OPENING AVENUES TO OVERCOME INFORMATION LIMITS IN SEASONAL FORECASTING

Report to the

Water Research Commission

by

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WRC Report No. 2249/1/17

ISBN 978-1-4312-0965-1

March 2018

Obtainable from

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Printed in the Republic of South Africa

EXECUTIVE SUMMARY

Background

As a water-stressed country with a large agricultural sector, South Africa has a long history of seasonal weather forecasting. Likewise, the southern African region with its strong reliance on rain-fed agriculture, has long looked to seasonal forecasts to avoid agricultural losses and food security crises that have periodically hit the region in the form of droughts and damaging floods. As other human systems such as urban water supplies become increasingly stressed, the need for information about the next month to several months' climate has become greater and more prominent. The 2015/2016 El Niño-related drought has once again highlighted the sensitivity of the region and the potential for seasonal forecasting to contribute to minimising impacts by allowing forward planning.

Rationale

Seasonal forecasts for southern Africa have for many years been provided by national, regional and international efforts and have usually been presented as large-scale maps associated with some measure of probabilities. At the level of international research, developments in modelling and the use of model ensembles continued to evolve, including, for example, in dynamical and statistical downscaling, linking to hydrological and crop forecasting, or in diversifying the approaches adopted. In particular, the recent decade saw a transition of operational forecasts from atmospheric models to those based on fully coupled atmosphere ocean global circulation models, both internationally, and locally. As a result of those developments, in some cases significant skill advances have been achieved with respect to specific physical processes, yet the reliability of these forecasts remain cast in a perspective of "*is the forecast reliable in differentiating from climatology*" at some large spatial scale.

At the decision scale, however, the advances in reducing uncertainty and improving confidence have been, arguably, only moderate and incremental. This strongly influences the uptake of seasonal forecast information. An array of studies exploring this issue highlight that forecast uptake is a complex issue. In general, the picture suggests that a seasonal forecast is deeply dependent on context and predicated on data products that are mostly generic in formulation with high uncertainty unless substantially aggregated in space and time, and weakly tailored to user and sector needs. At the core of the matter are questions of information: *What is information in the context of a use-application, how is the information derived and constructed, and what approaches are used to contextualise and communicate it to decision needs*?

A principal danger facing the community is that the current paradigm for seasonal forecasting and generated seasonal forecast information may be approaching a plateau in further advancing forecast skill – particularly when viewed from the users' perspective. Thus, the question is raised: *Are there alternative approaches to assess and construct seasonal forecast information that, if fully developed through new research, can benefit the decision-scale needs*?

This report explores this challenge to evaluate alternative ways to frame potential information in seasonal forecasts, and to lay a basis for new avenues of research.

Context and use of forecasts

Seasonal forecast information is always in a context; information in the context of a climate modeller is vastly different to information as communicated by a boundary organisation (e.g. a national weather service agency), which is again different to information as viewed by the unique contexts of decision makers. Specifically, the work reported here considers the context and the perspective of three communities: those engaged in the production of forecast data, those engaged in the analysis and interpretation of the data, and those engaged in the representation of the data and any derived products for communication to decision makers.

Project framing

In considering the question of information, the scope of work in the context of this project is to find added value in the data produced by the forecast tools, and in particular to explore new avenues that suggest potential value. The problem is framed as follows:

> *The forecast information seeks to inform a decision-scale need. This information is a function of the local, regional and global climate dynamics that force the seasonal evolution, mixed with a measure of natural internal variability of the climate system.*

Generically, one can write this as a conceptual equation:

$$Y = F(X) + \varepsilon$$

Where

- **Y** is the local response (rainfall, temperature, run-off, etc.).
- **F(X)** is the function (typically a forecast model or statistical relationship) representing how the local response relates to the forcing (**X**) from the atmosphere, ocean and land surface.
- **ε** is a noise component representing natural variability and forecast model error.

This expression of the seasonal forecast problem is conventionally addressed by using a climate model to capture the relationship *F*. The forecast information is then constructed from the simulation as a (probabilistic) description of the grid cell values of the climate model – usually with (substantial) aggregation in space and time.

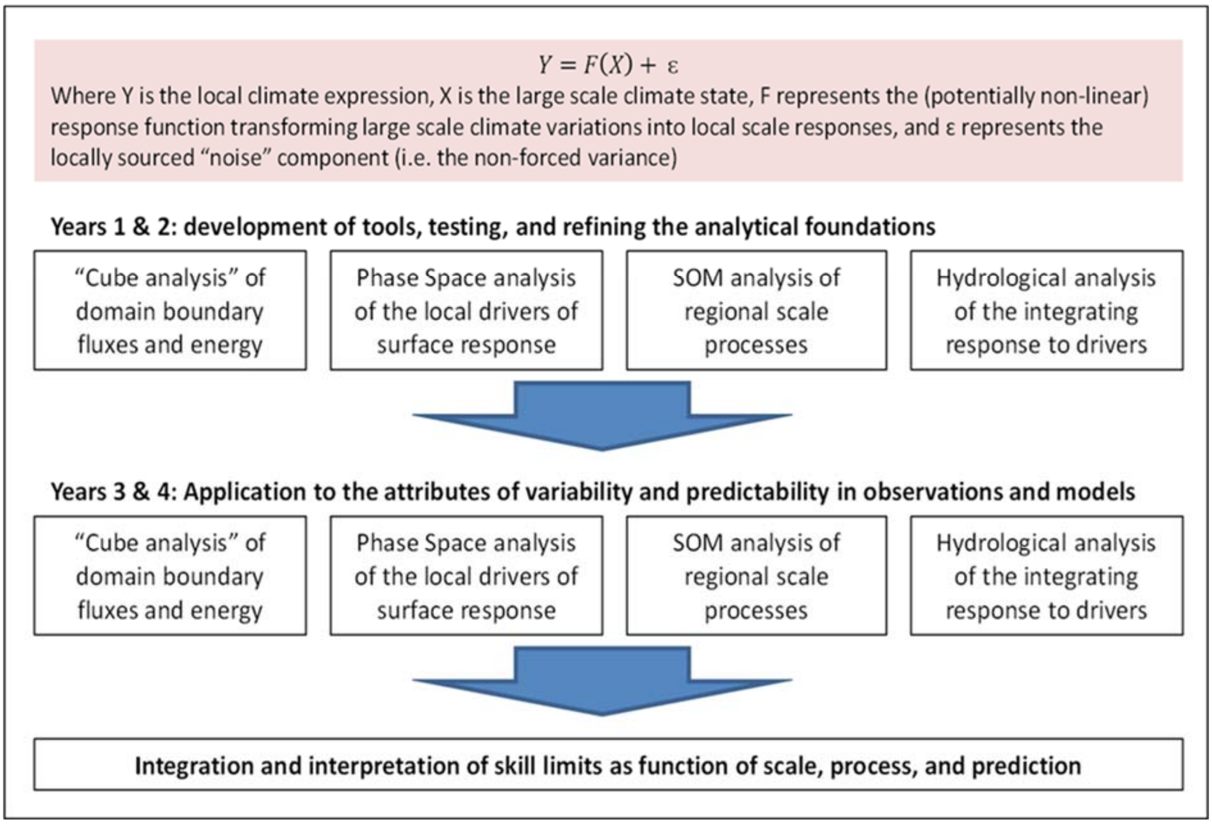
One clear challenge with traditional seasonal forecasts and forecast evaluation is that grid cell precipitation in dynamical models is parameterized (i.e. an estimate based on empirical models) rather than a fundamental physical process simulation. It is widely accepted that numerical model-based grid cell rainfall, particularly in lower resolution global models, is a poor representation of reality.

To break the dependency on derived grid cell variables, this project considers the model's simulation of the atmospheric processes instead – these are spatially integrated and a direct representation of the model's underlying physics and dynamics and are the drivers of the resultant surface climate. In effect, this project explores the fundamentals of the seasonal evolution of the climate system to construct alternate representations of information. The figure on the next page outlines the initial conceptualisation for the project development, and how four avenues were identified for the project to explore. The avenues are:

1. **Boundary information:** Information from the global and hemispheric signals presented at the boundaries of the domain. These signals reflect processes such as El Niño and are propagated to the local domain's response through the boundaries. As such, understanding how these hemispheric and global processes are being communicated at the boundaries is a source of information to understand how the domain will respond.
2. **Phase space:** 'Phase space' is a term that describes the range of states that occur in the climate, and how the climate system evolves over time within the range of states; this encompasses the daily weather progressions building to a seasonal development. Characterising the state internal to the domain thus affords a view to understand how the local response of interest (the decision-scale information) relates to this more complex mix of local and remote drivers.

3. **Circulation states:** New ways of representing the synoptic scale circulation. The information potential here is whether the seasonal forecast can capture the collection of synoptic states for the upcoming season, from which understanding can be drawn about both the seasonal mean outcomes and the possible distribution of the sub-seasonal events.
4. **Integration of signals in the hydrological response:** Linking the forecast through to hydrological responses to explore the information about where and in which hydrological environments does the hydrological response (run-off) reflect the principal elements of variability of climate forcing (rainfall and temperature) well.

Each of these avenues could be a major research project in itself. The objective here is to step aside from the traditional conceptualisation of a seasonal forecast, and instead explore new avenues to assess the added value, develop the supporting tools and methods, and lead to initial assessments of information potential and the associated application opportunities.



Results and discussion

Foundations for reassessing forecasts

Advancing the understanding of seasonal forecasting skill and how new approaches can expand the information to inform applications begin with recognising that the climate system is inherently coupled across scales of time and space with significant interdependencies, and that the global modes of variability reflect the underpinning processes that condition regional climate. The strength of this conditioning is variable and non-linear, and may be a function of a given mode of global processes.

For South Africa, the classically accepted conditioning mode is the El Niño Southern Oscillation (ENSO); much is made of the dominance of ENSO in determining the summer rains for South Africa. However, it is equally apparent that ENSO is only one among multiple processes of interest, and that in fact, the collection of global modes together is the conditioning factor on the regional seasonal climate.

From a forecast verification point of view, it is thus not sufficient that a global climate model (GCM) can capture the climatology of a region, nor that a GCM captures each of the global modes independently. Rather, a GCM credibly reflects the interconnected cross-scale behaviour of the dominant modes of variability that are relevant drivers of local climate responses, viewing the holistic interaction of the modes and atmospheric dynamics at a range of scales as the system semi-deterministically evolves through the seasonal cycles.

Information for decision scales

To make a difference to the information for decision scales necessitates rethinking the definition of information, and how this is derived and constructed. The multi-scale driving processes of the climate system is at the root of seasonal forecasts. These processes form the primary source of any derived information in a seasonal forecast and offer the best potential for new avenues to construct decision-relevant information.

Process-based lens and usability of the explored analytical avenues

By reframing the forecast skill question as one of information inherent in the driving processes, there is potential to advance model evaluation and selection, improve understanding of the underlying dynamics of a particular forecast, and so improve confidence and assess sources of uncertainty, and expand the usable seasonal forecast signal at the decision scale.

All the analytical avenues explored in this project offer some advancement in assessment of the added value of seasonal forecast. However, in the context of the stakeholder needs, one particular avenue suggests itself: there is a middle ground whereby the multi-variate state of the atmosphere at the synoptic time frame (which captures the driving dynamics of experienced seasonal climate) can be constructed into a low-dimensional expression. This allows rapid visualisation and quantification of the information and uncertainty in a model.

Recommendations for future research

On the scientific side, four core recommendations can be suggested:

- That new collaboration is established within the small South African seasonal forecasting community to reassess the construction of information through a climate process-based perspective.
- That the self-organising map (SOM)-based approach to model evaluation, selection and interpretation, including integration across models and ensembles, be applied to operational forecasts to optimise the derivation of information, constrain uncertainty, and inform applications.
- That support be sought to develop new post-graduate research activities on the range of intellectual avenues evaluated in this project to advance developing information from models, leveraging collaboration and understanding on these issues from the climate change community who face similar challenges.
- That impact modelling such as with a land surface hydrological model has value in constraining uncertainty, and could beneficially be more closely integrated into the seasonal forecast activities in collaboration with the climate modellers' research on constructing forecast information.

Recommendation for a community of collaboration has two key components:

- This needs to be a sustained community of dialogue between a small number of key stakeholders and the seasonal forecast science community. The ideal representation would include the atmospheric scientists engaged on seasonal forecasts, the impacts modelling community, and representatives of organisations that engage with key sector-specific decision makers (for example regional offices of water and agriculture, the energy sector, disaster risk management, and urban governance).

- This community of collaboration needs to operate on two levels: one where the discussion focuses on the scientific details of producing seasonal forecasts and constructing information, and one on the nature of information needs for different risk contexts. Both require collaborative co-exploration between partners of different skill sets and different experiences.

Key value outcomes

This project set out to tackle a fairly abstract and difficult to define question. This was intentional with the sub-objective of asking critical questions of the seasonal forecasting paradigm itself. In so doing, multiple avenues and alternative framings have been explored – some of which have revealed little; others have highlighted significant opportunities. As a whole, the project has delivered two significant returns.

The primary return is a renewed energy within the South African seasonal forecasting community to explore new avenues and activities in the area of seasonal forecast generation, information and communication within a broader producer and consumer community. This is a significant project achievement as such renewed energy and focus have been lacking for many years while the underlying need has been growing.

The secondary return relates to the many methodological and analysis avenues that have been trialled and prototyped. Some of these, such as the SOM analysis, have already been deployed in the context of urban climate change resilience. It is very likely that many of the other avenues such as hydrological model coupling and phase space analysis will equally develop and contribute more broadly both within seasonal forecasting as well as climate science, predominantly in applied context – in South Africa and globally.

ACKNOWLEDGEMENTS

The authors would like to thank the Reference Group of the Water Research Commission (WRC) Project K5-2249 for the assistance and the constructive discussions during the duration of the project:

Dr B Petja	:	WRC
Dr C Moseki	:	WRC
Dr J Botai	:	South African Weather Service
Dr M Shongwe	:	South African Weather Service
Mr A Moatshe	:	Eskom
Dr E van Garderen	:	Council for Scientific and Industrial Research (CSIR)
Dr W Landman	:	CSIR and University of Pretoria
Dr S T Beyene	:	University of Fort Hare
Dr B Mantlana	:	Department of Environmental Affairs

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LIST OF ABBREVIATIONS

AGCM	Atmosphere Global Circulation Model
AMIP	Atmospheric Model Intercomparison Project
AOGCM	Atmosphere Ocean Global Climate Model
CORDEX	Coordinated Regional Downscaling Experiment
CRU	Climate Research Unit
DJF	December/January/February
ENSO	El Niño Southern Oscillation
GCM	Global Climate Model
HadAM3P	Hadley Center Atmospheric General Circulation Model 3P
IPCC	Intergovernmental Panel on Climate Change
IQR	Interquartile Range
KDE	Kernel Density Estimate
MEI	Multi-variate ENSO Index
MOHC	Met. Office Hadley Centre
RCM	Regional Climate Model
RMSD	Root Mean Square Deviation
SOM	Self-Organising Map
SPEI	Standardised Precipitation Evaporation Index
SSI	Soil Saturation Index
SST	Sea Surface Temperature
TTT	Tropical Temperate Trough
VIC	Variable Infiltration Capacity
WRC	Water Research Commission

PART A: ISSUES AND OUTCOMES

Part A of the report is a narrative of the project's activities and outcomes, which are oriented to communities using seasonal forecasts. This focuses on the key issues, concepts, contexts and conclusions in relation to the complexity of seasonal forecasting of a semi-deterministic climate system.

1 THE CHALLENGE OF SEASONAL FORECASTING

From a user's perspective, seasonal forecasts for southern Africa have been provided by national, regional and international efforts for many years. The forecasts were usually presented as large-scale maps associated with some measure of probabilities. At the level of international research, developments in modelling and the use of model ensembles continued to evolve, including, for example, in dynamical and statistical downscaling (Yoon et al., 2012), using coupled ocean-atmosphere models (Beraki et al., 2014), linking to hydrological and crop forecasting (Malherbe et al., 2014; Yuan et al., 2015), or in diversifying the approaches adopted (Landman et al., 2012; Ratnam et al., 2016).

In some cases, 'significant' skill advances have been achieved with respect to specific physical processes (Vitart, 2014), and models continue to incrementally advance skill as measured by the standard verification statistics. Yet, the reliability of these forecasts from a users' decision perspective remain cast as "*is the forecast reliable in differentiating from climatology*" at some large spatial scale (Weisheimer & Palmer, 2014).

An array of studies (Jones et al., 2016; Kgakatsi & Rautenbach, 2014; Kniveton et al., 2015; Mberego & Sanga-Ngoie, 2014; Robertson et al., 2015; Sheffield et al., 2014; Tompkins & Di Giuseppe, 2015; Vogel, 2000) highlight that this is a complex issue. In general, the picture is one that suggests that the user's added value from a seasonal forecast is deeply dependent on context and predicated on data products that are mostly generic in formulation with high uncertainty unless substantially aggregated in space and time, and weakly tailored to user and sector needs.

