation	Aim
Root mean square error (RMSE)	$\sqrt{\frac{1}{N}\sum_{i=1}^{N}(F_i - O_i)^2}$	Assess the average magnitude of the forecast error
BIAS or Mean Error	$\frac{\frac{1}{N}\sum_{i-1}^{1} F_i}{\frac{1}{N}\sum_{i-1}^{1} O_i}$	Assess the difference between the mean of forecasts and the mean of corresponding observations
Spearman's Rank correlation coefficient	$p = \frac{\sum(F - \bar{F})(O - \bar{O})}{\sqrt{\sum(F - \bar{F})^2}\sqrt{\sum(O - \bar{O})^2}}$	Reflects the linear association between forecasts and observations
Agreement index (d)	$1 - \frac{\sum_{i=1}^{N}(O_i - F_i)}{\sum_{i=1}^{N}(\lvert O_i - \bar{O}\rvert + \lvert F_i - \bar{O}\rvert^2)}$	Measure the agreement between forecasts and observations
Accuracy	$\frac{O_i - F_i}{F_i}$	Measures the proportion of observations that are equal to the corresponding Forecasts

The selected scores were calculated for the entire time series for each of the variables (rainfall and maximum and minimum temperature).

9.2.5. Results

9.2.5.1. Rainfall

The CCAM model was found to be accurate in forecasting more than half of the observed daily rainfall events during the study period in terms of occurrences and magnitudes. A total of 10.91% were correctly forecast. The largest percentage of incorrect forecasts were found in the 10 mm over-estimation class equating to 67.41% followed by a total of 16.27% underestimations of 10 mm. Percentage frequencies of under- and over-estimations greater than 10 mm accounted for less than 5% (Figure 9-2). The average magnitude of forecast error over the catchment as a whole, represented by the RMSE was 7.507 mm with a mean difference of -1.36 mm between forecasts and observed values. A low linear association of 0.1 is shown over the catchment as well as a low overall measure of agreement (0.16) and accuracy between forecasts and observations (Table 9-5). Spatial variations of the models performance per quinary were then evaluated.

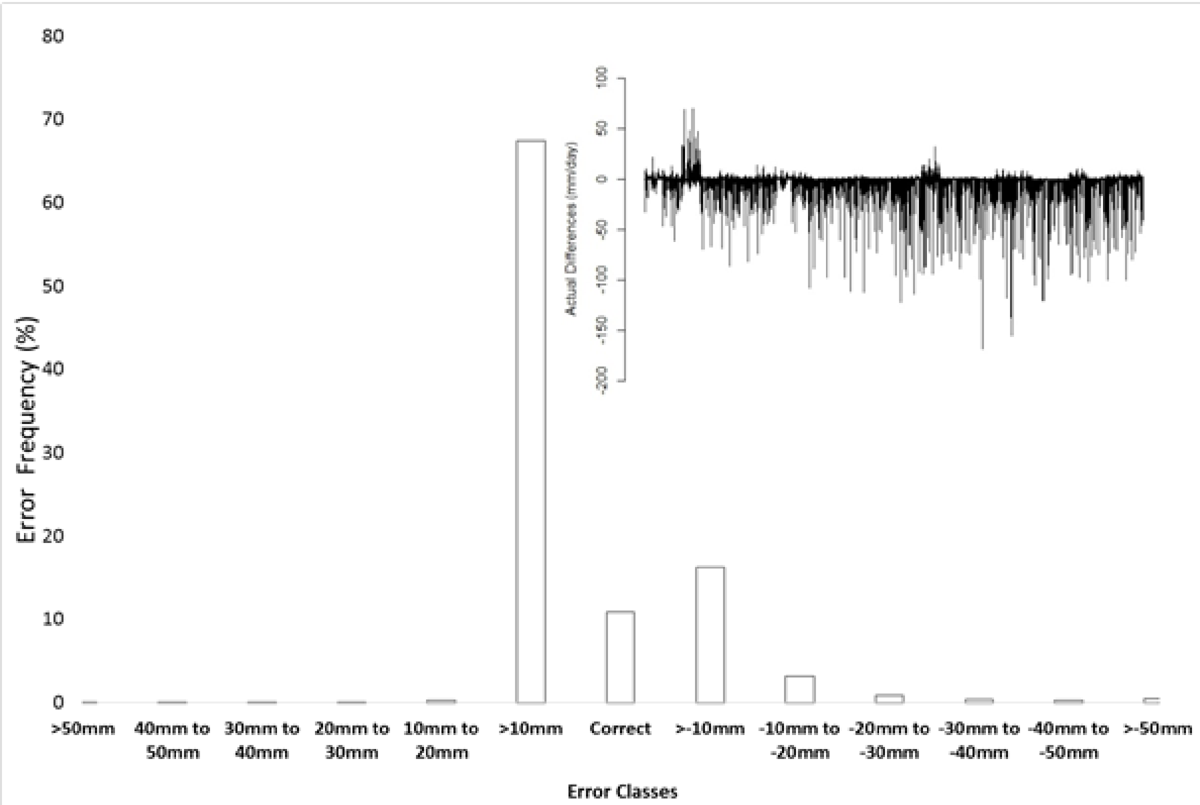

Figure 9-2 Frequencies of daily rainfall forecast errors for different classes of error

Table 9-5 Verification scores for the catchment as a whole

Verification score	Equation
RMSE	7.507
BIAS	-1.36
Spearman's Rank correlation coefficient	0.105
Agreement index (d)	0.16
Accuracy	0.115

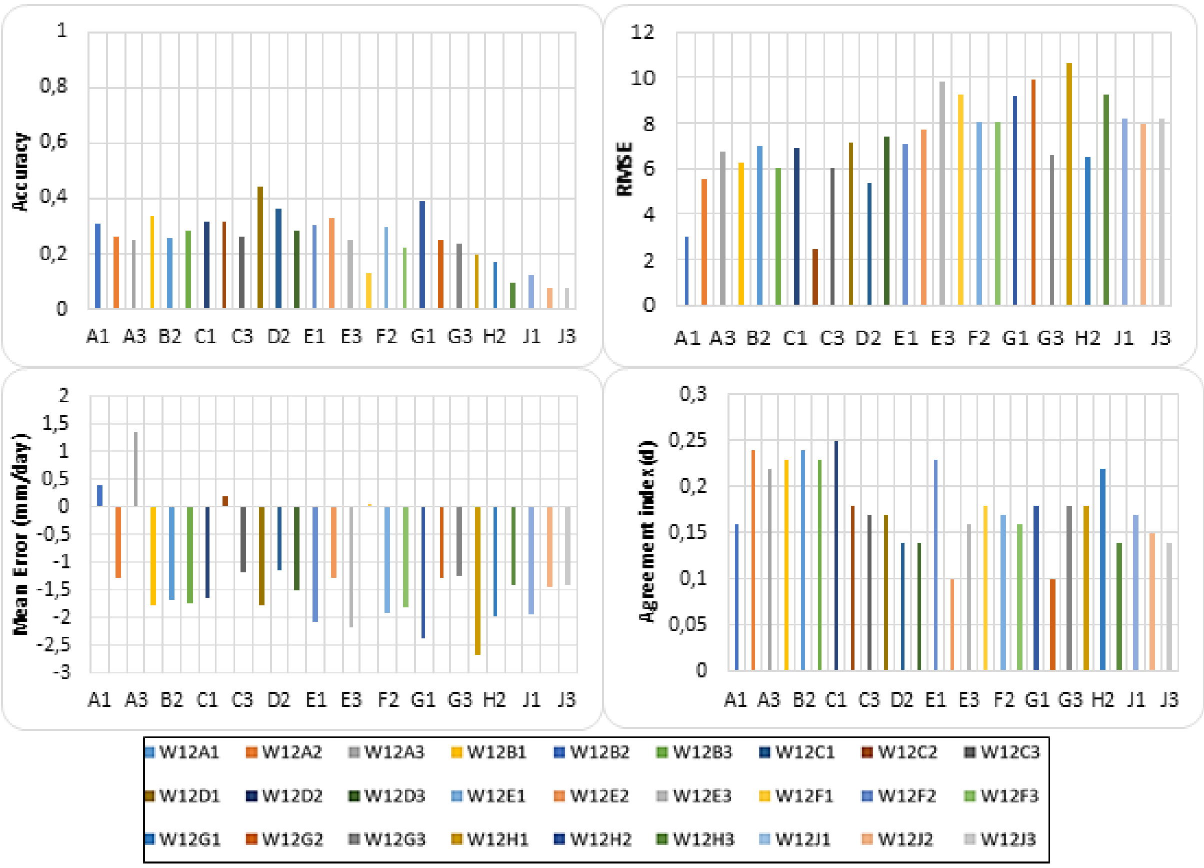

Figure 9-3 Verification scores per quinary a) Accuracy, b) RMSE, c) Mean error and d) agreement index

Verification scores calculated per quinary in Figure 9-3 showed large spatial variations across the catchment. Quinary W12D1 showed the highest proportion (0.45) of observations equal to forecasts represented by the accuracy score for the study period. The lowest forecast accuracy score of less than 0.1 was shown in coastal low altitude quinaries W12J2 and W12J3. RMSE values per quinary showed a maximum of 10.64 mm for quinary W12H1 and a minimum of 2.44 mm for quinary catchment W12C2. Mean errors per day or bias showed an overall under-estimation across the catchment with only two quinaries (W12A1 and W12A3). Maximum over- and under-estimations of 1.64 and 2.46 mm were shown in quinaries W12A3 and W12H1 respectively. A generally low overall agreement between forecasts and observed values per quinary was shown with the highest calculated agreement index of 0.25 in quinary W12C1 and the lowest agreement index of 0.1 for quinary W12G2.