Figure 1 captures the elements of the evolving landscape within which seasonal forecasts operate. The diversity of sources of potential information coupled with the complexity of communication and uptake have resulted in limited growth of ultimate value to society by seasonal forecast. Taking all the above issues collectively, it is arguable that for a decade or more there have been moderate incremental advances in the model's skill of capturing a measure of the evolving seasonal signal, but with less clear efficacy in reducing the uncertainty and improving confidence at the decision scale. At the core of the matter are questions of information: What is information in the context of a use application, how is the information derived and constructed, and what approaches are used to contextualise and communicate it to decision needs?

A principal danger facing the community is that the current paradigm for seasonal forecasting may be approaching a plateau in further advancing decision-relevant forecast skills despite model improvements still continuing. If this is the case, substantial resources will need to continue to be allocated to model development, but increasingly face competition for research to enhance decision value. Landman et al. (2012) note that "*The South African modelling community has over the past decade or so expended a large amount of resources to establish the use of Atmosphere Global Circulation Models (AGCMs) as operational seasonal forecast tools*". Along with a complementary study (Landman & Beraki, 2012), the authors present some of the methodological developments for advancing forecast skill as measured by different conventional meteorological skill metrics. However, the skill advances are limited in constraining uncertainty for user decision consequences and highlight notable circumstances where skill in forecasting remains very poor.

Thus, the question is raised: *Are there alternative approaches to assess and construct seasonal forecast information that, if fully developed through new research, can benefit the decision scale needs?* This report explores this challenge to evaluate alternative ways of framing potential information in seasonal forecasts, and to lay a basis for new avenues of research.

Figure 1: The landscape of actors engaged in the generation and uptake of seasonal forecasting

2 CONTEXT FOR SEASONAL FORECASTS

The material in this section reflects the project team's engagement with those who use seasonal forecast information and from the two consultative forums held during the project. The understanding developed through these activities is important as the framing context for a discussion on exploring new ways to develop seasonal forecast information.

When speaking of the construction of seasonal forecast information, it is important to note that information is always in a context; information in the context of a climate modeller is vastly different to information as communicated by a boundary organisation (Guido et al., 2016; Hoppe et al., 2013; Kirchhoff & Lemos, 2015; Lee et al., 2014; Lemos et al., 2014) (such as a national weather service agency), which is again different to information as viewed by the unique contexts of decision makers. Ideally, one should approach the question of developing relevant and robust information in a co-production/co-exploration approach (Steynor et al., 2016), where the different actors work together to construct information. This, however, is labour-intensive, and substantially exceeds the resource capacity of the existing seasonal forecasting community in South Africa. Hence, one is constrained in large part to developing information that can be delivered generically.

To help frame the issues of seasonal forecast information, it is important to consider the nature and context for the communities engaged with seasonal forecasts. Specifically for the work reported here, it is important to consider the current state of affairs from the perspective of the communities engaged in the production of forecast data, the analysis and interpretation of the data, and the representation of the data and any derived products for communication to decision makers.

First are the characteristics of the data, noting that the community typically works with data that:

- Is based on models (dynamical and statistical) with specific resolutions in time and space.
- Provides an ensemble of messages, which are presumed to characterise forecast uncertainty.

- Represents a mix of contrasting multi-model, multi-method and multi-scale data sets.
- Tries to make a prediction in a climate that is itself a moving target due to (possible) changing roles for key drivers and feedbacks as a consequence of climate change.

Second, the nature of those involved in the provider community likewise has important attributes:

- There are multiple players of different authority and motivations.
- The forecast community's efforts on the distillation of information across the contrasting and competing data/information products are weak.
- The methods of communication and how data is presented are very heterogeneous between providers.
- Generally, the target audiences are weakly defined.
- The providers' relationship with the emerging formalisation of climate services is weak.
- Support resources for developing guidance materials are limited and the existing materials often poorly match decision-maker competency.
- There is only limited application of impact models to translate the data into specific sector requirements (for example, water resources).
- Available products generally presume user competency to interpret relevant messages.

Considering these considerations, several challenges can be recognised as a priority when adopting seasonal forecast information. These include (not in terms of priority):

- A needed discussion with decision makers on the attributes of the most crucial data and information requirements when attempting to place forecast information in the context of other stressors arising from society, technology, the economy and the environment.
- The relationship between users and providers (including boundary organisations) need to be developed and sustained.
- As the decision contexts of users are exceptionally diverse, more understanding is needed about a user's reason for choosing a particular forecast product as this is often based on considerations unrelated to the skill of a particular product.
- The above raises a necessity to understand the user's risk and opportunities in relationship to what is to be gained from a seasonal forecast.
- The assumption that climate information is actually needed has not been well interrogated; let alone the type and timing of the information (on the part of both providers and users).
- There is little in the way of checks, balances and accountability in relation to the potential miss-interpretation/miss-application of information by users.
- There is a serious lack of relevant, unambiguous guidance resources tailored to user competency.
- The consequences of having a lack of usable information are not well understood according to a user's context, and in some cases might be trivial, if the case would help understand the importance of a seasonal forecast.
- The consequence of uncertainty in relation to a user's context is likewise poorly examined.
- Information 'need' is a complex question that is intrinsically dependent on individual and institutional context, co-dependencies on non-climatic factors, the nature of systemic vulnerability, thresholds, impacts and adaptation options, a user's awareness of these, and even individual culture and values.
- There is a deep ethical-epistemic dilemma: Value judgements based on perceptions of user contexts are made by scientists regarding the relevance and usefulness of the presented data and information; non-scientists and users make value judgements with presumptions about the robustness of climate information for their decision-scale and context. At the same time, boundary organisations make value judgements on what and how to deliver to user communities. The combined result is a heightened potential that the response measures may be poorly aligned with actual information.

In closing this section on context, the findings of a recent study (Rasmussen et al., 2017) on the use and uptake of climate information are of relevance here. The study noted that, despite the availability of tailored climate information, actual use of information remained low for a number of reasons, among which are the problems with the information itself. The study concluded that the need was to produce information that meets a range of decision needs, and which reserves intensive tailoring efforts for decision makers who have the willingness and authority to use climate information.

Hewitson et al. (2017, in press) further note that the landscape of current climate information providers is one of variable content and quality and unfettered by any code of practice. This raises four concerns:

- The ethics of information provision in a context of real-world consequences.
- Communications interfaces that present barriers to achieving robust decisions.
- A weak capacity of both users and providers to identify information of value from the multi-model and multi-method data.
- A tendency to include data that infers skill, but which on examination is uncertain.

The above all suggests that information limits in seasonal forecasting is as much a function of the ecosystem of operational practices (including the data analysis and interpretation) as it is a function of forecast tools. This emphasizes the continued need to enhance the information content of seasonal forecasts in ways that go beyond the ongoing model development work, and that are broadly applicable across multiple stakeholder communities. At the same time, there is a real need for substantially expanded work to understand the context of the decision maker, and what a seasonal forecast ‘information need’ represents in terms of resolution, variable, attribute, robustness and probability.

3 AVENUES OF EXPLORING SEASONAL INFORMATION

3.1 Conceptualising Alternative Views on Forecast Information

In considering the question of information, the scope of work in the context of this project is to find added value in the data produced by the forecast tools and, in particular, to explore new avenues that suggest potential value. The problem is framed as follows:

> *The forecast information seeks to inform a decision-scale need. This information is a function of the local, regional and global climate dynamics that force the seasonal evolution, mixed with a measure of natural internal variability of the climate system.*

A very simple example would be to forecast total seasonal rainfall over the Limpopo province to inform water storage management. This in turn is a function of driving global climate processes such as El Niño, coupled with a modulation from regional sea surface temperature changes and local land surface feedbacks, and all mixed with natural variability of the system.

A more complex example would be to forecast sub-seasonal rainfall intensity distributions to characterise catchment basin hydrological flows. Generically, one can write this as a conceptual equation:

$$Y = F(X) + \varepsilon$$

Where

- **Y** is the local response (rainfall, temperature, run-off, etc.).
- **X** is the forcing from the atmosphere, ocean, and land surface.
- **F** is the function (typically a forecast model or statistical relationship) representing how the local response relates to the forcing.
- **Ɛ** is a noise component representing natural variability and forecast model error.

In physical space, this can be represented as in Figure 2, which illustrates how a forecast of decision-scale information is necessarily constructed from driving signals at multiple scales that are both local and remote, and of differing natures.

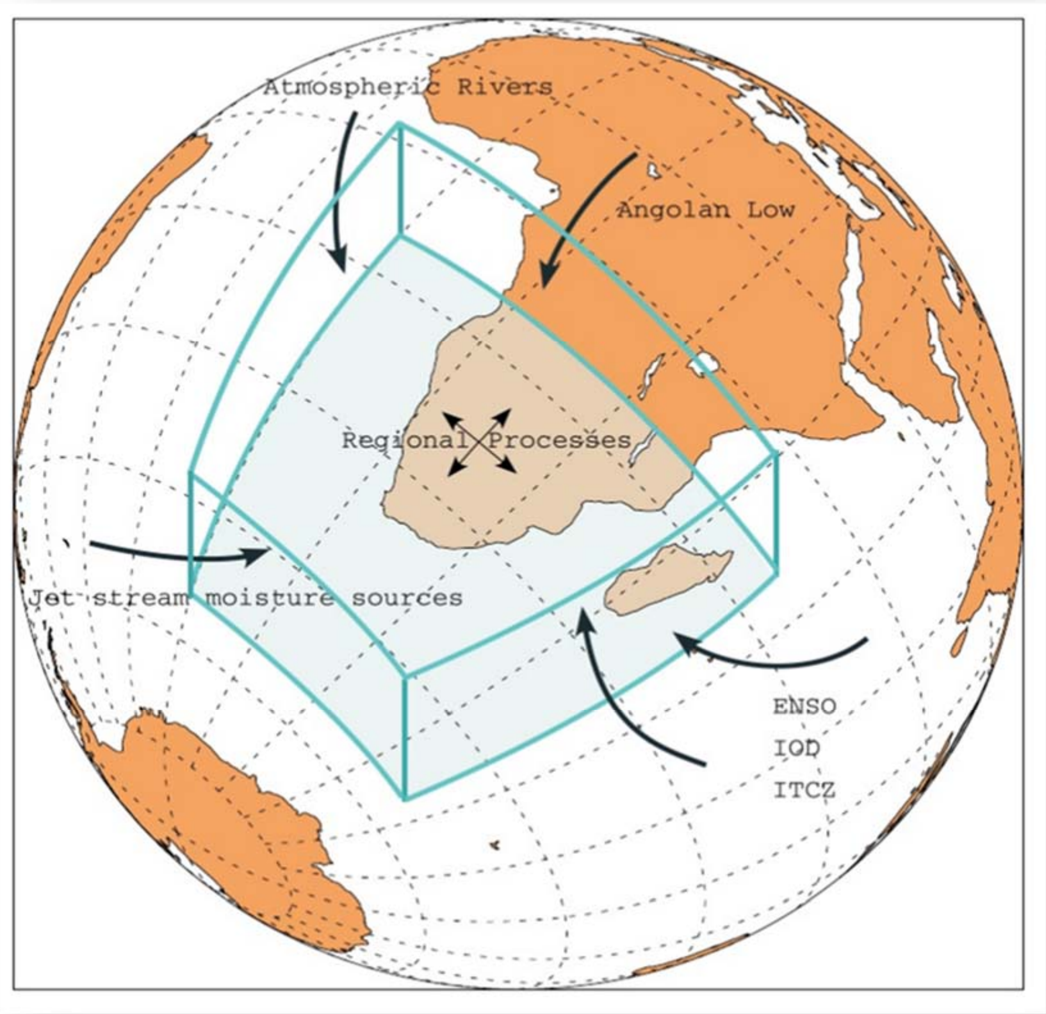

Figure 2: Representation of the notion of different drivers forcing a regional and/or local response. Indicated are drivers of atmospheric moisture feeding into the domain, circulation dynamics at the regional scale (e.g. Angolan low), and hemispheric/global

This expression of the seasonal forecast problem is conventionally addressed using a climate model to capture the relationship ***F*** between the drivers and the surface variables of interest, and in so doing simulate the seasonal evolution of the climate. The forecast information is then constructed from the simulation as a (probabilistic) description of the grid cell values of the climate model, usually with (substantial) aggregation in space and time (e.g. seasonal mean anomalies on a provincial scale with some measure of associated uncertainty).

This approach of using grid cell values of surface variables from a model simulation is the *de facto* standard in nearly all of seasonal forecasting and depends heavily on the skill of the model to accurately simulate the surface grid cell values consistent with the atmospheric dynamics. Typically, the surface variables of primary attention are precipitation and temperature, yet both are parameters that derived from the model's fundamental equations, not intrinsic to the model's calculations. The precipitation attributes from models are particularly low skill when considered in terms of most decision-scale information needs.

To break the dependency on the derived grid cell variables, this project considers the model's simulation of the atmospheric processes instead – these are spatially integrated and a direct representation of the model's underlying physics and dynamics and are the drivers of the resultant surface climate. In effect, this project explores the fundamentals of the seasonal evolution of the climate system to construct alternate representations of information. Figure 3 outlines the initial conceptualisation for the project development, and how four avenues were identified for the project to explore.

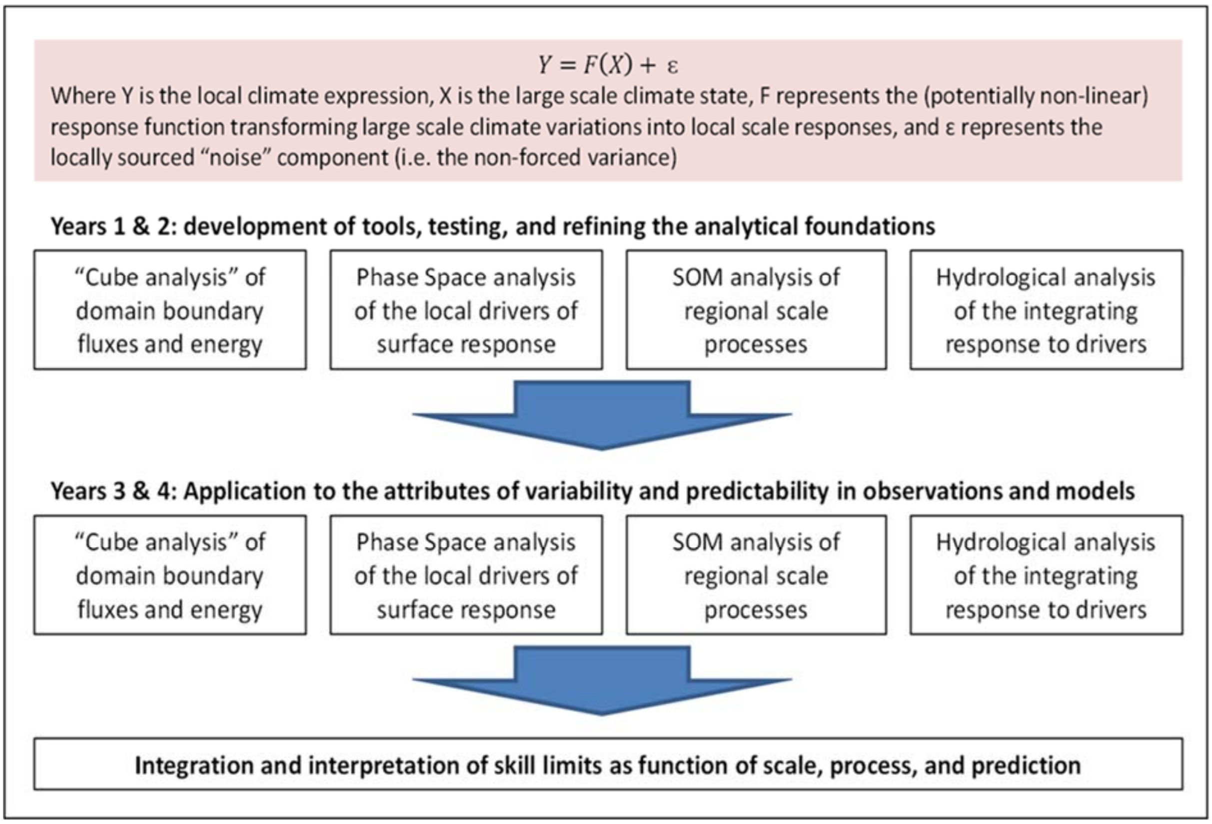

Figure 3: Different approaches explored to assess new ways to construct seasonal forecast information

The four avenues of Figure 3 relate to different ways of conceptualising information:

1. **Boundary information:** Information from the global and hemispheric signals presented at the boundaries of the domain. These signals reflect processes such as El Niño and are propagated to the local domain's response through the boundaries. As such, understanding how these hemispheric and global processes are being communicated at the boundaries is a source of information to understand how the domain will respond. This is in contrast to, for example, saying that there is an El Niño and so there will probably be a drought. Instead, it poses an alternate question that asks, "*How is the El Niño (and other global processes) being propagated into the domain?*" for not all El Niño's give rise to the same regional response.
2. **Phase space:** 'Phase space' is a term that describes the range of states that occur in the climate, and how the climate system evolves over time within the range of states; this encompasses the daily weather progressions building to a seasonal development. Here the focus is on the state of the regional climate that responds to the signals from the boundaries compounded with local drivers internal to the domain (e.g. soil moisture and vegetation state). The signals that propagate through the boundary interact with local drivers of the regional climate, such as soil moisture and attendant feedbacks. Characterising the state internal to the domain thus affords a view to understand how the local response of interest (the decision-scale information) relates to this more complex mix of local and remote drivers.
3. **Circulation states:** New ways of representing the synoptic scale circulation. The synoptic scale circulation features are dominant drivers of weather at the daily scale. For example, a ridging high-pressure system suppressing precipitation, a tropical-temperature-trough (TTT) catalysing convective storms, or a cold front bringing precipitation to the Western Cape. The information potential here is whether the seasonal forecast can capture the collection of synoptic states for the upcoming season, from which understanding can be drawn about both the seasonal mean outcomes, and the possible distribution of the sub-seasonal events.
4. Integration of signals in the hydrological response: Linking the forecast through to hydrological responses to explore the information about where and in which hydrological environments does the hydrological response (run-off) reflect well the principal elements of variability of climate forcing (rainfall and temperature).

Each of these avenues could be, in itself, a major research project. The objective here is to step aside from the traditional conceptualisation of a seasonal forecast, and instead explore new avenues to assess the added value, develop the supporting tools and methods, and to lead to initial assessments of information potential and the associated application opportunities.

3.2 Exploring Information

In practice, the different categories of approaches described above are idealised, overlap, and are in effect exploring the same fundamental 'phase space' of the regional climate. These approaches thus evolved as the project developed, which led to an integrated approach adopted as most informative for further exploring seasonal forecast information. Not all the avenues explored proved immediately fruitful – such is the nature of research – and greater technical detail on these investigations is presented in Part B of this report.

The exploration focused on finding new ways forward, which can lead to constructing information of decision relevance. The objective is to characterise the atmospheric system in ways that build statements about the predictability; that is, differentiating a forecast season from the climatology of natural variability and which informs about the regional responses and experienced climate (e.g. rainfall). Predictability in this context is seen in a deterministic sense, i.e. as the ability to differentiate between states of the system that underlay different types (classes, magnitudes) of responses. The focus is to limit the necessary assumptions and characterise the atmospheric system state and evolution in an objective way, and to do this on various spatial scales and temporal scales. This has the additional objective to identify optimal scales of space and time where skill and information are maximised.

The resulting research thus evolved as follows:

- Assessing the physical mechanisms by which global mode of variability are translated through the boundaries of the domain to the local-scale climate response at different temporal and spatial scales. This thread of work provided a backdrop to the more focused domain-specific studies.
- A strict phase space analysis using the three-dimensional state of the atmosphere as represented by the fundamental variables for moisture, motion and temperature on multiple levels in the atmosphere.[1] This approach presented a valid view of the atmosphere and allowed for conclusions to be drawn about the surface response. However, for practical purposes, it became apparent that the amount of noise – natural variability – was too great and required subjective decisions about filtering that undermined the robustness of the conclusions, which moved the research away from the intention to minimise the impact of assumptions.
- Following this, the focus turned to using simple models of physically meaningful variables to examine the ratio between the seasonal signal and the noise (natural variability) in relation to the spatial and temporal scale of averaging.
- The above two approaches represent respectively a high-dimensional approach, and a simple one-dimensional model. Building on the understanding developed in these views of the climate phase space, a third approach was developed that built on the best of the simple and complex views. This used the comprehensive set of the fundamental variables describing the three-dimensional state of the atmosphere projected and then onto a two-dimensional distribution of states, using a method of self-organising maps (SOMs). SOMs are particularly effective as they produce robust solutions with a minimum of subjective assumptions (Hewitson & Crane, 2002). This powerful approach facilitated visualisation of the time-evolving state of the atmosphere to:
    - Understand how seasons differ from year to year as a function of the global drivers.
    - Evaluate model forecasts to assess their representation of the climate.
    - Open a new view on how a forecast season relates to climatology, which in turn provides information on the nature of the forecast season.
- Parallel with the above was the theme on the integration of the seasonal signal through hydrological models to explore how the signal to noise ratio was affected.

3.3 The Region in a Global Context

Two underlying challenges are important. First, to evaluate the strength and stability of links between the global climate processes and the region of interest. It is apparent that El Niño, for example, does not always produce the same response over South Africa – the strength of the responses vary strongly between the winter and summer rainfall regions. Second, to explore the physical mechanisms driving local climate. To approach this, three avenues were explored:

- The exploration of the propagation of global modes of variability into regional domain with respect to an integrative regional response of the Standardised Precipitation Evaporation Index (SPEI) using station observations and reanalysis data sets, global coupled ocean-atmosphere model simulations, and regional climate model (RCM) downscaling simulations.
- Analysis of a regional atmospheric 'cube' as an exploration of the physical propagation of signal from outside the region through regional boundary 'walls' into the interior regional response.

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[1] The actual variables are the vectors of wind (u;v), specific humidity (q), relative humidity (RH), and temperature (t) for levels in the atmosphere near the surface, mid- and upper troposphere.

- Analysis of the multi-scale rainfall response to the corresponding multi-scale atmospheric state.

For the South African region, some models show completely reversed sign of correlation compared with others though several models do produce correlation patterns similar to observations – at least at the broader regional scale. This does raise significant questions around the ability of these atmosphere ocean global climate models (AOGCMs) to capture regional process and/or the propagation of global variability into the region.

The results from how the RCMs respond to the global forcing are generally encouraging. Most of the RCMs assessed [from the Coordinated Regional Downscaling Experiment (CORDEX)] (Giorgi & Gutowski, 2014; Hewitson et al., 2012; Kalognomou et al., 2013; Nikulin et al., 2012) are able to represent the observed SPEI response to El Niño using the Multivariate El Niño Southern Oscillation (ENSO) Index (MEI) to some extent with only a few models completely failing to capture a comparable correlation pattern or magnitudes.

The results for Global Climate Models (GCMs) are somewhat disturbing. There are strong differences between how the different AOGCMs propagate their own ENSO variability. The key conclusion in this regard is a strong message to carefully evaluate the GCM used for a seasonal forecast for the model's veracity in propagating global modes of variability into the region of interest.

However, bearing in mind the priori comments on GCMs, a RCM can only propagate the signals as presented on the boundaries. If these signals from the GCM are erroneous, the RCM results will be equally problematic. Nonetheless, the results suggest that there is value to be gained in dynamical or statistical downscaling of GCMs both for seasonal time scales.

The cube analysis results raise difficult questions. Large local climate deviations can occur in the domain without a corresponding ENSO signal, and large ENSO signals do not always result in large local climate deviations. In particular, it is apparent that the response in the domain under La Niña is very complex.

In the cube approach to the regional climate, the thinking stems from the regional modelling exercise and the reality that any signal or information about global modes of variability such as ENSO must be communicated to a region through the boundaries of the region (see also Figure 2). When considered in terms of anomalies on the boundaries of the cube, the results concur with the climate deviations seen internal to the domain. These results could perhaps be interpreted as discouraging as they appear to impose a strong limit to seasonal forecast skill. However, it must be noted that the cube approach is an unusual and experimental analysis that needs further exploration and analysis to better understand how informative these results are regarding limits to skill. The approach was tested with respect to only four different events' and a far more rigorous analysis of the regional response needs to be done. Indeed, this work has already inspired other such investigations beyond the project.

3.4 High-Dimensional Phase Space

The high-dimensional phase space work was experimental. The approach sought to explore the phase space of the atmospheric states in its full temporal/spatial/parameter resolution. Initial plotting of the relation between surface climate and the atmospheric states shows clear general discrimination between seasons. However, the results are particularly noisy at the intra-seasonal scale. For example, a portion of the phase space related to wet days could be clearly identified; however, there remained a mix of dry and wet days within that portion of the phase space.

Figure 4 shows an example of the phase space results. It is clear that summer and winter are readily distinguishable from each other, but also that some summer-type days occur during winter, and vice versa. The summer rainfall season also clearly distinguishes rain days but comingles these with days having similar atmospheric states on which it did not rain. Comparing the Hadley Center Atmospheric General Circulation Model 3P (HadAM3P) GCM’s simulation of the historical period, it is clear that the model occupies a similar phase space overlapping with the historical record but shows differences in the region of the phase space it occupies, and with a different shape to the distribution of daily states.

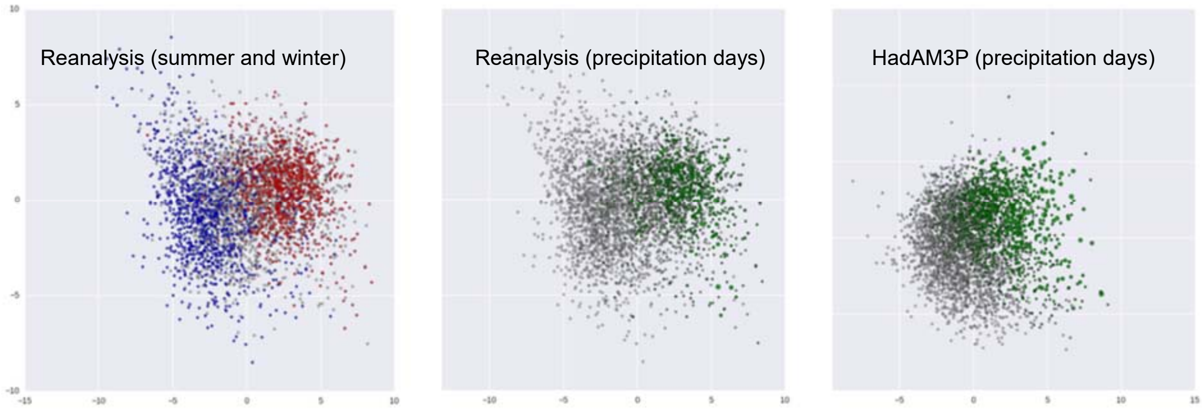

Figure 4: Two-dimensional projection of the cloud of data points from a high-dimensional data space. Each point represents the atmospheric state for one day centred over Johannesburg; it is characterised by values of wind, temperature and humidity at multiple levels in the atmosphere. The left-hand panel is historical data (reanalysis) with the red dots showing summer and the blue dots showing winter. The centre panel is the same set of data with the green dots representing those days on which it rained. The right-hand panel is the equivalent for the HadAM3P climate model

The results remain suggestive of potential added value – especially in terms of developing probabilistic messages, but the work needed to reach that stage fell beyond the scope of this project. However, there remains rationale for a more detailed exploration of this approach, and the concept is taken forward in part by the simpler SOM-based methods.

3.5 Simple Models and Low-Dimensional SOMs

This thread of work approaches the information question from the other end of the spectrum: If one simplifies the representation of the data substantially, what may be learned?

Two approaches are adopted. The first approach builds a simple regression (probit) model to explore the surface response of rainfall to the atmospheric state in terms of the probability for above or below median rainfall. The second approach uses a SOM to explore the trajectory of the climate system in a reduced-dimensionality phase space, and how this relates to hydrological responses to atmospheric forcing.

While the general outcome of the probit model is somewhat to be expected, it importantly allows for a quantification of how the 'skill' of the model changes as the temporal aggregation increases. This is especially informative on how the potential predictive skill will change as a function of the desired prediction target time-scale and serves to help constrain expectations of what predictive skill is potentially available at different time scales for an 'ideal' climate model used in seasonal forecasting, aside from any other constraints introduced by the climate model. The information about aggregation and its location dependency is also particularly relevant to understanding the potential is best for developing skilful predictions at sub-seasonal time scales.

The probit model addresses the question of the relationship between precipitation levels and estimates of moisture fluxes over the region, and how this relationship looks at different levels of time/space aggregation. The moisture balance in the atmosphere is fundamental to precipitation processes, and hence these estimates point to at which scales, within a given model world, precipitation is a function of moisture balance and at what scales the chaotic dynamics are the determining factors. In particular, three interesting aspects of the regional climate system and surface response can be interpreted; the variability of time aggregation for stations nearby to each other, the separation of the winter and summer rainfall regimes; and the spatial cohesion and positioning of stations that require exceptionally high levels of temporal aggregation.

The SOM-based view of the climate system frames the information objective through the following questions:

- Do synoptic conditions differ between seasons/years with above and below average run-off?
- Do the differences in the run-off-synoptics relationship manifest regionally?
- Are the run-off-synoptics relationships scale-sensitive?

Without getting into the details of a SOM and how it operates (see Part B and Hewitson, 2002; Hewitson & Crane, 2002) for more details), the method allows one to visualise the trajectory of the seasons as a two-dimensional plot, and to evaluate the frequency distribution of atmospheric states as the distribution alters under different global and regional drivers of variability. Using a measure of similarity (the Hellinger distance), the discrimination of different seasonal modes by the SOM based on the frequency distribution of discrete synoptic states is readily achieved. Importantly, the SOM method also allows for direct interpretation in terms of physical properties of the atmosphere.

As applied here, a direct relationship is hypothesized between the variables characterising atmospheric circulation and an integrative environmental response; in this case surface run-off as represented by a land surface hydrological model.

In the first instance, the SOM was used to explore how well hydrologically wet and dry seasons may be discriminated as a function of the seasonal frequency distribution of synoptic events – that is, the set of atmospheric states that give rise to the experienced surface hydrological response. Two approaches are adopted: representing the atmospheric states by the large-scale spatial pattern of the atmosphere across South Africa, and then in a more computationally intensive approach representing the atmospheric states of each local domain by a small 8° × 8° window. Figure 5 provides indicative results for the December/January/February (DJF) period.

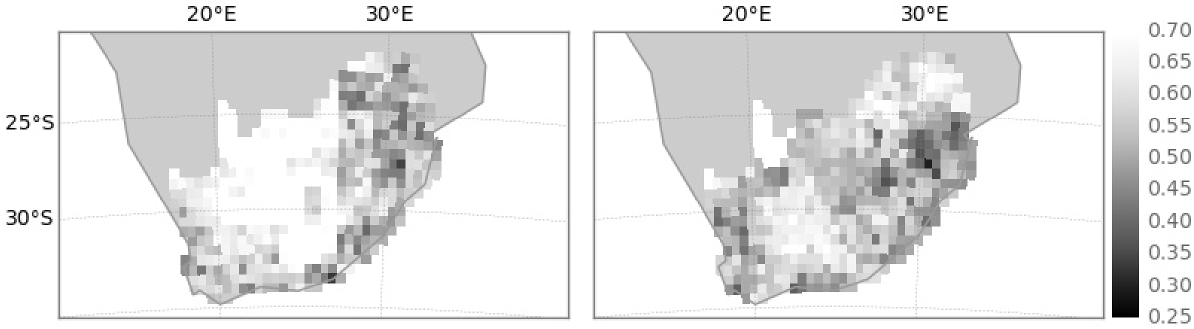

Figure 5: Map showing Hellinger distance indicating the separation between the frequency distributions of synoptic states as captured by the SOM for hydrologically dry and wet DJF season. The atmospheric states are based on ERA-Interim reanalysis data for DJF and applied to the SOM using: (left) a moving local 8° × 8° atmospheric window and (right) a single atmosphere domain spanning South Africa. Lighter shades indicate good discrimination between hydrologically wet and dry seasons as a function of the atmospheric forcing

The results in Figure 5 are particularly revealing of the complexity of the relationship between atmospheric forcing at the synoptic scales of daily events through a season. For example, when expressed in terms of the response to the full spatial domain of the atmosphere across South Africa, the Limpopo province shows that the large-scale circulation is a reasonably good basis for discrimination between hydrologically wet and dry seasons. By contrast, using a smaller 8° × 8° moving window to capture the atmospheric states reduces the discrimination skill over the Limpopo province, but shows enhanced discrimination skill elsewhere.

This difference in results depends on the spatial scale at which the atmospheric state is represented and provides information about the spatial scales of the important processes driving seasonal differences at different locations. This offers a valuable avenue on how best to achieve regional detail from seasonal forecasts. In the broader context of the project, these differences have implications for statements about the predictability of hydrological responses, and thus also about the predictability of meteorological responses driving the surface hydrology.

3.6 Integration in Hydrological Models

Picking up from the above section where hydrological responses to the atmospheric forcing was introduced, further work is also undertaken to leverage that hydrological responses integrate several climate variables (rainfall and temperature, but also wind and humidity etc.). This offers opportunity to look at aspects of forecasts that integrate errors and uncertainties about individual climate variables, and potentially enhances skill. Additionally, hydrological analyses speak directly to one of the principal ways seasonal forecast is interpreted by its users, which is through the implications to water resources and other hydrology-related indices such as surface run-off, streamflow, soil moisture, groundwater recharge, dam storage and flood susceptibility. The work was undertaken using two different hydrological models, namely, Variable Infiltration Capacity (VIC) and PyTOPKAPI, which are both grid-based (see Part B for further details).