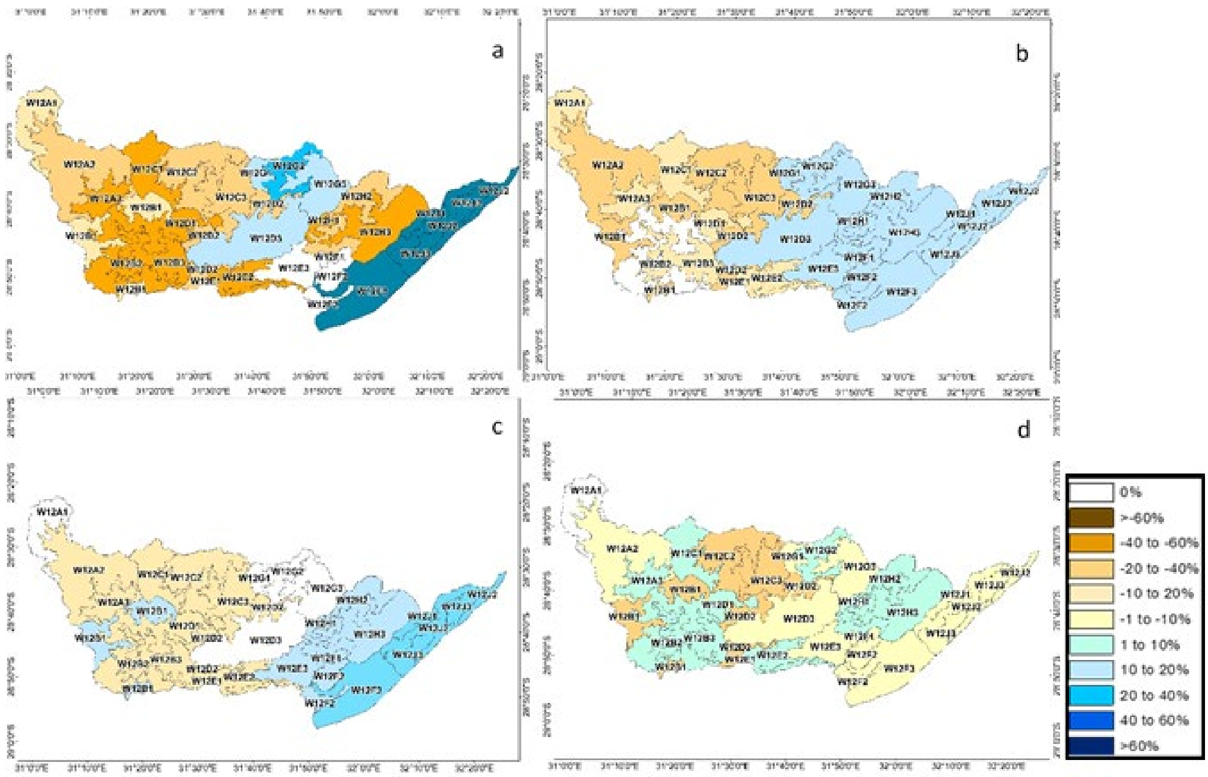

Figure 9-4 Percentage differences between daily rainfall forecasts and observations in terms of the frequency of occurrence of events of varying magnitudes: a) Light Rainfall (1 to 10 mm) b) Moderate Rainfall (10 to 20 mm) c) Heavy Rainfall (20 to 40 mm) and d) Extreme Rainfall (> 40 mm).

The ability of the CCAM rainfall forecasts to represent the frequency of occurrence of different-sized rainfall events for the study period was analysed for each quinary catchment and represented as percentage differences from the observed frequency. Dark blue and dark brown colours indicate higher percentages of over- and under-estimations by the model, respectively (Figure 9-4a to d). The forecast occurrences of light rainfall magnitudes (1 to 10 mm) significantly under-estimate the observed number of occurrences in the most high and middle altitude inland quinaries with underestimations reaching a maximum of 40% and 60%, respectively (Figure 9-4 a). For the low altitude and coastal quinaries the model has a tendency to over-estimate the frequency of events by over 60%. In three low altitude quinaries

(W12E3, W12F1 and W12F2), the forecasts were able to correctly (-1 to 1%) forecast the frequency of events for the study period.

Lower percentage differences were found for the moderate rainfall category (10 to 20 mm) compared to the light category (Figure 9-4 b). However, similar spatial variations were seen in relation to altitude across the catchment. The frequency of occurrence for moderate rainfall was under-estimated in the headwaters of the catchment by a maximum of 40%, while in some middle and low altitude coastal catchments frequencies were over-estimated by 10 to 20%, with only a single quinary catchment (W12B1) being correctly forecast for the study period.

The forecast frequency of heavy rainfalls (20 to 40 mm) for the catchment showed similarities to that of the moderate rainfall category in terms of the deviation from observations (Figure 9-4c). Additionally, forecasts for the heavy rainfall category showed the highest number of correctly forecast quinary catchments (W12A1, W12D3, W12G1, W12G2, W12G3),

Forecasts of the frequency of extreme rainfall events (> 40 mm) showed a distinctly different spatial pattern across the catchment (Figure 9-4 d). Coastal catchments were under-estimated by less than 10% and a majority of the middle-altitude inland catchments were over-estimated by less than 10%. Similar to the heavy rainfall events, the quinary catchment with the highest altitude (W12A1) was correctly forecast.

The frequency of forecast sequences of consecutive wet days across the catchments showed a predominant underestimation, with the largest deviations relative to observations being evident for two and three day sequences during the study period (Figure 9-5a to d). The relationship between altitude and errors in the rainfall forecasts continued to be evident. The CCAM model has a tendency to under-estimate the frequency of consecutive wet day sequences for the middle and high-altitude catchments, and overestimate frequencies for the coastal catchments. Percentage differences between forecasts and observations showed an increase for shorter sequences of consecutive wet days, with the maximum under- and over-estimations observed for sequences of two days (deviations of over 60%). The model was found to perform best for forecasting sequences of four consecutive wet days, where the error (underestimation) for the upper high-altitude quinaries was less than 10%, and a total of two quinary catchments (W12A2 and W12H3) were correctly forecast (Figure 9-5 c). In contrast, for forecasts of three consecutive wet days, coastal catchments showed a slightly higher over-estimation with deviations being in the range of 20% to 40%. The frequency of occurrence of sequences of two consecutive wet day with rainfall of over 10 mm per day, was then analysed (Figure 9-5 d). However, evaluation of the map revealed no clear spatial pattern in the differences between forecasts and observations across the catchment.

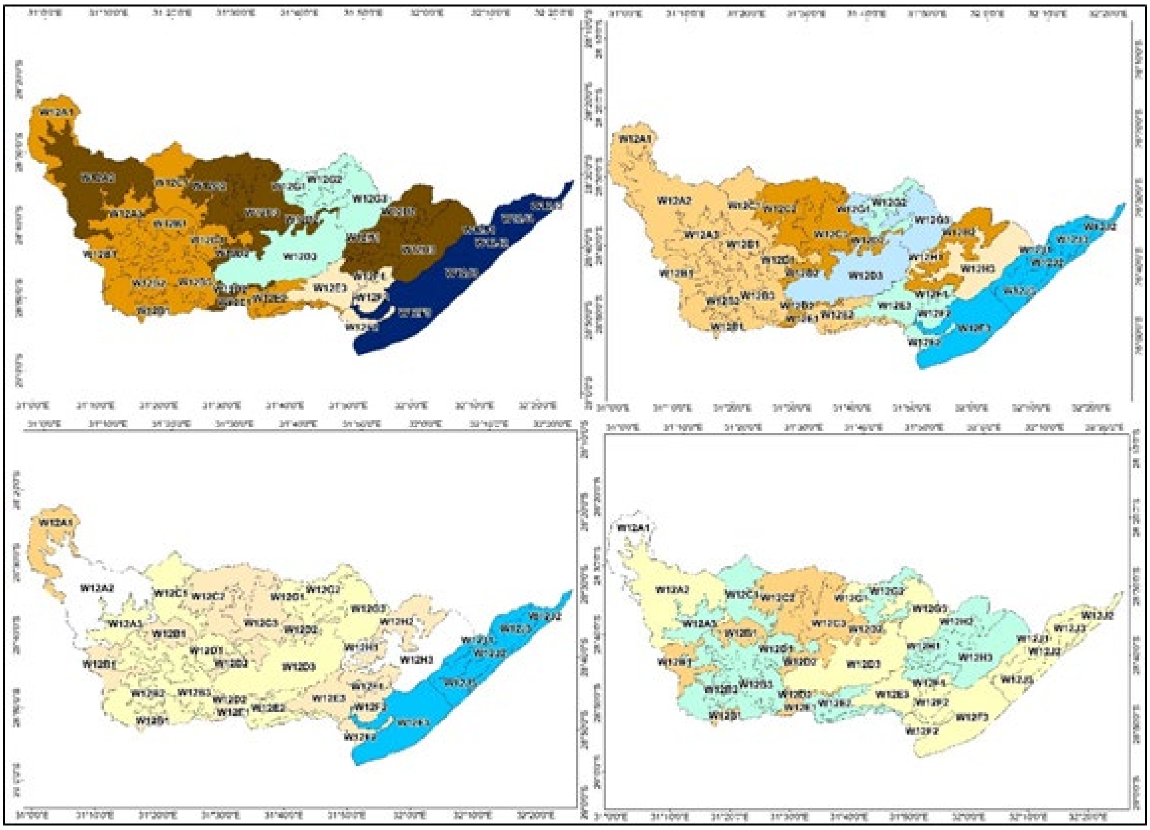

Figure 9-5 Percentage differences between forecast and observed frequencies of occurrence of sequences of consecutive wet days: a) Two consecutive wet days b) Three consecutive wet days c) Four consecutive wet days d) Two consecutive wet day sequences with rainfall >10 mm per day.