The key questions being addressed here are:

- In which hydrological environments within South Africa do we expect hydrological response (run-off) to reflect the principal elements of variability of climate forcing (rainfall and temperature) well?
- When, where and at what temporal integration scales do specific combination of hydrological processes enhance the robustness of the hydrological forecast robust, or in other words, decrease sensitivity to uncertainty in the climate forcing?

In testing the hydrological model's ability to reflect the key seasonal attributes of response to the different seasonal combination of synoptic states indicates a continuum of responses that is not easily broken into classes of response. However, the strength of association between the atmospheric forcing and hydrological response is somewhat stronger in the east of the country; that strength reduces toward the west. This indicates a sensitivity to arid zones where the skill of the response becomes more dependent on accurately reflecting a lower frequency of rain bearing weather systems.

Overall, the method offers opportunities for formulating robust seasonal climate and hydrological responses that do not rely on the traditionally used indices (which typically focus on mean responses). There is, nonetheless, a location dependency with more potential skill in wetter regions.

The approach is further used to analyse model experiments and investigate the role of hydrological processes (as represented by a land surface hydrological model) in integrating the uncertainty of climate forecasts (or simulations) and how this is transformed into uncertainty of hydrological responses. Key concepts as used here are:

- Uncertainty: from the combination of the models' simplifications, resolution, error, bias, and the coupling of the climate and land surface hydrological models.
- Reliability: which relates how well the distribution of atmospheric states simulated by the forecast maps onto the possibility space of the modelled hydrological system.
- Predictability: the extent to which events/states can be known in advance.

To explore this uncertainty issue, the experiments are conducted within a pseudo-reality paradigm, i.e. relating the multi-model ensemble of the climate system to model responses under reference conditions rather than to observations (see Part B for details).

The results of simulations are examined in terms of the soil saturation index (SSI) and run-off. While the temporal evolution of SSI does display a considerable spread for different driving ensemble members, the spatial patterns of SSI for the various ensemble members when juxtaposed against the differences in spatial pattern of rainfall/temperature/evaporation show that a considerable narrowing of uncertainty takes place within the modelled hydrological environment. By contrast, run-off response generally inflates the uncertainty of the driving ensemble. However, there is a considerable spatial heterogeneity in the uncertainty reduction factor throughout the modelled domain.

Overall, the approach appears informative for understanding of spatial and temporal aspects of the propagation of signal uncertainty within the hydrological environment. However, it appears that its applicability is limited to assessment of relative effects between various locations, or between various seasons. Considering this limitation, the approach is still useful to differentiate between the regions (or the seasons) where hydrological responses are likely strongly sensitive to the forecast variables, and where they are less sensitive. This knowledge does inform about the robustness of a hydrological forecast.

3.7 Integrated Approach of SOM Trajectories and Their Application in Seasonal Forecasting

The final stage takes the strengths of what have been uncovered and considers in more detail which of these concepts offer low-hanging fruit: a readily applicable way to develop new approaches for advancing how seasonal forecast data can be evaluated.

The starting point for this is rooted in the need to assess the processes that underlay the predictability of climate; to evaluate the process representation in the model and in the forecasts so that the model credibility can be considered, and the forecast contextualised. There are two avenues to do this; assessing processes/modes independently or considering the cohesive whole of the climate system. Recognising that the climate system is inherently coupled across scales of time and space with significant interdependencies, and that the global modes of variability reflect the underpinning processes that condition regional climate, it is optimal to consider the cohesive whole of the system. This can occur either regionally and/or globally, and for this purpose, SOMs offer several methodological advantages.

SOMs are a well-established methodology; initially introduced to the climate community in 2002 (Hewitson & Crane, 2002), it has since received wide adoption (Sheridan & Lee, 2011). Advantages of the technique include the minimal assumptions about the data, robustness in the presence of noise, ability to handle complex multi-dimensional data, and facilitate helpful visualisation of the generalised data.

The SOM identifies a user-determined number of exemplar states that represent the span of the continuum of data. Multiple variables can be included to establish exemplar states and so capture the covariate relationships. In the example here, the SOM is used to map out the exemplar states of the global system to capture the full state of the global modes of variability. The exemplars are established using the historical record (using reanalysis data). The forecast models are then mapped to the exemplar states to evaluate the model's representation of the climatology, and how a forecast deviates from the climatology. By examining the differences between the observed and modelled climate states, and with examination of the underlying differences in the atmospheric variables, the SOM can help assess, firstly, whether climate predictability arises within the part of the atmospheric system that is resolved by a GCM, and secondly, where and how the models are weak in their representation of drivers of climate variability.

The SOM represents the continuum of the data space by a matrix of exemplar nodes; adjacent nodes are marginally dissimilar and represent the progression of change in state. Likewise, nodes widely separate are markedly dissimilar and represent fundamentally different modes. Figure 6 shows an example of the SOM matrix of exemplar states. This SOM was trained on wind, temperature and specific humidity. Figure 6 shows the exemplars for the specific humidity variable. Matching matrices exist for the other variables. The matrix represents a continuum of states; similar states being positioned close to each other and very different states are far apart. The distribution further clearly shows the seasonal distribution.

From this, a significant amount of information can be derived about the historical evolution of the climate, and about how well a climate model or ensemble member maps into this set of states. For example, one can look at the frequency of occurrence of different states by season, year, or El Niño, or examine the time evolution between states. Figure 7 shows the frequency of occurrence of the different states in each of the classic four seasons. Particularly notable is the clear discrimination of seasons.

However, while such breakdowns of attributes offer valuable insights to the behaviour of the climate system, it is the time evolution of the system that offers the most immediate potential for added value in seasonal forecasting. Here we present one perspective (See Part B for more examples and additional details).

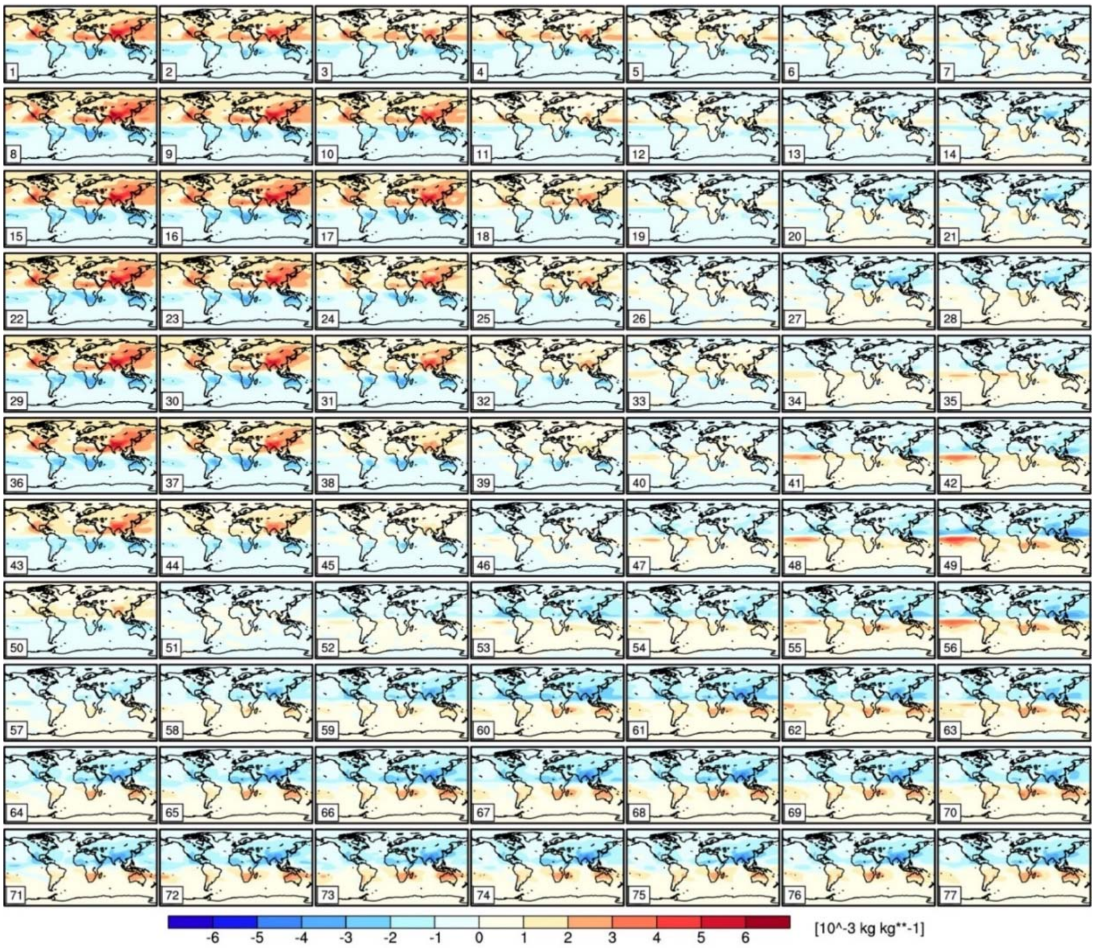

Figure 6: Anomalies of specific humidity (departure from the mean) at 700 hPa for a SOM with a 7 × 11 array of nodes trained on the collective set of air temperature, specific humidity, and winds for 1972–2012 from the ERA-Interim reanalysis

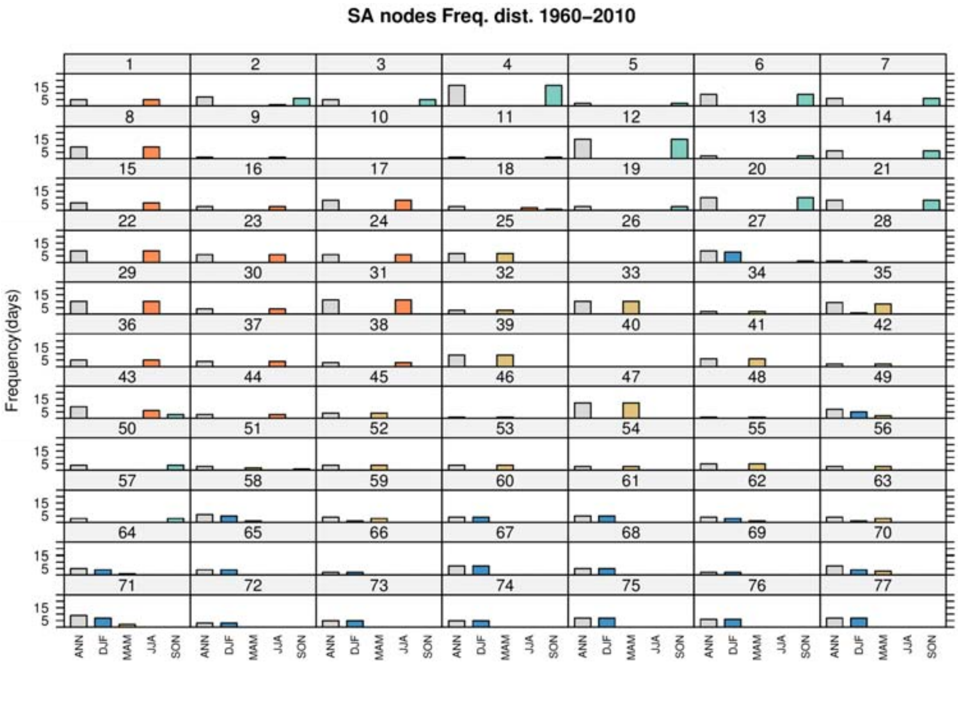

Figure 7: Frequency of occurrence (reanalysis data) of climate states across each node, expressed in absolute numbers of months mapping to each node, and broken down as the annual and seasonal totals

Figure 8 shows the time-evolving trajectory of the climate system. This is complicated at first sight but taken step-by-step, the interpretation is quite straightforward: Considering first only one panel to begin with:

1. The panel represents the matrix of exemplar states as shown in Figure 6. One can calculate the average position in this matrix of each month, which is represented by the grey line that shows the historical average state of each month – the historical climatology.
2. The red line is the equivalent climatology of the HadAM3P model when run in hindcast mode – forced by historical observed sea surface temperature (SST).
3. The line for the model's forecast climatology is in light blue is here the model has been run in forecast mode for the DJF season. The blue line thus represents the climatology of the model in this mode; i.e. the average of forecasts.

When run in hindcast mode, the model has a good match to the historical climatology with relatively small deviations. When run in forecast mode for the DJF season, the models climatology has a bias, and projects February to be more like March.

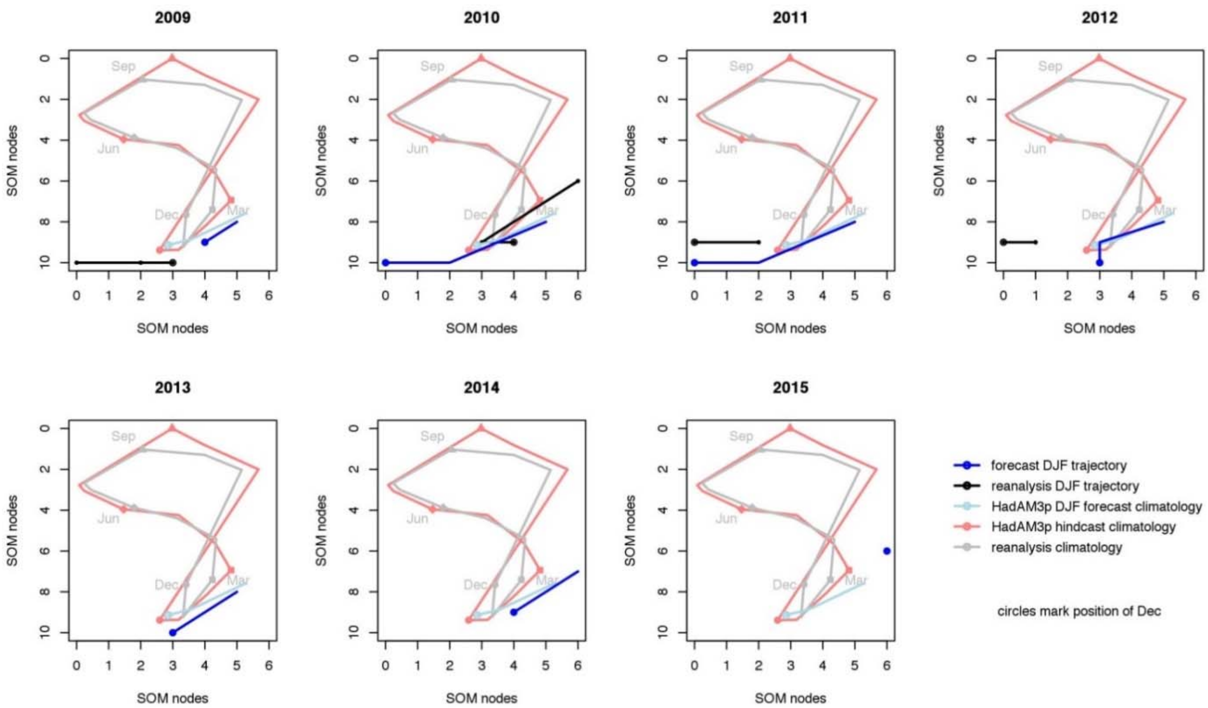

Figure 8: HadAM3P AGCM model performance in forecast mode for DJF and related reanalysis trajectories

Consider each panel: these represent a range of years. The red, grey, and light blue lines are identical in each panel and serve as references. The two additional lines to consider are:

- The black line is the actual evolution of monthly states for that particular year (not shown for the years 2013–2015 as the data was not available at the time of the analysis). Thus, for example, in 2009 the DJF season began in a state quite different from the historical climatology but ended in a state close to normal. In contrast, 2010 began quite normal, but by February was notably different from climatology.
- The blue line is the trajectory of DJF for the models forecast for these years. The key issue here is not so much how it deviates from climatology, but how it deviates from the historical season. For example, in 2011, the model began the DJF period in a state similar to the historical record, but

advanced through the DJF season far faster to end in a state more similar to March, and very differently to how the historical season really ended.

This serves to indicate some of the power of SOMs to consider the seasonal forecast information and skill through the lens of atmospheric state and process evolution:

- The model's performance in terms of climatology is easily evaluated against the observed historical states.
- Individual years can be quickly assessed for how they differ from climatology and whether the model has captured this.
- Forecasts can be assessed for how they deviate from the actual events and interpreted for diagnostic purposes.

Much more information can be constructed from the SOMs. For example, assessing the model bias as a function of season (HadAM3P clearly has a forecast bias for February), and examining the frequency distribution of daily states in the mode with that of the historical data to explore why type of states are introducing the model error. Moreover, multiple models and ensemble members can be assessed quickly to better the full uncertainty envelope explore and avoid overconfidence in predicting a particular seasonal outcome.

This information can then be used to inform how to interpret the forecast and assess under what states and modes skill can be expected, and when not.

For example, a particular forecast month can be unpacked further in to the set of atmospheric states to understand how the changes in the season are caused and are particularly valuable to help understand the sub-seasonal attributes of a forecast. Further, the associated surface expression of climate associated with each state can be evaluated to perform a scalable forecast of relevant variables, and associate these with a confidence statement based on the models evaluated performance. Key here is that the resultant surface climate prediction is inherently consistent with the driving atmospheric dynamics including the mix of signals from multiple scales.

More detailed regional insight can be attained by running SOMs over limited domains to better examine the process behaviour internal to the domain, and how this connects to the lager continental, hemispheric, and global scales.

4 IMPLICATIONS, CONCLUSIONS, AND RECOMMENDATIONS

4.1 Foundations for Reassessing Forecasts

Advancing the understanding of seasonal forecasting skill and how new approaches can expand the information to inform applications, begins with recognising that the climate system is inherently coupled across scales of time and space with significant interdependencies, and that the global modes of variability reflect the underpinning processes that condition regional climate. The strength of this conditioning is variable and non-linear and may be a function of a given mode of global processes.

For South Africa, the classically accepted conditioning mode is the ENSO, and much is made of the dominance of ENSO in determining the summer rains for South Africa. However, it is equally apparent that ENSO is only one among multiple processes of interest; that ENSO is not consistently influential as a function of the state of ENSO; and that the influence varies in nature between years. This indicates that the southern Africa region can, in large part, be considered a ‘climate receiver’, which means that the collection of global modes together form the conditioning factor on the regional seasonal climate.

In considering skill of the GCMs for seasonal forecasting, the ability of a GCM to reflect these global modes of variability is essential; not all modes are critical for southern Africa. However, at the same time, the interaction of the modes can be as important as each mode by itself. Again, the cross-scale interactions in time and space of the climate system makes this of deep importance to the forecast skill. While in isolation, a mode may or may not be of key importance to the region; nonetheless, all modes influence other modes and hence are indirectly important.

The short perspective is this: it is not sufficient that a GCM can capture the climatology of a region, nor that a GCM captures each of the global modes independently, but rather that a GCM credibly reflects the interconnected cross-scale behaviour of the dominant modes of variability that are relevant drivers of local climate responses.

There is a long history in the scientific literature of considering the global modes in their independent nature, and in many cases, this is reduced to an index (e.g. ENSO). These indices are useful because they help characterise key modes of variability, but the indices are nonetheless imperfect representations and assume a measure of spatial stationarity. Furthermore, the lead-lag interrelationship of these modes is notably non-stationary and introduces a multi-dimensional complexity reflective of the chaos basis of the climate systems variability. The simplicity of indices is appealing, and De Viron et al. (2013) is one example that lists and characterises indices, constructs a set of relationships between indices, consider their teleconnection in context of SST fields, and examine the lead-lag differences and spectral behaviour of the indices.

From this perspective, it is clearly possible to analyse firstly to what extent the individual indices, or their combination, explain the variance in rainfall/temperature or any other variable relevant from the point of view of impact at seasonal time scale. It is also possible to assess the ability of a GCM to replicate these indices. At one level this is useful, and such approaches are helpful for assessing the deterministic predictability and evaluating the relative performance of different models [e.g. see the GCM chapters of WG1 in the Intergovernmental Panel on Climate Change (IPCC) assessment reports]. However, such an approach is limited as it relies on a set of variables, or indices that are defined a priori, and do not necessary take cognisance of cross-scale behaviour of processes within the climate system.

The exploration of the literature indicates a strong need to consider the problem differently, in particular by taking an approach that views the holistic interaction of the modes and atmospheric dynamics at a range of scales as the system semi-deterministically evolves through the seasonal cycles.

4.2 Conclusions

The classic approach to seasonal forecasting through model simulations and using derived diagnostic surface variables is well-established but has shown slow, incremental advances in meteorological skill with limited change in finding added value for the decision scale; the decision context is critical to understand the information of value.

Thus, to make a difference to the information for decision scales necessitates rethinking the definition of information, and how this is derived and constructed. At the root of seasonal forecasts is the multi-scale driving processes of the climate system, which form the primary source of any derived information in a seasonal forecast, and offer the best potential for new avenues to construct decision-relevant information.

This process-based lens is a common theme to the key outcomes:

- By reframing the forecast skill question as one of information inherent in the driving processes, there is potential to advance model evaluation and selection, improve understanding of the underlying dynamics of a particular forecast, and so improve confidence and assess sources of uncertainty and expand the usable seasonal forecast signal at the decision scale.
- Different approaches exist to take a process-based view of information – some complex, and some simple. Each of these have been explored, and each offers potential added value if taken to their logical conclusion. However, some approaches would require significantly more research to achieve the full benefit, while others offer a more rapid avenue to advancing information for seasonal forecasts.
- In the context of stakeholder needs, one particular avenue suggests itself: there is a middle ground where the multi-variate state of the atmosphere at the synoptic time frame (which captures the driving dynamics of experienced seasonal climate) can be constructed into a low-dimensional expression. This allows rapid visualisation and quantification of the information and uncertainty in a model. The approach can be implemented through SOMs, affords rapid application across multiple models and ensembles and provides direct interpretation of underlying physical processes.

4.3 Exploring the Outcomes in a Consultative Forum

Through the project and two consultative forums, these issues have been explored in the stakeholder context and have led to a number of emergent messages from the participants that speak about the context of users of seasonal forecast information. These messages complement the project's core science findings, are essential to considering the developments for future seasonal forecasts, and critical to informing how the community moves ahead in new ways to construct relevant information.

The messages from participants include:

- There is a scale mismatch of both space and time: users do not really want a three-month forecast that gives large area average values.
- The forecast community is poor at communicating a message of "*I don't know*" – this is one of the 'limits to skill' – how the message is communicated.
- Different forecasts contradict, and there is little effort to reconcile these contrasts between available products.
- The bottom line need is "*what does it mean for my use case?*", yet the diversity of use cases is extensive.
- Seasonal forecasting has become devalued because of the focus on climate change.
- Engagement with users has been neglected and there is a need to rebuild trust, but this takes sustained contact time.
- Users are poorly equipped to evaluate the relative strengths and weaknesses of the different forecast products.
- There is a perception that useful information exists, but this needs a professional and concerted effort to change the status quo (a lot of negative perceptions toward seasonal forecasts).
- Repeatedly the point is made that it is a small scientific community engaged in seasonal forecasting, with substantial difficulties to sustaining a user engagement to understand user 'needs' and decision contexts, and this is compounded by limited funding for sustained engagement activities.

These messages from stakeholders – that there is an inherent problem with seasonal forecasts – are perhaps not surprising to the modelling community, but is indicative that the community is clearly not engaging effectively with the issues involved. At the heart of addressing these is the need to develop a better information product; without this, there are few options for improving the situation of decision makers. The avenues explored here have identified and evaluated both near term and long-term opportunities to build this process.

4.4 Recommendations

As noted early on in this report, the information limits in seasonal forecasting are as much a function of the ecosystem of operational practices (including the data analysis and interpretation), as it is a function of the forecast tools. In that respect, two levels of recommendations are suggested. First, move forward with the scientific aspects of developing seasonal forecasts and the attendant information products; second, to build the knowledge base about decision contexts and so enhance the framing, communication, and uptake of seasonal forecasting information.

On the scientific side, four core recommendations can be suggested:

- Establish new collaboration within the small South African seasonal forecasting community to reassess the construction of information through a climate process-based perspective.
- Apply the SOM-based approach to model evaluation, selection and interpretation, including integration across models and ensembles, to operational forecasts to optimise the derivation of information, constrain uncertainty, and inform applications.
- Seek support to develop new post-graduate research activities on the range of intellectual avenues evaluated in this project to advance developing information from models, leveraging collaboration and understanding on these issues from the climate change community who face similar challenges.
- Impact modelling, such as with a land surface hydrological model, has value in constraining uncertainty, and could beneficially be integrated more closely into the seasonal forecast activities in collaboration with the climate modelers' research on constructing forecast information.

For the broader question of informing science and society and so derive mutual benefit from seasonal forecasts, there is one key recommendation: build a community of collaboration. This was a major outcome from the consultative forums.

A recommendation for a community of collaboration has two key components.

- This needs to be a sustained community of dialogue between a small number of key stakeholders and the seasonal forecast science community. The ideal representation would include the atmospheric scientists engaged on seasonal forecasts, the impacts modelling community, and representatives of organisations that engage with key sector-specific decision makers (for example regional offices of water and agriculture, the energy sector, disaster risk management, and urban governance).
- This community of collaboration needs to operate on two levels: one where the discussion focuses on the scientific details of producing seasonal forecasts and constructing information, and one on the nature of information needs for different risk contexts. Both require collaborative co-exploration between partners of different skill sets and different experiences.

In closing, the project team notes that this work has catalysed a renewed discussion in South Africa, with strong expressions of interest in following up on the recommendations above, and for the identification of possible resource opportunities to initiate these actions.

PART B: RESEARCH DETAILS

Following are a set of appendices covering the project's component research that present the essentials of the avenues explored, methods used and developed, and main findings of the different approaches.

Appendix A: REGIONAL SCALE ANALYSIS

There is substantial research and associated literature exploring the linkages between global modes of variability and local South African climate responses on the seasonal time scale (Landman & Mason, 1999; Reason & Jagadheesha, 2005; Reason et al., 2006; Rouault & Richard, 2005). Indeed, this understanding traditionally forms the basis for most seasonal forecasting in South Africa – whether using statistical models capturing observed linkages, or through dynamical modelling that translate global SST anomalies, typically Pacific, Indian, and to some extent tropical Atlantic, into local South African rainfall and temperature anomalies at seasonal or sub-seasonal time scales.

However, two challenges emerge:

- The strength of the linkages is limited with some suggestions that, on average, only around 30% of local rainfall variability can be explained by ENSO). While the inclusion of indices of the Indian Ocean Dipole or other related indices may arguably increase this fraction, the point remains that much local-scale variance is not explained by global modes of variability. For the winter rainfall in the south-west of the country, these linkages are even weaker and subtler (Philippon et al., 2012; Reason et al., 2002; Reason & Rouault, 2005). This is certainly not a unique challenge for South Africa, but does limit the skill of both statistical and dynamical model-based seasonal forecasting.
- There is poor understanding of the physical mechanisms driving local climate. Shifts in the Walker circulation can be used to explain tropical rainfall responses to tropical SST variations (Nicholson, 2015), but the physical process drivers of local rainfall and temperature anomalies are understood poorly in the sub-tropics. In particular, the role of mid-latitude variability in the sub-tropics through mechanisms such as tropical temperature troughs (Cook, 2001).

The regional scale analysis component of this project was conceptualised to begin exploring some of these challenges. In particular, exploring the physical mechanisms through which global models of variability translate into local-scale climate response at different temporal and spatial scales are explored. A number of avenues were explored and will be described in more detail below:

- The exploration of the propagation of global modes of variability into regional domain with respect to an integrative regional response (SPEI) using observations and reanalysis, global coupled ocean-atmosphere model simulations, and RCM downscaling simulations.
- Analysis of a regional atmospheric 'cube' as an exploration of the physical prorogation of signal from outside the region through regional boundary 'walls' into the interior regional response.
- Analysis of multi-scale rainfall response to corresponding multi-scale atmospheric state.

A.1 Observed and Climate Model Diagnostics

As described above, there has been much work investigating the relationship between global modes of variability and local climate responses. This work did not set out to repeat previous work but rather to use different tools and approaches to better understand the linkages. However, a baseline analysis of observed relationships was undertaken to provide a common comparison of relationships across methods. This baseline analysis, and subsequent analyses used the relationship between the MEI and observed regional SPEI (Hayes et al., 2000) values.

A.1.1 SPEI analysis

Regional climate response is often described in terms of rainfall or temperature variability. However, much societal impact occurs through more complex responses such as drought. There are of course many definitions of drought including meteorological drought (low rainfall), hydrological drought (low soil moisture/run-off), and agricultural drought (rainfall-driven reduced crop yields). Drought indices can be useful because they are integrators across time and variables. The SPEI is a useful index because it is fairly simple and yet integrates through time and across both rainfall and evaporation.

Analysing observed correlations between ENSO and SPEI shows stronger correlations than found when correlating ENSO and rainfall or temperature individually [Figure A-1(a); (b)]. This is very likely because SPEI responds to both rainfall and evaporation; evaporation is partly driven by temperatures. Positive ENSO has positive correlations with reduced rainfall and increased temperatures; the combined effect is to increase correlations with SPEI. This result in itself points to the need and advantage of understanding drivers of integrative indices such as SPEI rather than single variables such as rainfall and temperature.

A.1.2 Global Climate Model (GCM) simulations

As noted above, much seasonal forecasting is dependent on the use of GCMs. There are two distinct groups of GCM configurations used, namely, atmosphere-only, or coupled ocean-atmosphere models. Atmosphere-only models use prescribed or forecast SSTs to drive the atmospheric response. Couple models, called AOGCMs, initialise the ocean temperatures, both surface and sub-surface at the start of the simulation. The models then simulate both the ongoing ocean dynamics as well as the atmospheric dynamics. Both configurations have been used for seasonal forecasting. For longer period forecasting such as decadal and climate change, fully coupled models are exclusively used as statistical methods of predicting SSTs to drive atmosphere-only models are only suitable on the sub-annual time horizon.

While GCMs are useful and essential tools for investigating possible future evolutions of the climate, (and ocean), they can also be useful tools for exploring different climate dynamics. In this work we analysed the ability of several AOGCMs to simulate the observed correlations between ENSO MEI and regional SPEI values. The analysis is based on a suite of AOGCMs as detailed in Table 1.

Table A-1: GCMs used in the study

Modelling Centre	***Institute ID***	***Model Name***	***Resolution***
Canadian Centre for Climate Modelling and Analysis	CCMA	CanESM2	2.8° × 2.8°
NOAA Geophysical Fluid Dynamic Laboratory	NOAA GFDL	GFDL_ESM2M	2.5° × 2.0°
Max Planck Institute for Meteorology	MPI-M	MPI-ESM-LR	1.8° × 1.8°
Norwegian Climate Centre	NCC	NorESM1-M	1.5° × 1.9°
Atmosphere and Ocean Research Institute (University of Tokyo), National Institute for Environmental Studies and Japan agency for Marine-Earth Science and Technology	MIROC	MIROC5	2.8° × 2.8°
Centre National de Recherches Météorologiques – Centre Européen de Recherche et de Formation Avancée en Calcul Scientifique	CNRM-CERFACS	CNRM-CM5	1.4° × 1.4°
UK Met Office Hadley Centre	MOHC	HadGEM2-ES	1.875° × 1.25°

Analysis of AOGCM responses (Figure A-2) shows that there are strong differences between how the different AOGCMs propagate their own ENSO variability. For the South African region, some models show completely reversed sign of correlation compared with others, though several models do produce correlation patterns similar to observations, at least at the broader regional scale. This does raise significant questions around the ability of these AOGCMs to capture regional process and/or the propagation of global variability into the region.

While the ability of these models to represent observed correlations tells us something about the native performance of the models, the real value of this analysis comes when using RCMs to downscale the regional climate while being forced at their boundaries by AOGCM circulation and thermodynamic fields. This comparison can begin to provide insight into the source of the AOGCM performance (or lack thereof). If an RCM is able to improve the performance of the AOGCM, noting that the RCM is completely dependent on the AOGCM for its boundary conditions and any global variability signal embedded in the boundary condition variance, then it provides evidence that the AOGCM is providing such signal to the RCM. In this case, it is possible that the poor AOGCM performance is a result of the inability of the AOGCM to translate the local component of the global teleconnection signal into an accurate local climate response (SPEI in this case). However, conversely, if the RCM is unable to improve on the performance of the AOGCM, then we can conclude that either the AOGCM is not providing a regional expression of global modes of variability, or else the RCM is itself unable to translate this signal into an accurate local-scale response.

The inclusion of pseudo-observed (reanalysis) boundary conditions to force the same set of RCMs provides some insight into the native performance of each RCM. Additionally, the use of a matrix of AOGCMs and RCMs allows us to, in a sense, triangulate some of the model performance combinations to build a stronger message. If an RCM consistently performs poorly across reanalysis and GCM forcing, then we can begin to conclude that it is unable to translate boundary variance into local-scale response. However, if an RCM performs well when forced with reanalysis but poorly when forced by a GCM that also has poor performance, we can conclude that the GCM is not representing the global mode of variability well.

A.1.3 CORDEX Africa

The availability of the CORDEX simulations for Africa (Giorgi et al., 2009) provides a unique opportunity to explore the propagation of global modes of variability into a region. While the CORDEX Africa experiment defines a simulation domain covering the whole of Africa and is therefore not specific to the South African context under question in this work, the methodological approach as well as some of the learnings from this exploration are still informative.

The CORDEX project defines two experiments that are of value to this work: The first is the simulation of the African climate forced by reanalysis (quasi-observed) boundary conditions. Because dynamical models only receive ‘information’ or signal at their lateral boundaries, they are useful to analyse how global signals are propagated through these boundary areas into a region and how the regional climate may moderate the global signals. The reanalysis simulations provide one view of this where we have some confidence that the teleconnection signal at the boundaries is reasonably realistic and the different.

The second CORDEX experiment is where the regional models are driven by GCM climate change simulations data at the boundaries. This allows us to explore two aspects of regional response. The first is how the GCMs translate teleconnections into the region climate response, and the second is how RCMs improve the GCM response or deteriorate the GCM response.