The percentage difference between the forecast and observed frequency of consecutive dry day sequences showed a clear decrease in magnitudes (i.e. in both over- and under-estimations) with an increase in the number of consecutive dry days (Figure 9-6a to f). The opposite spatial patterns were observed as compared to the number of consecutive wet days. Coastal catchments are under-estimated for all consecutive dry day categories (two to seven), with the highest under-estimations observed in the five day sequences (errors of over 60%).

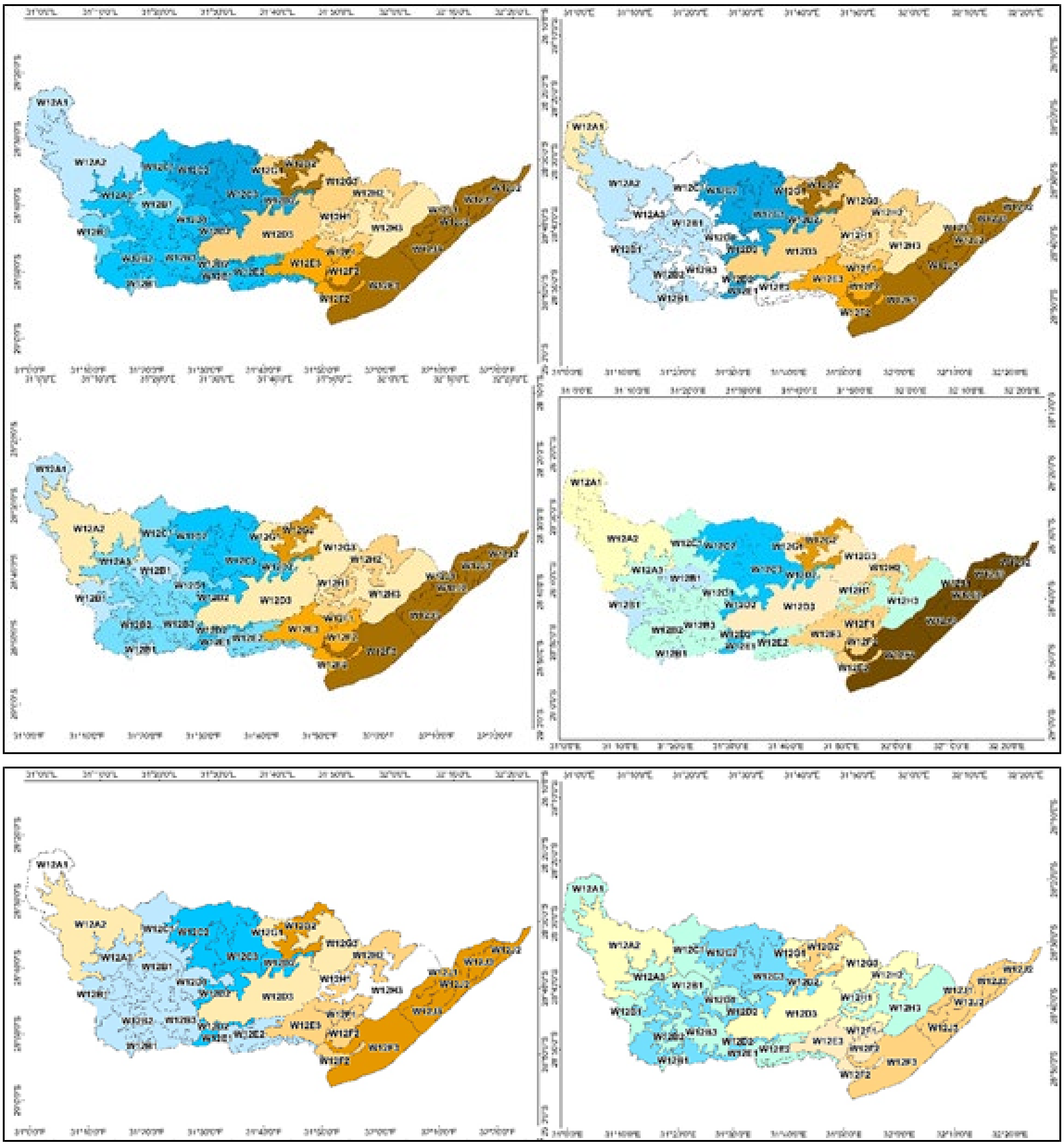

Figure 9-6 Percentage differences between forecast and observed frequencies of occurrence of sequences of consecutive dry days: a) Two consecutive dry days b) Three consecutive dry days c) Four consecutive dry days d) Five consecutive dry days e) Six consecutive dry days f) Seven consecutive dry days.

9.2.5.2. Temperature

Examination of the departure of the CCAM maximum and minimum daily temperature forecasts from the corresponding observations showed that, in general, there was a higher level of forecast accuracy for minimum temperatures. Both maximum and minimum temperatures showed higher frequencies of over-estimations within the range of 1 to 10°C than under-estimations within the same error category. Maximum temperatures, however, showed higher frequencies of over- and under-estimations relative to observations than minimum temperatures. The frequency of errors greater than 10°C (for both maximum and minimum temperatures) were found to be below 5%, with maximum temperatures showing higher frequencies in all error categories. (Figure 9-7).

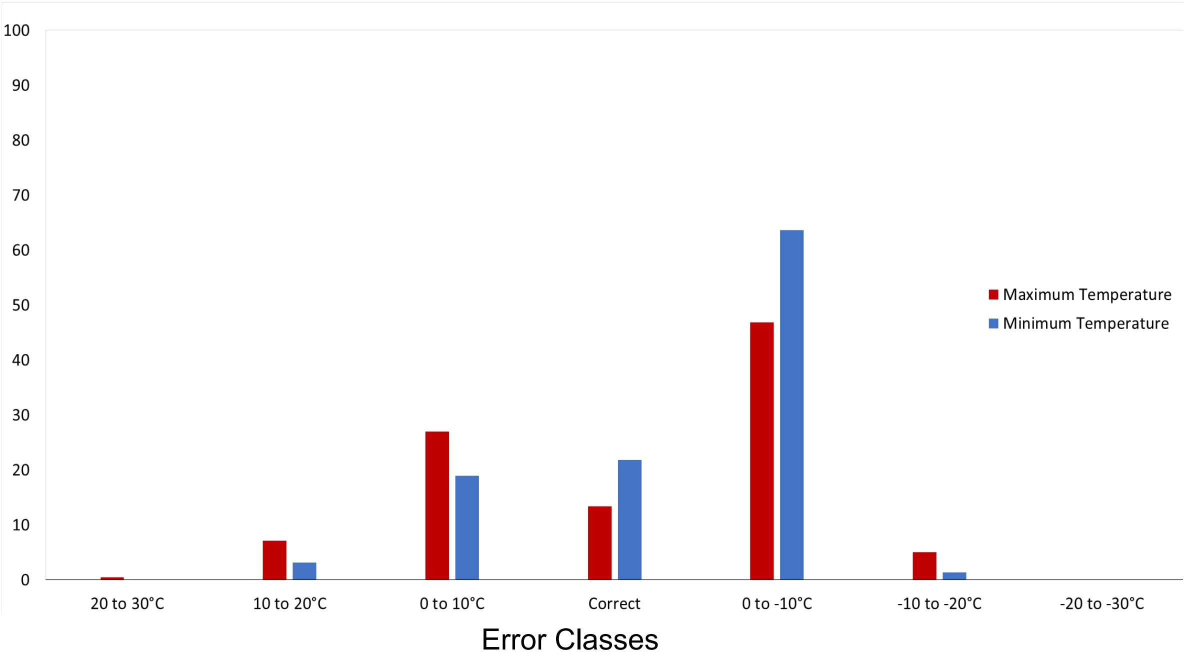

Figure 9-7 Frequencies of daily maximum and minimum temperature forecast errors for different classes of error

Daily differences between the observed and forecast maximum and minimum temperatures per quinary showed large spatial variability (Figure 9-8 a and b). The spread of the errors overall are larger for maximum temperatures as compared to minimum temperatures as shown by the larger IQR's. Errors reach maximum over and underestimations of 17.77°C and 10.81°C for minimum and maximum temperatures respectively.

Maximum daily temperatures are predominantly over-estimated by 3.39°C on average. Overestimations are placed mainly over middle and inland catchments while average under-estimations of 1.53°C occur over high altitude and low coastal catchments. Similarly minimum daily temperatures are predominantly underestimated across the catchment by 3.88°C on average placed mainly over the lower altitude catchments. In general, the spread of forecast errors show a decrease with altitude for both maximum and minimum daily temperatures.

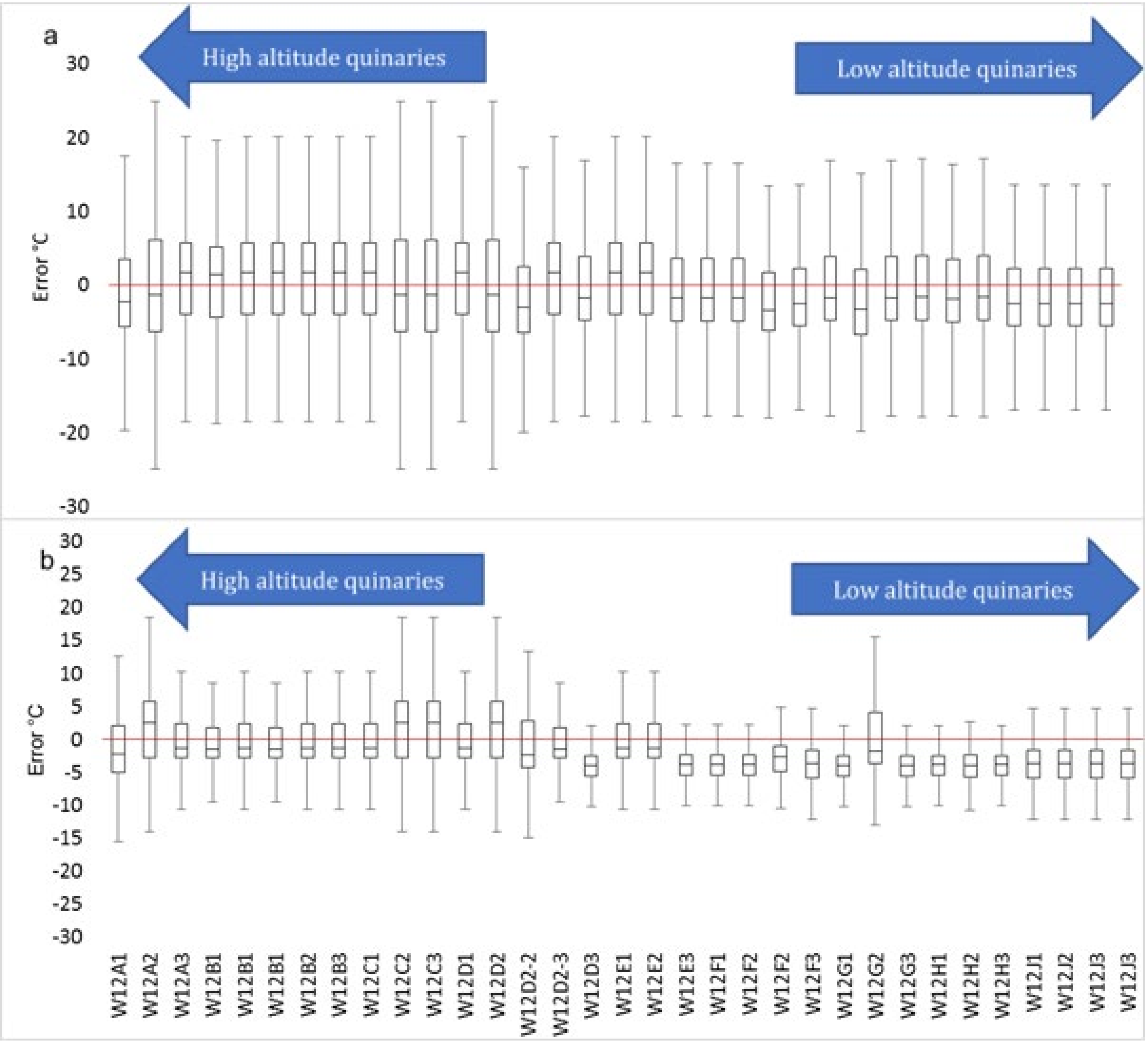

Figure 9-8 Box plots showing the variation in the daily differences between observed and forecast maximum temperatures per quinary catchment

The ability of the CCAM maximum temperature forecasts to represent the frequency of occurrence of different ranges of temperature for the study period was analysed for each quinary catchment and represented as percentage differences from the observed frequency (Figure 9-9 a, b and c). For the temperature range (27 to 32°C) an overall under-estimation across the catchment was found, with the largest errors (of over 60%) being evident in the coastal catchments. For the 32 to 35°C category, a distinct spatial pattern between the high altitude catchments and the middle and lower coastal catchments can be seen. In three high altitude catchments, the frequency of occurrence was correctly forecast for the study period while a general over-estimation (peaking at 40%) was observed in surrounding quinary catchments. In the highest altitude catchment W12A1, the frequency of occurrence was under-estimated by less than 10%, while the lower altitude and coastal catchments were under-estimated by less than 20% and 40%, respectively. For the critical extreme temperature threshold of more than 35°C, a large area of the catchment was characterized by over-estimations of the frequency of occurrence, with the errors mainly being in the range of 20 to 40%. The frequency of occurrence in the coastal catchments was under-estimated by a maximum of 40%, while in the highest altitude catchment the frequency was under-

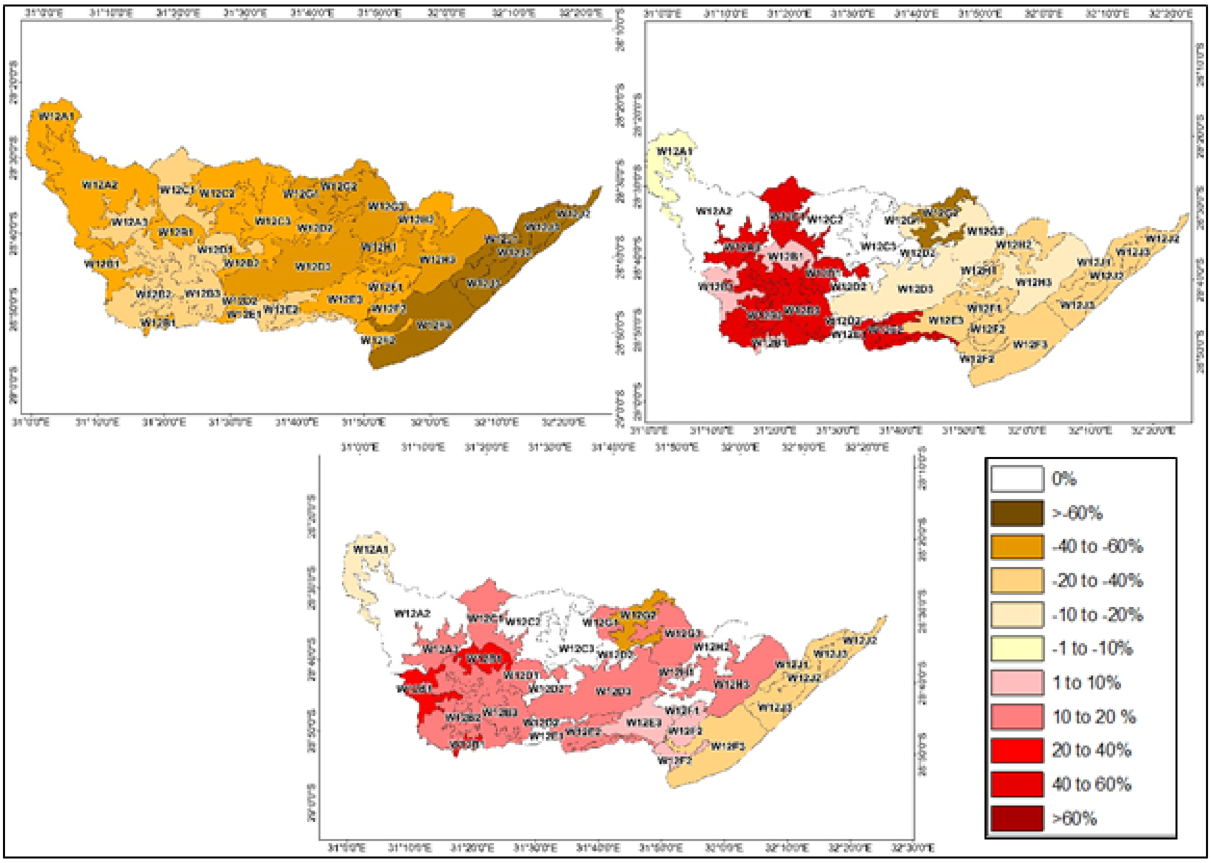

Figure 9-9 Percentage differences between maximum temperature forecasts and observations in terms of the frequency of occurrence of temperatures in the range of: a) 27 to 32°C, b) 32 to 35°C and c) >35°C

estimated by less than 10%. The frequency of occurrence of extreme temperatures was correctly forecast in a total of four quinary catchments during the study period.

With the exception of the middle-altitude quinary catchments, the Mhlathuze catchment lies within a frost free area (Schulze et al., 2016). Minimum temperatures below 0°C are not common. The frequency of temperatures in this range were over-estimated in the coastal and highest altitude catchment (W12A1) by a maximum of 10% (Figure 9-10a). The frequency with which temperatures in the range 1 to 5°C were forecast for the study period was over-estimated by 10 to 40% for the middle-altitude and coastal catchments (Figure 9-10b). A larger portion of the lower altitude catchments were under-estimated for the 5 to 10°C minimum temperature interval (Figure 9-10c). A distinctly different spatial pattern was observed for the 10 to 20°C minimum temperature interval, with a 10 to 20% under-estimation being evident in the coastal catchments, a 20 to 40% under-estimation in the middle catchments, and an over-estimation in high altitude catchments of 20 to 40% (Figure 9-10d).