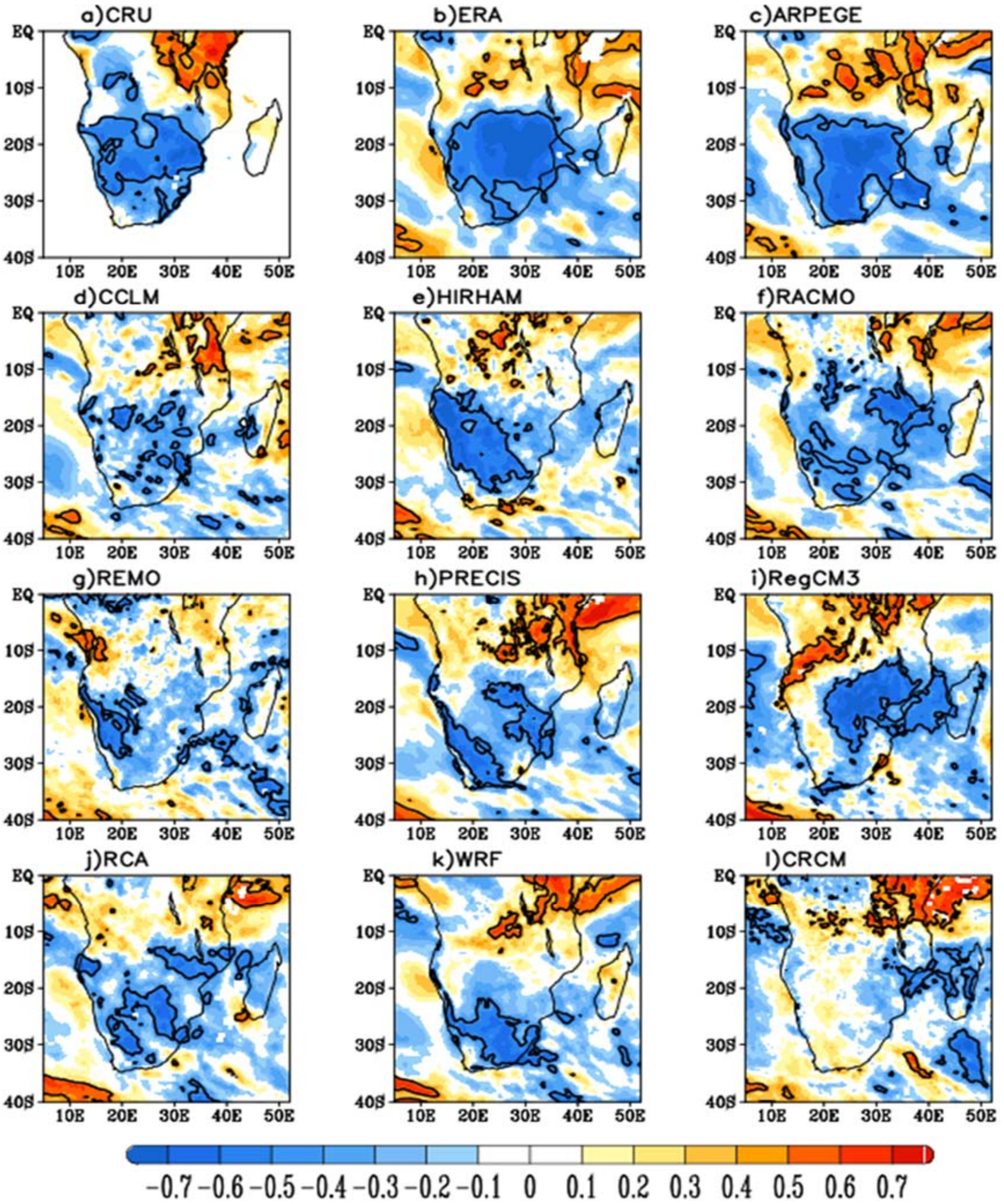

Figure A-1:The coefficient of correlation between ENSO and drought (SPEI) over southern Africa in summer (DJF, 1989–2008) as observed [Climate Research Unit (CRU) and ERA-Interim) and simulated (CORDEX RCMs)]. The contours show areas where the correlation is significant at 95% using

A.1.4 Results

Results in Figure A-1 indicate that many CORDEX RCMs are able to represent the observed SPEI response to MEI to some extent with only a few models completely failing to capture a comparable correlation pattern or magnitudes. The RCMs generally capture the positive/negative dipole structure of the sub-Saharan African SPEI correlations. This gives us some confidence that we can use the RCMs to explore the nature of the AOGCM performance.

Figure A-2 shows the same correlation analysis for the driving AOGCMs as well as the ERA-Interim reanalysis reference. These results show that many AOGCMs completely fail to capture the observed dipole of correlations across the region, with many actually reversing the correlation pattern compared to observations. However, a few models (including the NOAA GFDL model and the MOHC model) produce a reasonable correlation pattern. It is important to note that these models are all coupled ocean-atmosphere models. This means that the ENSO pattern indexed by the MEI is all purely model-generated. This analysis does not explore the nature of the ENSO dynamic generated by these models and it is widely documented that many AOGCMs fail to accurately capture observed patterns of SST anomalies across the Pacific or related shifts in the east Indian Ocean (Bellenger et al., 2014; Guilyardi et al., 2012; Kim & Yu, 2012; Zhang & Jin, 2012; Zhang & Sun, 2014).

Finally, we can examine the performance improvement provided by RCMs. In the interests of space, and also because many CORDEX RCMs only simulated the downscaled response driven by one or two AOGCMs, only the Swedish Meteorological and Hydrological Institute (SMHI) RCA RCM results are shown in Figure A-3. The RCA model has been forced by seven different AOGCMs as well as the ERA-Interim reanalysis. This means that we can examine the performance improvement across a wide range of AOGCM forcings.

The results of the MEI/SPEI correlation analysis of the RCA RCM results are presented in Figure A-3, which shows that generally the RCA correlation patterns improve on those of the original driving GCM. The concept of added value has many interpretations, but it can be argued that improving the SPEI-MEI correlation patterns is a measure of added value of the RCM. If we consider a model such as the MIROC model, which in the GCM analysis showed very unrealistic correlation patterns across the region, we see that the RCA model is able to almost completely reverse these patterns and significantly improve the performance. Remembering that the RCA model only receives ‘information’ about ENSO state through its boundary conditions (moisture, winds and temperature fields), this suggest that the MIROC GCM is actually propagating an ENSO signal into the domain but failing, perhaps due to poor representation of the regional convective dynamics or position of key systems such as the Angola heat low, to correctly translate the signal into a realistic local SPEI response. This does also suggest that there is value to be gained in dynamical or statistical downscaling of GCMs both for seasonal time scales as well as for climate change experiments.

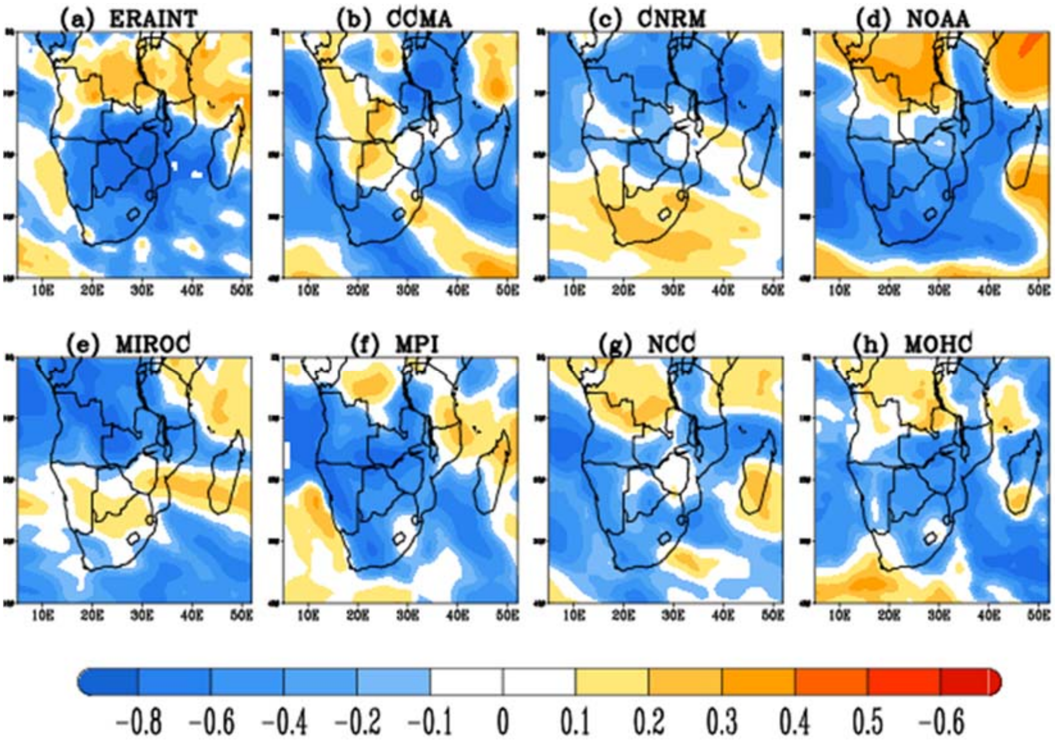

Figure A-2: The coefficient of correlation between ENSO (i.e. Nino3.4) and drought index in ERA-Interim and GCM simulations

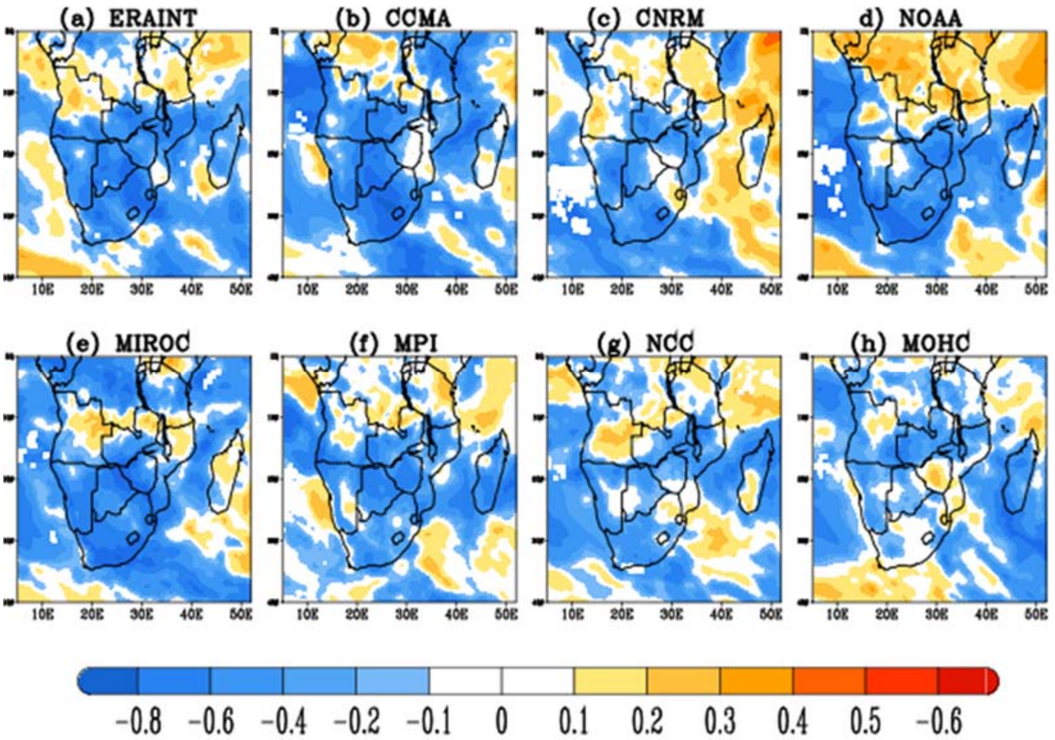

Figure A-3: The coefficient of correlation between ENSO (i.e. Nino3.4) and drought index in RCA simulations forced with ERA-Interim and GCM data sets

A.2 The 'Cube' Analysis

The second approach explored in this work is that of the 'cube'. The thinking behind the cube approach stems from the regional modelling exercise described above and the reality that any signal or information about global modes of variability such as ENSO must be communicated to a region through the boundaries of the region. Teleconnection responses simply cannot drive local-scale responses without a physical mechanism connecting the local scale to the global scale. This physical mechanism must manifest itself in suitable characterisations of a boundary surrounding the region of interest. Schematically, the cube can be visualised a three-dimensional box surrounding a region as in Figure A-4, which also schematically indicates the inflow of information through the boundaries and the domain interior processes at play. The positioning of the bounds of the cube is not an objective process but is designed to capture our current understanding of important processes at play such as the mid-latitudes and tropical process.

The boundaries of the cube are characterised by the cross-boundary (i.e. perpendicular to the boundary) fluxes of moisture and heat. The internal response condition is, at this point, characterised by the 2 m temperature and vertically integrated moisture content of each 50 km grid cell of the ERA-Interim reanalysis grid.[2] The variation of the internal state for each month was characterised as the root mean square distance (RMSD) between a specific month's vector of 2 m temperature and vertically integrated moisture across all grid cells, and the mean vector of those same variables for all grid cells. This ensures that pattern differences evaluate to large differences even when the mean values across the domain may be similar to the long-term time mean.

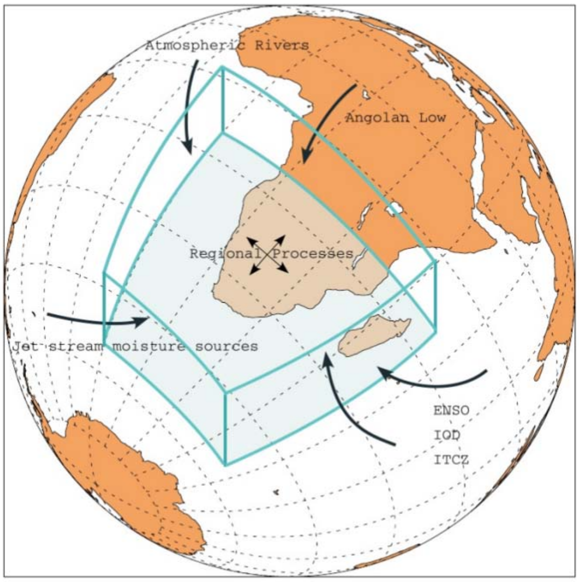

Figure A-4: Initial cube configuration and schematic of large-scale forcing impinging on the boundaries of the cube

[2] The ERA-Interim reanalysis was used for all the cube analysis work due to its physical consistency across both surface and upper air variables. This contrasts with using different products for surface variables and upper air circulation variables

A.2.1 Results

The first results consider simply how the internal domain response, as characterised above in the RMSD values, responds to the classic ENSO MEI index. The results are presented in Figure A-5 and show that there is very little clear regional interior response to ENSO. This result was unexpected given the previous analysis and much earlier literature showing linkages between ENSO and regional southern African climate.

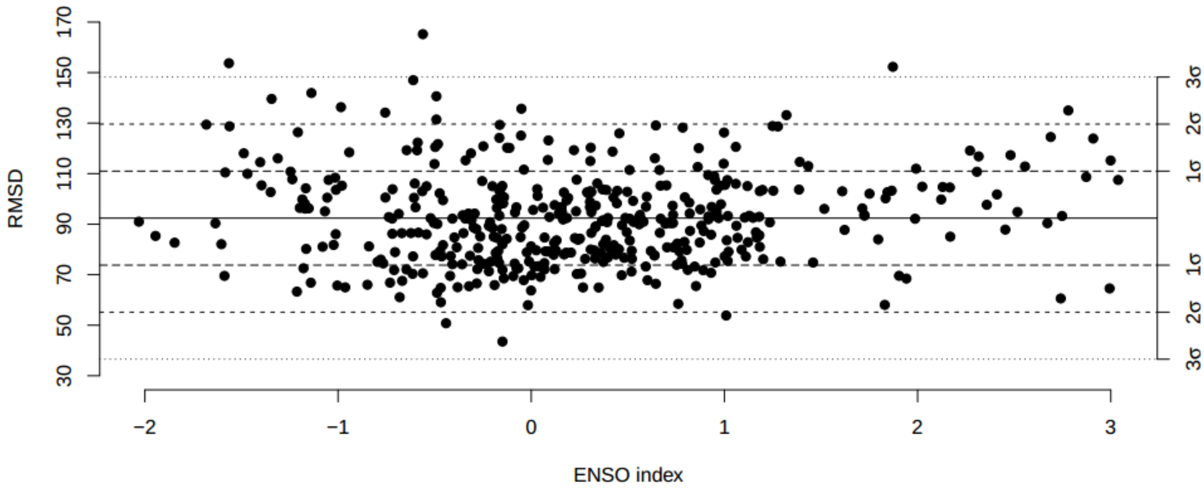

Figure A-5: Relationship between RMSD regional variation from climatology (y-axis) and ENSO (x-axis)

To better explain these results, the months during which the highest local atmospheric deviations, as determined by the above characterisation of 2 m temperature and total column moisture RMSD, were identified and plotted on a time series plot of the MEI index. The result is shown in Figure A-6 where the months with high deviations are marked with blue dots. Additionally, the months with high ENSO deviations (large positive or negative MEI values) that also correspond to large RMSD values are marked with a cross.