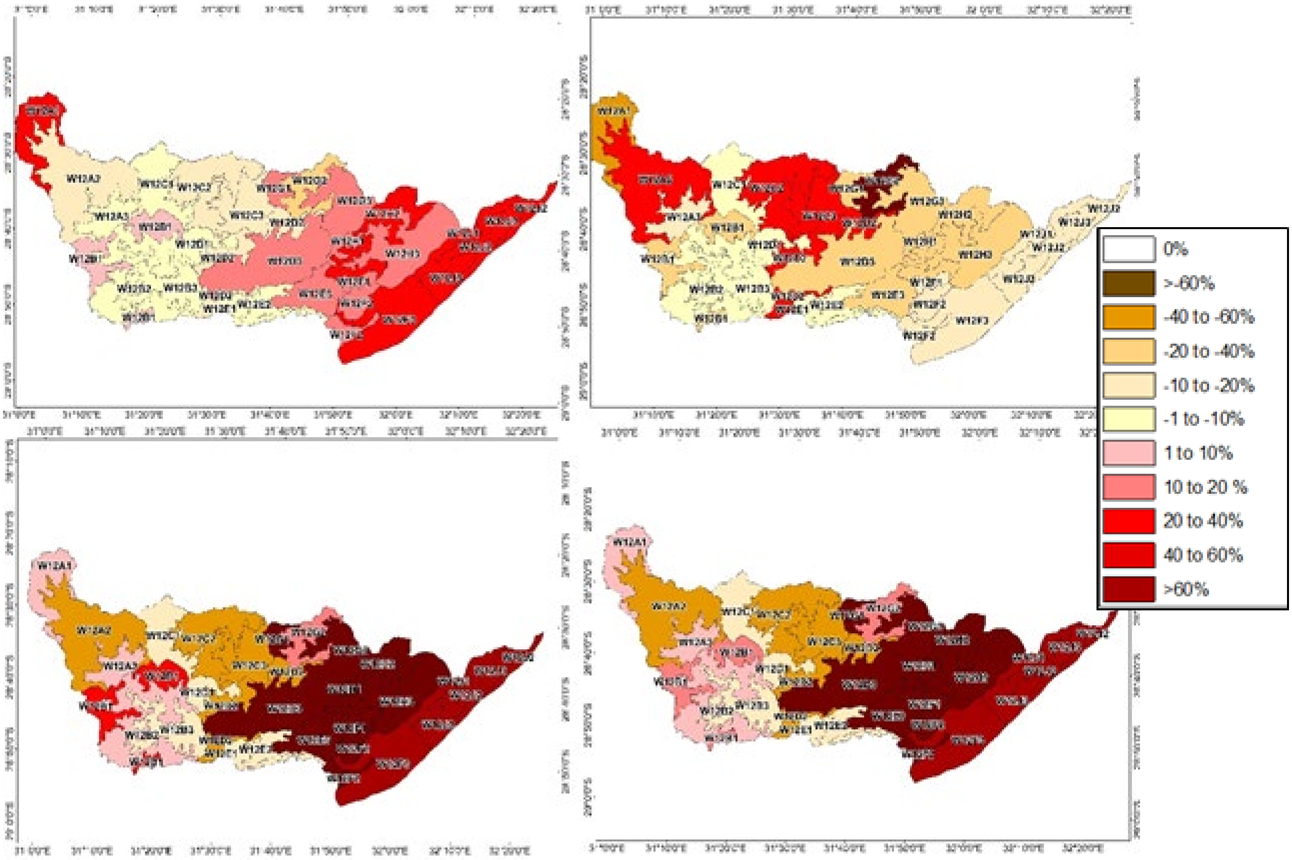

Figure 9-10 Percentage differences between minimum temperature forecasts and observations in terms of the frequency of occurrence of temperatures in the range of: a) <0°C, b) 0 to 5°C and c) 5 to 10°C and d) 10 to 20°C

9.2.6. Discussion

Rainfall

The limitations of applying NWP models in forecasting rainfall in South Africa are well documented. The highly variable spatial and temporal rainfall patterns makes it one of the most difficult variables to predict (Davis-Reddy et al., 2016; Wolski et al., 2017; Davis, 2011). In the case of the CCAM model used in this study, the model was able to correctly forecast both the occurrence and magnitudes of daily rainfall over the Mhlathuze catchment for more than half of the study period.

The limitations of applying NWP models in forecasting rainfall in South Africa are well documented. The highly variable spatial and temporal rainfall patterns makes it one of the most difficult variables to predict (Davis-Reddy et al., 2016; Wolski et al., 2017; Davis, 2011). In the case of the CCAM model used in this study, the model was able to correctly forecast both the occurrence and magnitudes of daily rainfall over the Mhlathuze catchment for more than half of the study period, distinct spatial patterns across the catchment in relation to altitude was shown. In general, most of the errors fell below 10 mm, with higher frequencies and magnitudes evident in over-estimations, than in under-estimations. In spatial terms, the model over-estimated rainfall in the lower altitude and coastal catchments, while in the higher altitude catchments rainfall was under-estimated. Although the errors were small, the difference between the short and longest daily rainfall forecast lead times was higher in the high altitude catchments, than at the coast. This indicates a higher accuracy for daily rainfall forecasts at a shorter lead time in high altitude catchments. In contrast, coastal catchments showed lower accuracy

The ability of the CCAM model to accurately forecast selected rainfall intervals showed similar results to studies evaluating the model from a purely meteorological perspective. For example, light rainfall occurrences over the catchment, defined as 1 to 10 mm in this study, showed the largest percentage differences between forecasts and observations when compared to other rainfall intervals. This is in accordance with the documented low skill of the model in predicting the occurrence of small rainfall values (i.e. 1 mm/day or less) over the country (e.g. Landman et al., 2009). Additionally, the frequency of the interval is largely under-estimated in the high altitude catchments and significantly over-estimated in the coastal catchments. The over-estimation of light rainfall is often associated with the limitation of NWP models in representing low level stratiform clouds (Shrestha et al., 2013; Golding, 2000).However, the under-estimations at a local catchment scale of light rainfall thresholds over high altitude areas found in this study are different to the overall over-estimations found by Landman et al., 2009 over the interior areas of the country. This highlights the relevance of the size of the selected verification area, which is typically different for meteorological and hydrological studies.

The under representation of heavy and extreme rainfall events for the study period over the catchment largely influences the results, and suggests that the under-estimation of heavy rainfall thresholds in high altitude areas of the country such as the eastern escarpments is still evident on a catchment scale. These are major runoff producing storms and are particularly important to capture for the accurate estimation of water availability in a catchment.

The ability of the CCAM model to forecast sequences of wet and dry days is particularly relevant in terms of representing antecedent soil moisture conditions. Representing antecedent soil moisture conditions is important for purposes such as hydrological model initialization and for forecasts related to future irrigation scheduling within the catchment. The model showed a higher capability of forecasting sequences of wet days beyond two consecutive wet days. The highest accuracy was for four consecutive wet days and the least accuracy was for two consecutive wet days. A similar increase in accuracy with longer sequences was observed for dry day sequences. The CCAM model was able to forecast seven consecutive dry days better than the shorter sequences, with the lowest accuracy observed for a two day sequence. Lower accuracy for two consecutive wet or dry days could have implications in terms of soil moisture estimations, which are important for crop growth stages such as germination. The ability to more accurately forecast longer sequences of consecutive wet or dry days has the potential to improve decision making in the context of irrigation water allocation and irrigation scheduling

Temperature

The implications on the secondary derivative estimations of temperature such as potential evaporation, can be large. The number of studies focused on the evaluation of daily maximum and minimum temperature forecasts over the country are significantly less than those focused on rainfall. When considering the capability of the CCAM model to forecast daily maximum and minimum temperatures, in general, a lower accuracy was found for maximum temperature forecasts when compared to minimum temperature forecasts. The model over-estimates maximum temperatures over the high altitude catchments and under-estimates these temperatures towards the coast. Minimum temperatures are predominantly under-estimated across the catchment by a small amount (less than 10°C).

The air temperature at 2 m above the ground is one of the main meteorological parameters forecast by NWP models, but this prediction is closely tied to the topographic position assigned by the model to each grid point. Air temperature is strongly affected by topography, and large-scale models can be a source of strong bias in complex terrain. This can be the reason for the higher variability of the both maximum and minimum temperatures over higher altitude quinary catchments when compared to the coast.

The model shows greater accuracy in forecasting the higher maximum and minimum temperature thresholds. For maximum temperatures, the highest accuracy is shown for the extreme critical temperature threshold of greater than 35°C, while for minimum temperatures the highest accuracy occurs for 10 to 20°C threshold. Opposite spatial patterns of over- and under-estimations occur between maximum and minimum temperatures, where maximum temperatures are over-estimated and under-estimated at the coast and high altitude catchments, respectively. In contrast, for minimum temperatures, the coastal areas are over-estimated, while for inland areas there is an increase in the frequency of over-estimations with an increase in minimum temperatures. However, the opposite spatial pattern was observed for the highest minimum temperature threshold.

The present study has enabled a better understanding as to how well the CCAM model is able to simulate daily rainfall and surface temperature in terms of spatial patterns and accuracy at a local catchment scale. It is known that NWP models are able to better predict large scale synoptic systems in comparison to local small scale weather generating systems. In the case of the Mhlathuze catchment there are various small scale influences that need to be considered. For the high altitude catchments which are the runoff generating areas of the catchment, small topographic features of the landscape play a significant role in influencing the local weather systems such as the predominant convective processes. At the coast, the influence of the warm Mozambique current causes a rise in temperature in the adjacent areas, as well as heavy rainfall due to the high rates of evaporation and the prevailing winds which are moist. The CCAM model is able to successfully capture the influences of these systems in terms of where to place the rainfall and temperature maxima and minima within the catchment overall, however, the maxima are over-estimated and minima under-estimated. Basing parameterization schemes at synoptic scales cause higher over- and under-estimations of weather at the local catchment scales at which the forecasts are needed for decision making. Further analysis is necessary to understand the accuracy of the model’s forecast at higher resolutions, as well as at seasonal and monthly temporal scales, to understand the effect on future generated agrohydrological forecasts at a catchment scale.

9.3. Reducing uncertainty and error in agrohydrological forecasting through improved initialization of ACRU

The need to initialize stores in an agrohydrogical model such as ACRU when producing agrohydrological forecasts has been explained in Chapter 6. The benefit of doing so for key stores in the model (baseflow and soil moisture) related to the simulation of dam inflows and irrigation requirements was also demonstrated. In the case of dam inflows, the initialization of baseflow and soil moisture stores in the catchment area resulted in reducing the error in forecasts by approximately 65%. This large reduction in error is likely to mainly be attributed to the initialization of the baseflow store, since this store commences at zero if it is not initialized. In this context it is highly unlikely that any baseflow will be produced over a 7 day simulation period, highlighting the critical need for initialization.

The benefit of model initialization (in this case relating to the soil moisture store) when forecasting net irrigation requirements were also significant, with reductions in error of 58% and 84% for the inland and coastal catchments, respectively. Soil moisture is a key driver in the determination of irrigation requirements and therefore the benefits of initializing this variable are clear.

A third scenario for model initialization that was not tested due to time constraints would involve the use of store values from a previous forecast run, rather than from a historical simulation run based on observed weather (as used here). This would represent a scenario where up to date weather observations are not acquired in time before generating a new forecast, resulting in the need to use store values output from a previous forecast run. The forecast error associated with such a scenario would be a relevant line of research in a future investigation.

9.4. Assessing improvements in agrohydrological forecasting when incorporating temperature forecasts into the forecast methodology

9.4.1. Methodology

The assessment of potential improvements in hydrological forecasts when incorporating temperature forecasts into the forecast methodology was focused at the 7-day forecast range. This range was chosen as the relevant weather forecast data were readily available at the time of the assessment. The 7-day forecast period spans the short and medium forecast ranges (relevant to Aim 1 of the project). The 7-day forecasts include daily values of rainfall and maximum and minimum temperature for the 7-day period. The forecasts were generated at a grid resolution of 0.15 degrees.

The potential benefit of incorporating temperature forecasts in the development of hydrological forecasts (produced by ACRU) was assessed in terms of improvements to forecasts of irrigation crop water demand. The focus on irrigation crop water demand was chosen due to its strong dependence on evaporation, and thus temperature. Therefore, any improvements to the representation of temperature are likely to be evident in the crop water demand forecasts.

To assess whether there is a benefit to applying temperature forecasts, irrigation demand forecasts generated using temperature forecasts were compared to irrigation demand forecasts generated using long term mean monthly temperature values. The latter source of temperature information is a readily available alternative to temperature forecasts, and was used in a previous WRC project (Lumsden and Schulze, 2012). The application of the two sources of temperature information was compared against the application of observed temperature data. A-pan reference evaporation (a key driver of irrigation demand) was calculated using the Hargreaves and Samani (1985) equations for daily (forecast and observed) and monthly (long term mean) temperature inputs.

Sugarcane is a major irrigated crop in the Mhlathuze catchment (along with citrus to a lesser extent) and formed the focus of the irrigation crop water demand forecasts. Forecasts were developed for quinary subcatchments W12D3, W12H3 AND W12F3, these being the subcatchments where irrigated sugarcane is grown.

Five discrete 7-day periods were selected from the 2013-2016 forecast data set for the evaluation. To minimize the influence of rainfall (which may or may not be accurately forecast), the selected 7-day periods had minimal (< 2 mm) rainfall in both the forecast and observed data sets. Rainfalls of less than 2 mm, whether concentrated into a single day or spread over several days, would be intercepted by the plant and not have any impact on the soil moisture and irrigation demand simulations. The 7-day periods were selected to be from October to March, when temperatures are warmer and levels of crop water demand are more significant.

The configuration of ACRU referred to in Chapter 4 (based on the NLC data set) was used for the simulations discussed here. Variable values, assumptions and sources of information specific to the irrigation demand aspects are presented in Table 9-6.

9.4.2. Results and discussion

The irrigation demand simulations for the five selected 7-day periods are plotted in Figures 9-11, 9-12 and 9-13 for quinary subcatchments W12D3, W12H3 AND W12F3, respectively. The simulations labelled as ‘Forecast Temperature’ and ‘Mean Temperature’ both use forecast rainfall, while the simulation labelled ‘Observed Temperature’ uses observed rainfall. As discussed previously, both forecast and observed rainfall totals for the 7-day periods are small (< 2 mm).

The percentage difference between the ‘Forecast Temperature’ and ‘Observed Temperature’ simulations and the ‘Mean Temperature’ and ‘Observed Temperature’ simulations is calculated in Table 9-7.

Table 9-6 Variable values, assumptions and sources of information specific to the irrigation demand simulations

Model Component	Variable Values or Assumptions	Source
Weather	7-day forecasts of rainfall and temperature on a 0.15 degree resolution grid	CSIR
	Mean monthly temperature per quinary subcatchment	Schulze et al. (2011)
	Observed rainfall and temperature (Stations 460, 478 and 51)	SASRI Weatherweb
Crop	Crop coefficient: 0.87 (mature crop Richards Bay)	ACRU model database
	Interception storage: 2 mm / event	ACRU model database
	Critical leaf water potential: -1100 kPa	Van Antwerpen et al. (1996)
Soil	Total Available Moisture (TAM): 75 mm (W12D3), 60 mm (W12H3), 60 mm (W12F3)	SASRI, Schulze et al. (2011)
(varies with subcatchment)	Management depth: 1 m (W12D3), 0.64 m (W12H3), 0.66 m (W12F3)	
Irrigation	Scheduling strategy: Irrigation applied once every 7 days. The amount applied is that required to restore soil water content to the starting level.	
	Soil water content at start: 80% of TAM	
	Water availability for irrigation is non-limiting	
	Net irrigation demand excludes additional water required to satisfy spray evaporation, wind drift and conveyance losses, but includes water required to satisfy interception losses	

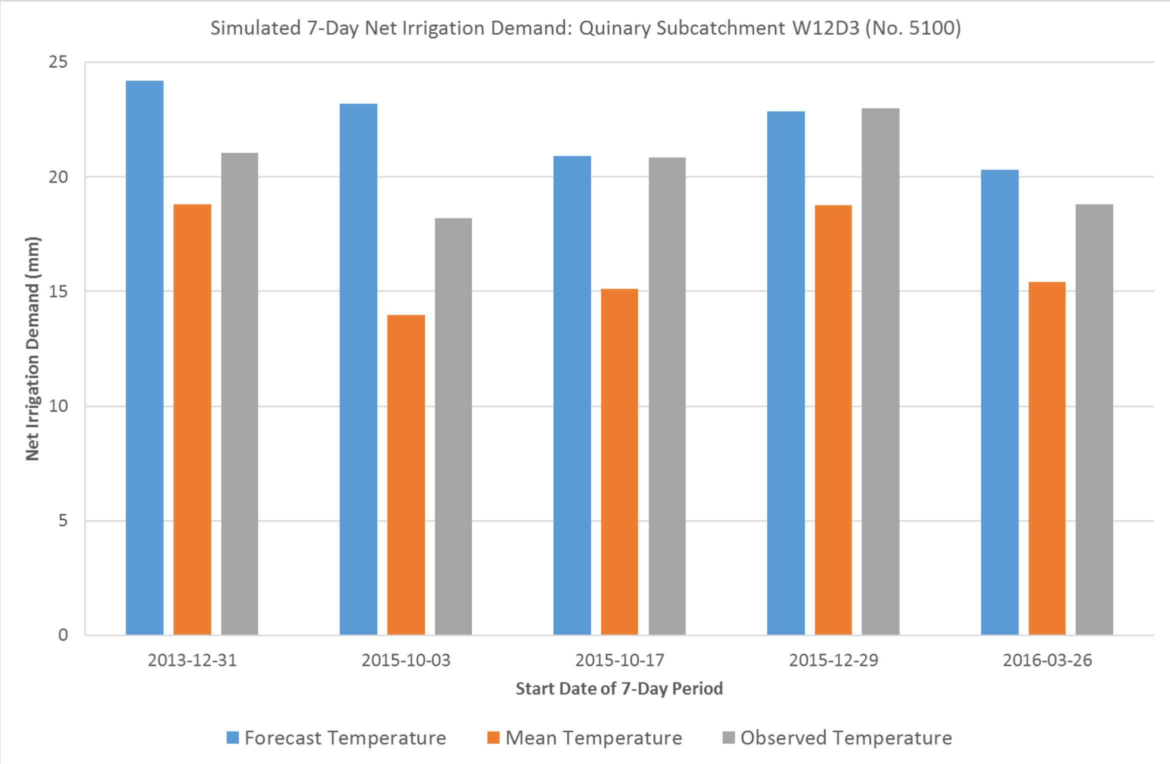

Figure 9-11 Net irrigation demand simulations driven by forecast temperatures, mean temperatures and observed temperatures: Subcatchment W12D3