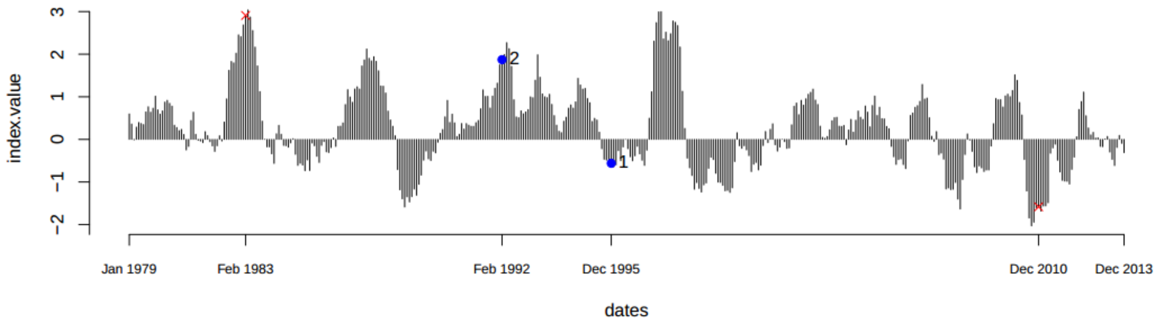

Figure A-6: Annotated ENSO cycle with high RMSD local response deviations plotted as blue dots, and high ENSO deviations coinciding with high local response deviations (greater than 3 sigma) plotted as red crosses

Figure A-5 and Figure A-6 are not exhaustive analyses but rather illustrate the two related characteristics of the regional climate. Firstly, large local climate deviations can occur without a corresponding ENSO signal; secondly, large ENSO signals do not always result in large local climate deviations. While we know this from studies of seasonal forecast skill, those studies tend to focus on rainfall responses, which are likely to capture a lot of natural variability at local scales. This analysis captures a large-scale bulk atmospheric deviation from the norm (vertically integrated moisture and 2 m temperature pattern deviations across the sub-continent), which we might expect to have a more direct and reliable response to ENSO.

Two separate comparisons of regional RMSD values were performed. The first is illustrated in Figure A-7, which compares the strong RMSD event of December 1995 with the RMSD associated with the strong ENSO signal of December 2010. This comparison shows the surprising result that the strong RMSD deviation, which occurred in December 1995 during a weak La Niña, is almost opposite in pattern to that of the strong La Niña even in December 2010. The high RMSD event exhibits a moist 'Angola low' anomaly to the north-west of the region and a dry core to the east of the Madagascar. Inversely, the strong La Niña event displays a slight dry anomaly to the north-west and strong high moisture anomaly to the east. The high RMSD event displays a strong cool anomaly of the south-west of the continent while the strong La Niña conditions display the inverse – a warm anomaly in the same region. It seems clear therefore that the interior response of the La Niña condition is very complex.

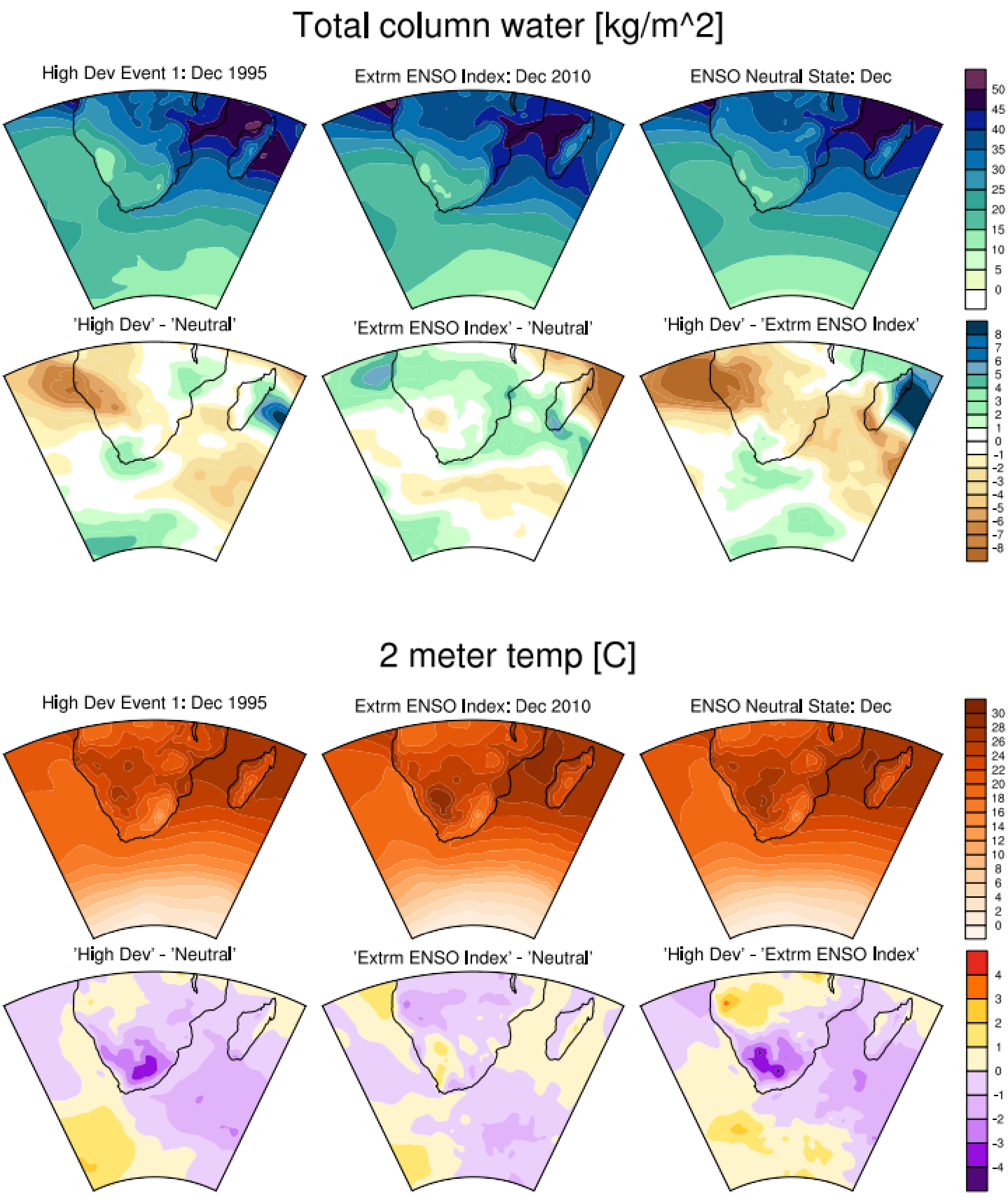

Figure A-7: December 1995 high RMSD event and December 2010 La Niña event total column moisture and 2 m temperature anomaly maps

Figure A-8 illustrates the second comparison between the strong RMSD event of February 1992 and the strong El Niño event of February 1983. Here, we see that the pattern of the high RMSD event agrees somewhat better with that of the El Niño event though several notable differences remain.

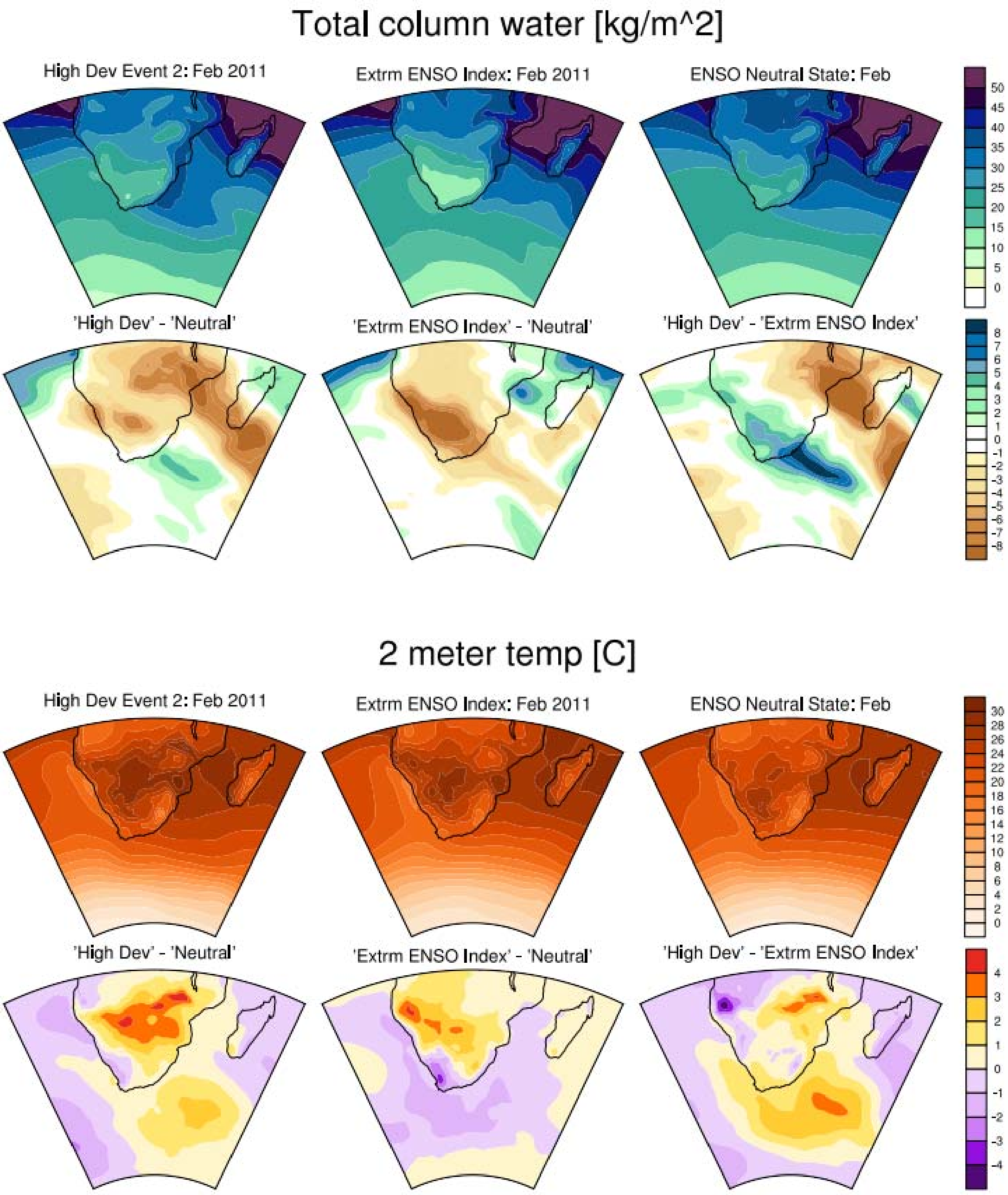

Figure A-8: February 1992 high RMSD event and February 1983 El Niño event total column moisture and 2 m temperature anomaly maps

A.2.2 Boundary flux anomalies

Complementing these two analyses, are analyses of the cube boundary flux anomalies for each of the four events described above. These are found in Figure A-9. Figure A-9 displays the boundary moisture and heat flux anomalies for the December 2010 high ENSO La Niña event, while Figure A-10 displays the same for the December 1995 high RMSD deviation event. Positive anomalies always indicate inward anomalies, i.e. positive moisture anomalies always indicating positive inflow of moisture into the domain, and the same for heat fluxes.

These figures concur, as expected, with the previous results. Key differences are that the high RMSD event is associated with much weaker fluxes along the northern boundary but stronger fluxes along the southern boundary, suggesting it is driven more by dynamics from the south. The eastern and western boundaries also display differences from the ENSO event with stronger southern inflow of moisture in the western boundary, again suggesting a mid-latitude driver of the variability rather than a north and eastern tropical drive.

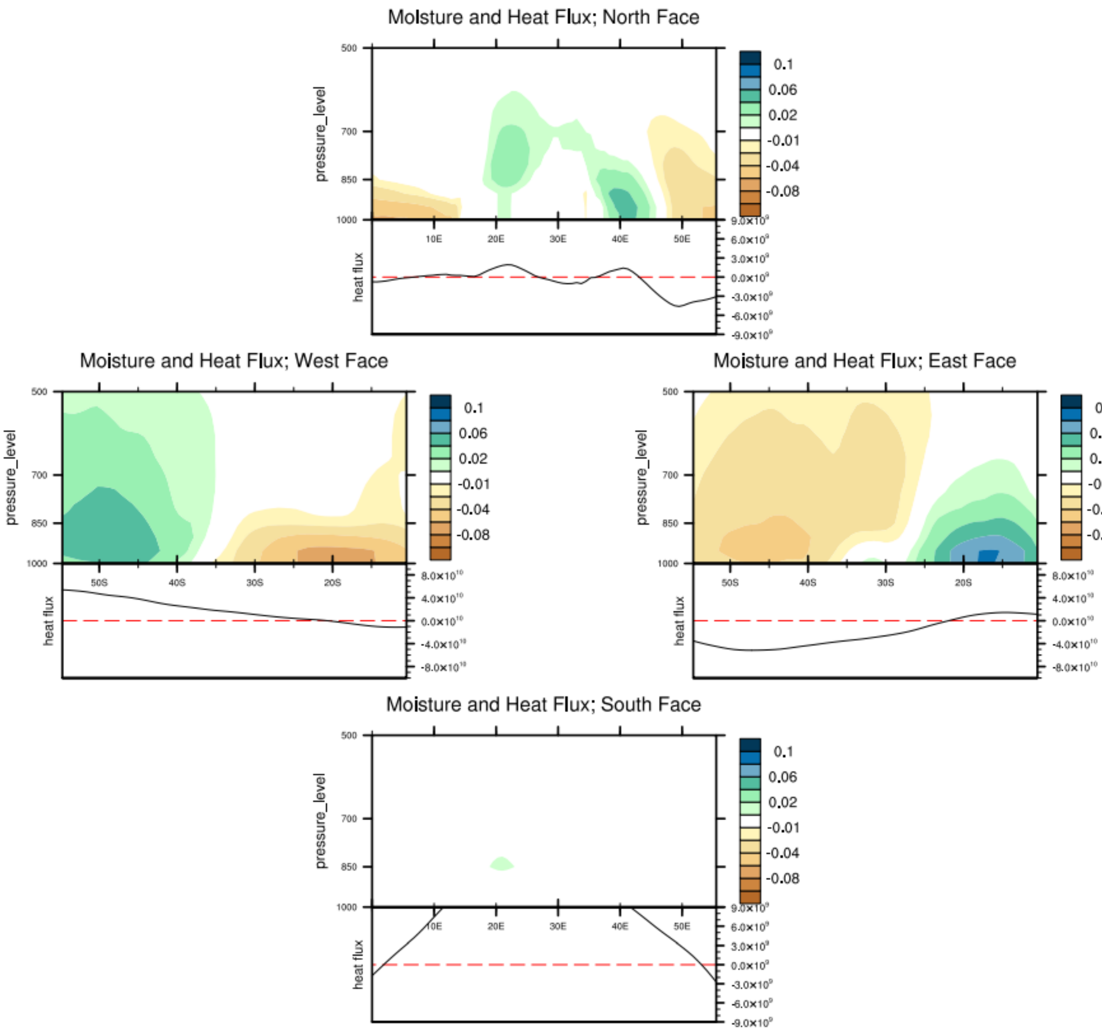

Figure A-9: Cube boundary anomalies of moisture flux and heat flux for the December 2010 strong ENSO La Niña event

For the second set of results, the boundary anomalies for the strong February 1983 ENSO El Niño event are calculated and compared with the boundary anomalies for the strong February 1992 RMSD deviation. As with the previous results, both these events occurred under strong ENSO El Niño conditions, so we would expect great agreement in the regional responses and in the boundary anomalies which is indeed the case.

The results demonstrate that in both cases, strong anomalies in moisture and heat flux are seen on most boundaries of the cube. In particular, strong dipoles of moisture flux are seen on the western and eastern faces of the cube indicating anomalous moisture inflow in the north-east of the domain and anomalous outflow of moisture in the south-east of the domain. Inversely there is strong anomalous inflow of moisture in the south-west of the domain and outflow of moisture in the north-west. There is also anomalous inflow of moisture on the northern boundary to the east of the domain. This is the case for both events. However, for the high RMSD event, there is a particularly strong anomalous inflow of moisture from the east as seen in the right-hand panel of Figure A-10.

A.3 Conclusions

This GCM and RCM ENSO/SPEI correlation and analysis are encouraging as they suggest that many AOGCMs are able to reasonably accurately translate an ENSO signal to the region even if they are often unable to translate this signal into a realistic rainfall response. The fact that some RCMs are able to improve on this translation suggests that the RCMs are receiving the signal/information they need to do this supporting the argument that the AOGCMs are propagating the signal in the atmospheric processes. Further work outside of the context of this project (Pinto, Jack and Hewitson, 2017, in review) examines this further and concludes similarly that RCM added value or improved performance is a consequence of improved representation of the local rainfall response to circulation anomalies rather than significant changes to regional scale circulation.