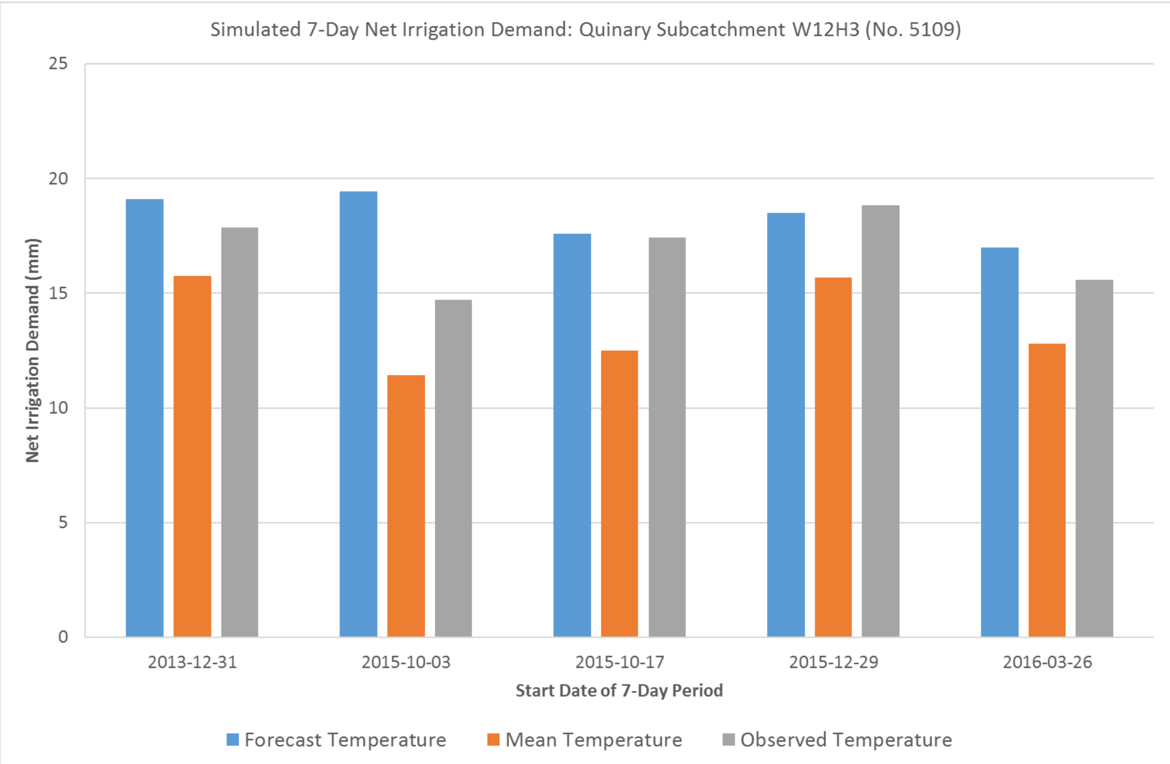

Figure 9-12 Net irrigation demand simulations driven by forecast temperatures, mean temperatures and observed temperatures: Subcatchment W12H3

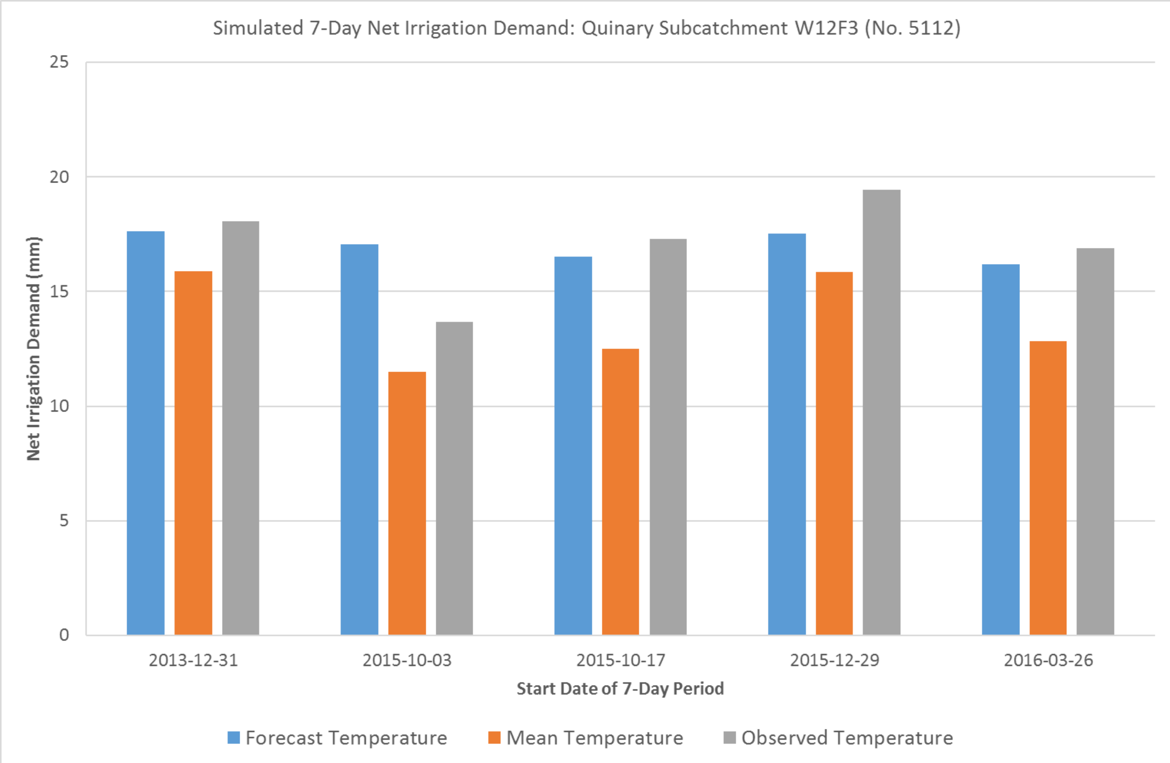

Figure 9-13 Net irrigation demand simulations driven by forecast temperatures, mean temperatures and observed temperatures: Subcatchment W12F3

Table 9-7 Percentage differences between the 'Forecast Temperature' and 'Observed Temperature' simulations and the 'Mean Temperature' and 'Observed Temperature' simulations for the five 7-day periods and 3 subcatchments

7-Day Period Commencing	W12D3		W12H3		W12F3	
	Forecast Temp.	Mean Temp.	Forecast Temp.	Mean Temp.	Forecast Temp.	Mean Temp.
2013-12-31	15.0	-10.6	7.1	-11.9	-2.4	-12.0
2015-10-03	27.4	-23.2	32.2	-22.4	24.8	-16.0
2015-10-17	0.3	-27.5	1.0	-28.3	-4.4	-27.7
2015-12-29	-0.6	-18.4	-1.8	-16.8	-9.8	-18.5
2016-03-26	8.0	-18.0	8.9	-18.0	-4.2	-23.9

Examination of the plots in Figures 9-11-9-13 and Table 9-7 reveals that for most cases, the application of forecast temperatures produces a better irrigation demand forecast than the use of mean temperatures. The exceptions to this include the first 7-day period for Subcatchment W12D3 and the second 7-day period for all three subcatchments. This result suggests that the application of temperature forecasts aids in reducing the error in hydrological forecasts. However, by examining 7-day periods that have minimal rainfall in both the forecast and observed data sets, it is possible that the selection of 7-day periods was biased towards periods when CCAM was simulating weather conditions well. Thus, the results may represent a best-case scenario of the benefit of incorporating temperature forecasts into the hydrological forecasting methodology. It is recommended that this analysis be extended to include wetter periods having similar forecast and observed rainfall totals. This would show whether the benefits of incorporating temperature forecasts are high for wetter conditions too, thus revealing insights into how robust the findings presented here are across different moisture conditions.

It is noted that the application of mean temperatures always results in lower irrigation demand simulations than the use of observed temperatures. If temperatures tend to be warmer during dry periods, this could explain why the irrigation demand simulations based on observed temperatures were higher (than those based on mean temperatures) for the particular set of (dry) 7-day periods assessed in this analysis.

It is possible that other types of hydrological forecasts (for example, streamflow forecasts) may show a lower benefit from the incorporation of temperature forecasts, compared to the irrigation demand forecasts presented here. This is because irrigation demand is highly dependent on evaporation, and thus temperature, while other variables (such as streamflow) are more indirectly dependent.

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CHAPTER 10. CONCLUSIONS

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10.1. Volume 2 – SEAMLESS FORCASTS AND SUGARCANE

The work done in the Mhlathuze case study was found to be technically challenging. These challenges included the hydrological modelling of the catchment, the development of the ACRU/Delft-FEWS forecasting system and attempting to produce seasonal forecasts of crop yield and water productivity with the AquaCrop model.

In terms of modelling the catchment (cf. Chapter 4), the operation of the Goedertrouw Dam was difficult to capture given the complex system of river releases for downstream irrigation and urban/industrial abstractions. Data describing the operation of the system was fairly limited, and required a number of assumptions to be made. Thus, the overall time required to configure the catchment in ACRU was longer than expected.

While the Delft-FEWS system (cf. Chapter 5) is a powerful tool to enable hydrological forecasting (in terms of managing the large amounts of data associated with this activity), it is not a user-friendly system to configure. This situation is often found in modeling systems where there is a trade-off between utility and user friendliness. Hence the development of hydrological forecasting was somewhat delayed in the project. This resulted in there being little time within the project to convey final results and explore the implication of these with stakeholders. However the technical capacity to use this software that has been developed in the team during the project has been very valuable, and will continue to yield benefits in future hydrological forecasting efforts.

Another technical challenge experienced was in attempting to apply probabilistic-categorical seasonal climate forecasts in AquaCrop to produce crop yield forecasts (cf. Chapter 8). While there is value in utilizing a probabilistic climate forecast as uncertainty is quantified in the forecasts, models such as AquaCrop are not designed to utilize this kind of information, as they require a daily time series of weather information as input. It was thus not possible within the timeframe of the project to produce crop forecasts using AquaCrop.

Despite the technical challenges, the results of certain aspects of the agrohydrological forecasting in the Mhlathuze were encouraging. This was particularly so for the 7 day forecasts of crop water requirements, where the correlations with simulated historical values were high (R^2 above 0.8 for the two catchments assessed). Although the forecasts of Goedertrouw Dam inflows and net irrigation requirements at the 7 day time scale did not perform as well as those for crop water requirements, it is still believed they have potential to be useful in decision-making. Further research is required to evaluate the benefits of such application.

Research into developing seasonal forecasts of storage in Goedertrouw Dam (cf. Chapter 7) revealed that there is predictability in autumn storage using the method developed. This method involved correlating historical summer rainfall with autumn storage. This correlation was made after analysing seasonal cycles of rainfall and dam storage and determining the strongest relationships present in the data. The method is simple to apply and forecasts can be produced quickly. A demonstration of how the forecasts could be applied in decision-making was given.

An alternative approach to producing seasonal dam storage forecasts would be to apply seasonal climate forecasts in ACRU. However, this would require downscaling of the seasonal climate forecasts to produce daily time series. This challenge was also encountered in the application of the Aquacrop model to produce crop forecasts. Methods are available to do this, such as through the use of historical analogue weather data or through the application of weather generators, however this adds another layer of complexity to the forecasting development process. The advantage of adopting this approach is that forecasts could potentially be developed for all seasons. The simulation-based approach also allows for exploring the potential to change the management of the dam, in response to forecasts,

10.2. OVERALL PROJECT CONCLUSIONS

10.2.1. A worthwhile effort

From planning to the design and execution of this project, a long path was walked, which we believe was a worthwhile process. We started with a challenging research proposal, with measurable societal impact potential. This report argues the steps taken, demonstrates the knowledge contribution made, and emphasises the need for dedicated engagements. The project led to measurable scientific outcomes and youth driven capacity building, former and latter accumulating to a successful project, grounding a new vision to improve the integration, acceptance and educated use of seasonal forecast information by smallholder farmers.

With a clear research ambition to leverage seasonal forecast information for the benefit of smallholder farmers in South Africa, and to do so using numerical tools such as crop models, the project positively contributed to a number of advances in knowledge.

- Local relevance and heterogeneity of conditions
- Optimal crop decision, per farm types, and across seasonal forecasts
- Indigenous relevance for reception and assimilation of numerical information
- Acceptance and Use, and Communication imperatives
- Remote sensing, and unlocking potential of numerical tools where ground data is scarce
- Empowerment of rural farming communities.

This project is recognising water and agricultural systems, as complex systems evolving at the centre of various communities (e.g. academics or farmers), dealing with information of varying skills and relevance (e.g. skills of seasonal forecast or relevance of time scale), which must be communicated iteratively and faces communications challenges (e.g. language, concepts such as uncertainty, trust) and beyond. While importance and provision must be made for the inclusion of some extent of all these aspects, we believe the improvement of the part we deal with in this report, is taking a measurable role in the development of better managed agricultural systems, particularly under global (e.g. population increase, climate change) and national (e.g. wealth and food share, economic development) challenges.

This project demonstrated the value of using numerical tools, purposefully for the benefit smallholder farming communities, with the imperative involvement of rural university and extension offices. This process, although clearly still facing challenges for operationalization and scaling up, used the right ingredient of such future development. Amongst the multitude of ways this work can be taken forward, it seems evident that the success of national scale operationalization of this sort of approach must explicitly develop and involve the local university-extension link, which in terms will most likely be the owner of the combined numerical skills and local heterogeneity relevance.

Despite a number of technological challenges that were encountered in the development of agrohydrological forecasts for commercial sugarcane production, the efforts in this activity showed some promise. The capacity that has been developed in this pursuit (through development and application of relevant tools, etc.) has been valuable, and should be maintained going forward to address the challenge of increasing climate variability.

10.2.2. Enablers and barriers

We do not expect to be exhaustive on the listing of challenging and enabling characteristic of such a large effort. The following table (Table 10-1) describes the major topics which had to be formally addressed in the application of seasonal forecasts to smallholder farmers. Some were foreseen (e.g. language during workshops), some were not and were included in the project (e.g. Indigenous Knowledge), some known or not are not part of this project but would arise from a continuation, for instance aiming at the up scaling of such an approach.

Engagement likely is the element that has make this project well received with communities, and it is our hope that the network built through this project including local universities, extension officers and farming communities, will find the sufficient support to continue engaging and thus maintaining an active network which over time (longer than a project time frame) will benefit the good two way communication that is needed to slowly adapt agricultural systems to global challenges.

10.2.3. Lessons and recommendations

The heterogeneity highlighted in this project is once again emphasized through the different audiences, decision makers, systems and consequently the responses to climatic factors. As much as better understanding, communication and integration of forecast information is useful for any decision maker, the capacity to produce such information and communicate it at a very rapid time rate is still technically very difficult, mostly due the large uncertainty involved, as well as the technical operationalization of the process, leading to low reliability of its execution on a regular basis. While the weather forecasts on (very) short time horizon remain accurate, its process through modelling tool does not provide large added value to smallholder farmers, while it requires large computation demand, and appropriate

Table 10-1 Summary of enablers and barriers

	Challenging characteristics	Recommended enabling characteristics
Data	• At station scale, access inconsistent through time • At larger scale, consistency in space, and systems representation	• Facilitation of renewable agreements • Remote sensing for scaling up and unlocking numerical tool
Climate-crop integration	• Multiple technical choices with related consequences • Embedded assumptions, uncertainty and hypothesis	• Hardware capacity held within institution • Technical skills (climate and crop)
Indigenous knowledge	• Identification of knowledge holder • relevant/sufficient representation of IK	• Group gathering/workshop offering preliminary contacts • The researcher goes to the farmers
Remote sensing	• Technical skills required • Specific communication challenges	• Available and easy access • Large space and time coverage • Potential to unlock numerical approach where field data is scarce
Heterogeneous systems	• Local relevance, acceptance • High range of “systems”	• Local characterisation • Building of local relevance • High level low resolution AND ground level high resolution, each in their own sphere (approach, actors, etc.)
Engagement and Communication	• Language • Various stakeholder types • Relevance • Network	• Involvement of local universities and their academics and their students • Attracting full range of stakeholders (typically extension offices in between universities and farmers)

interpretation to facilitate its efficient communication and integration in the decision process. Although this remains a very interesting and promising research avenue for the future, the ambition to progress towards operationalization through better use of forecast information into the decision-making of agricultural practices, must account for the added value of the information produced, against its cost and reliability of production. At this time, operationalizing very short term climate-crop information is very demanding while its benefits for the farming communities are limited compared to the value of the original weather forecast. On the other hand operationalizing crop-based seasonal forecasts information, while being comparatively demanding to produce, offers measurable improvements of the use of seasonal forecast as well as sufficient time to produce it, communicate it, and hopefully integrate it to agricultural decisions.

This recommendation obviously must be considered in the light of the user of the information. Likely commercial farmers with extensive access to numerical tools and internet, will be much likely willing and capable of receiving short-term processed information. On the other hand farming communities with limited access to such tools and information on a regular basis, are more likely to prefer seasonal time scale information, through the extension offices, and consequently better communicated, interpreted, understood and most likely to be integrated. While production of useful information, desired information, must be continued, there is no doubt that local stakeholder must be involved, including academics in local University, extension services, as well as farming communities in order to make this information relevant and useful but also to allow for local interpretation, communication and use. As much as the process can be run remotely, and the heavy computation should benefit from high computation capacities at national, governmental and/or educational institutions, the communication, the interpretation and as much expertise as possible must lie within local Universities, local government institutions, and ultimately support and encourage the extension offices in their communication with the farming communities.

The work in the KwaZulu-Natal case study revealed that there is promise for the application of forecast information at a range of time scales, including short-term horizons tailored for commercial agricultural sector, usually with greater access and interest for computationally intensive forecast information and tools. For sugarcane production for instance, forecasts relating to water supply and demand were of the greater interest, since there is already an operational crop forecasting system in place. Improved water management (relating to, for example, irrigation and dam operations) has the potential to improve crop production and profitability. Recommendations going forward include expanding the seasonal forecasts of water supply to other seasons (beyond autumn) and the application of simulation modelling in this pursuit (in parallel with statistical modelling). Interest in seasonal forecasts of water supply extend beyond the sugar industry, with interest being expressed from other catchment' water managers. Work conducted in this project to develop shorter (7-day) forecasts of crop water requirements will complement work from another WRC project (K5/2819), the latter being focused on producing this information in a smartphone app for the fruit industry. As recommended in a smallholder context, the application of remote sensing information in modelling would also benefit agrohydrological forecasting in the commercial agriculture context, as demonstrated by other services (e.g. FruitLook).

From a technical perspective numerous ways exists to progress forward. We are confident that the combination of forecasts and water/crop modelling tools offer a tailored perspective on forecast information that allows for specific agricultural decisions. Following this numerical direction, we believe the use of remote sensing data and particularly the value thereof in areas where there is limited field data, is promising. The explicit use of indigenous knowledge could further benefit forecasting studies through an improved description of local systems, as well as to communicate changes and recommendations related to climate/agricultural systems.

APPENDICES

APPENDIX I: CAPACITY BUILDING REPORT

Refer to Volume 1

APPENDIX II: PROJECT OUTPUTS

Refer to Volume 1