We can conclude from this tentative analysis that the regional response, as characterised by this bulk RMSD metric, is complex and inconsistent through different events. This is not surprising considering the relatively low skill of seasonal forecasts in many areas of the sub-continent and South Africa; however, it is useful to identify inconsistencies of response in a bulk measure, such as has been demonstrated here, rather than in a rainfall response that introduces new uncertainties about model performance and natural variability.

The cube analysis results could be interpreted as discouraging as it appears to impose a strong limit seasonal forecast skill. However, it must be noted that this is an unusual and experiment analysis and needs further exploration and analysis to better understand how informative these results are limits to skill. The approach was tested with respect to only four different events, and a far more rigorous analysis of the regional response needs to be done. In particular, there would seem to be some value in combining the two approaches presented here to gain a more holistic understanding of regional responses to global modes of variability. It would also seem to be important to extend this work to further teleconnections or global modes of variability. Indeed, this work has already inspired other such investigations.

Appendix B: REGIONAL MULTI-SCALE RESPONSES

B.1 Introduction

The concept of phase space analysis was posited early on the project and various approaches to analysing and unpacking the phase space 'clouds' using ideas such as phase space volume, overlap, density, etc. were explored. However, as the work progressed, these avenues proved quite abstract and difficult to translate into concepts of predictability of surface variables. The explorations were not without value, however, as they did provide a new lens on the projects overarching formulation of the predictor/predicatand relationship captured by the formula:

$$Y = F(X) + \varepsilon$$

In this expression, **Y** is the local climate expression of predictive interest, × is the large-scale climate state, **F** represents the (potentially non-linear) response function transforming large-scale climate variations into local-scale responses, and **ε** represents the locally sourced 'noise' component (i.e. the non-forced variance).

This section therefore focuses on the more concrete outcomes of the project to understand the local-scale surface response to regional scale synoptic 'states' or, in the phase space framing, the phase space states. In particular, we report on two productive avenues explored. The first is a multi-scale (time and space scales) exploration of local surface response, namely, probability of above or below median rainfall, to regional atmospheric state. The second leverages the SOM trajectory analysis approach to explore hydrological responses to different progressions of regional atmospheric states. In each of these, different characterisations of both the atmospheric state and the surface response are used, and different transfer functions (**F**) are used. This allows for a rich exploration of the methodological characteristics.

In the first instance we explore a key question about the predictor-predictand relationship*: At what levels of time/space aggregation can we construct a linear relationship between precipitation levels and estimates of moisture fluxes over the region?*

Given that the work is principally concerned with precipitation, the question is explored using the metric of moisture, notably moisture convergence/divergence. The moisture balance in the atmosphere is fundamental to the precipitation processes, and hence these estimates point to at which scales, within a given model world, precipitation is a function of moisture balance and at what scales the chaotic dynamics are the determining factors.

B.2 Probit Modelling Method

The method to assess the relations of the large-scale bulk moisture is to fit a probit model to the predictors (moisture divergence) and the predictand (precipitation). A probit model is a type of regression where the dependent variable can only take two values. For the predictors we use the mean, standard deviation, and first-order auto-regressive term for a variable time window of vertically integrated moisture divergence. The predictand is whether rainfall is expected over that each time window (no removal of seasonal cycle). This approach was settled on after trying several different ideas. In developing the probit model it was considered to be a 'successful' model if it has a 75% classification success rate. This 75% is subjective, and for these purposes does not need to be a critically exact number. It is chosen here to be a quartile higher than a 50% success rate that would be the expected result from using persistence or random guessing.

B.2.1 Data

For the analysis we use predictors from the ERA-Interim reanalysis data set. For the predictand – precipitation – there is a range of choices available. To explore some of the impact of this choice of gridded spatially continuous representation, we assess three options. First, the ERA-Interim precipitation fields that represent an internally consistent response to the reanalysis model's dynamics. In addition are two additional precipitation products termed the WATCH forcing data products, which are intended to be more consistent in terms of moisture budgets than the direct ERA-Interim precipitation since in the ERA-Interim reanalysis only the atmospheric fields are nudged. We assess two WATCH products – one based on bias correction using the Global Precipitation Climatology Centre (GPCC) data set, and one using CRU data.

In addition, we use station data as the predictand for assessing point-scale response to the atmosphere. This approach excludes the aspect of measuring skill as a function of (spatial) scale as it is not practical with the available station density to do defensible spatial averaging. Hence with the station data only temporally averaging is done.

B.2.2 Station results

Initial site selected from the centre of the region of interest [25.0E 27.05S]:

To explore the method of using moisture divergence we begin with one station located in the gradient between the dry west and moist east – a location of significant complexity and also of relevance to the agricultural sectors.

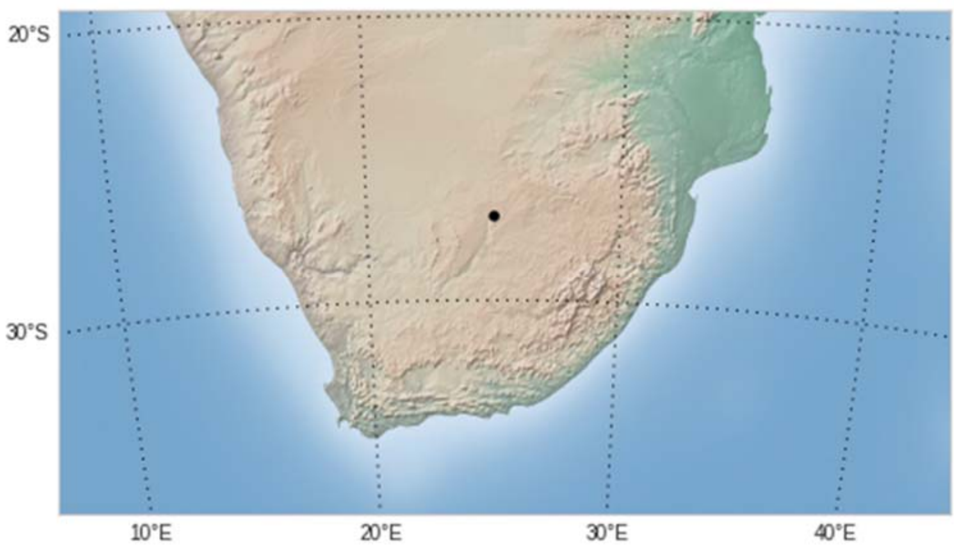

Figure B-1: Initially tested station location

The approach begins with charting how the probit model uses the different predictors. The images in Figure B-2 to Figure B-4 show making predictions for the station using the divergence statistics form the grid cell it is contained in. The probit model uses a 10-day temporal aggregation.

The points at 0.0 and 1.0 mark whether there was above- or below-expected rainfall amount observed for a given predictor value. Density approximations are shown [the Kernel Density Estimate (KDE) for rainfall occurrence is shown upside down] to see how much "*predictor values that produce rain events"* overlap with "*predictor values that do not*".

The scatter points are the probability of an above average rain event that the probit model assigned a given predictor set. Since the model is multi-variate, these scatters are noisy rather than sigmoid curves as would expect for the univariate model.

For this station and aggregation, one can see from Figure B-2 to Figure B-4 that the standard deviation of the divergence time series (within the brief window) is the strongest single predictor, and that this is the predictor value that has the cleanest distinction between values where events happen and where they do not.

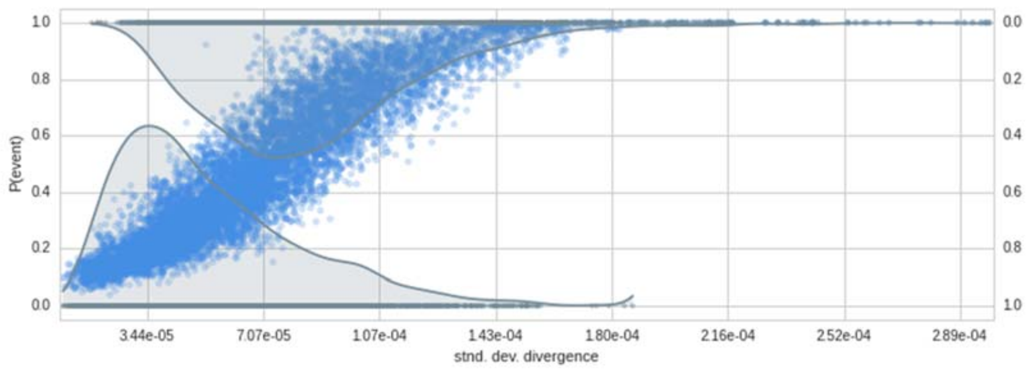

Figure B-2: Probit model using the standard deviation of the moisture divergence as the predictor. KDE curves are provided for both no-rain events and (shown upside down) rain events (10-day temporal aggregation)

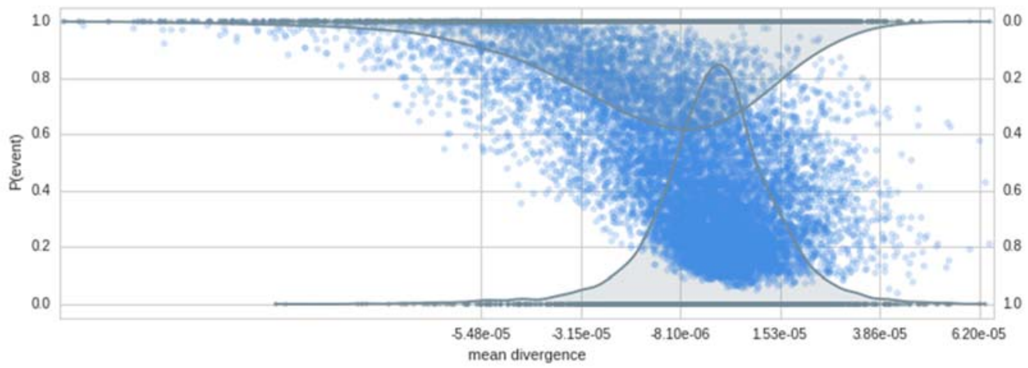

Figure B-3: Probit model using the mean of the moisture divergence as the predictor. KDE curves are provided for both no-rain events and (shown upside down) rain events (10-day temporal aggregation)

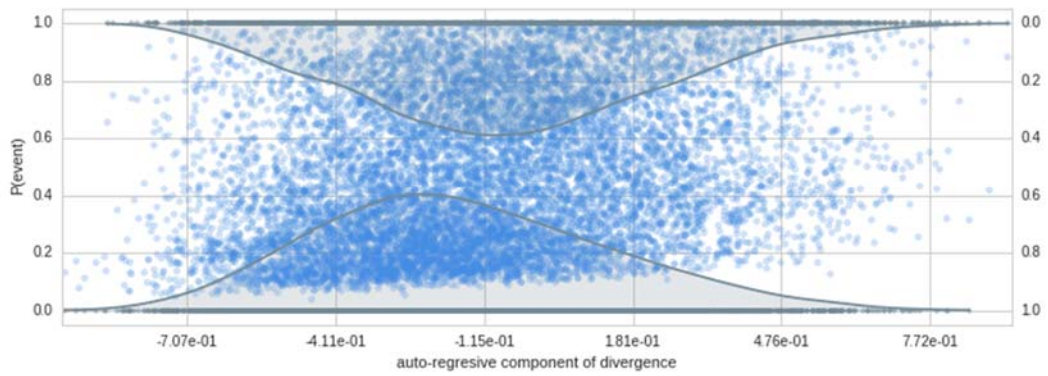

Figure B-4: Probit model using the auto-regressive component of the moisture divergence as the predictor. KDE curves are provided for both no-rain events and (shown upside down) rain events (10-day temporal aggregation)

Following this, other temporal scales of aggregation can be assessed. In Figure B-5 to Figure B-7, the probit model is developed using a 30-day temporal aggregation. The distinctions get subtly sharper for the different predictors.

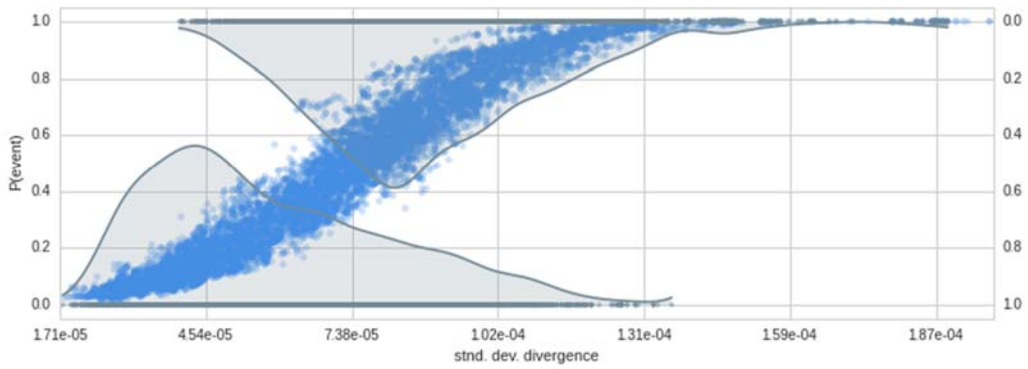

Figure B-5: Probit model using the standard deviation of the moisture divergence as the predictor. KDE curves are provided for both no-rain events and (shown upside down) rain events (30-day temporal aggregation)

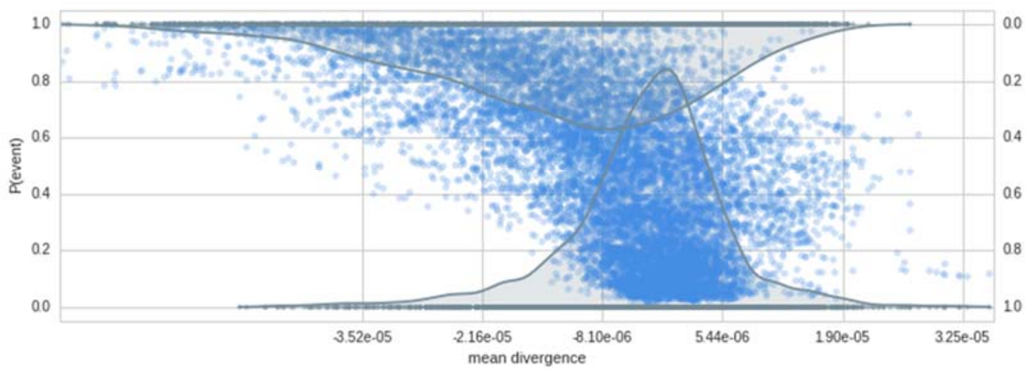

Figure B-6: Probit model using the mean of the moisture divergence as the predictor. KDE curves are provided for both no-rain events and (shown upside down) rain events (30-day temporal aggregation)

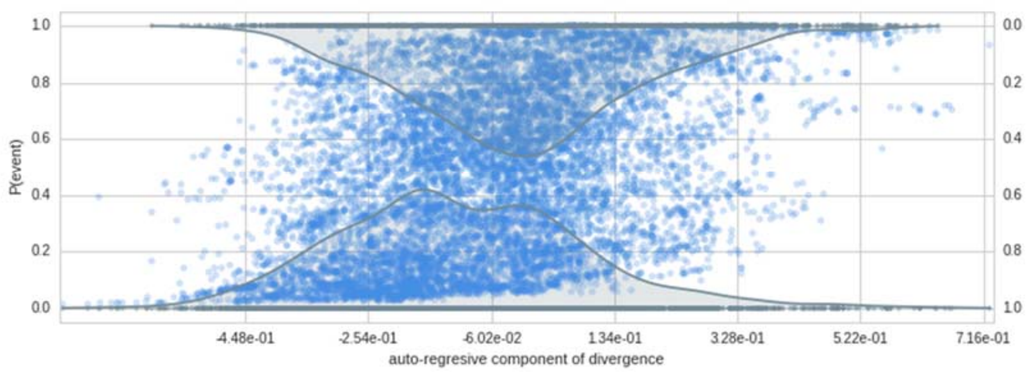

Figure B-7: Probit model using the auto-regressive component of the moisture divergence as the predictor. KDE curves are provided for both no-rain events and (shown upside down) rain events (30-day temporal aggregation)

While somewhat to be expected, it is apparent how the ‘skill’ of the model changes significantly as the temporal aggregation increases. This is especially informative on how the potential predictive skill will change as a function of the desired prediction target time scale and serves to help constrain expectation of what predictive skill is potentially available at different time scales for an ‘ideal’ climate model used in seasonal forecasting, aside from any other constraints introduced by the climate model.

With that in mind, Figure B-8 shows the distribution of probabilities that the probit model assigns to the correct solution for each sample at different levels of temporal aggregation. The dashed line shows the 50% mark, and one may defensibly call the model ‘skilful’ when top three quartiles are above this line (a definition that is somehow simultaneously arbitrary and conservative). Depending on this definition of skill, one may suggest that, for this location at least, a temporal aggregation on the scale of two to three weeks is desirable.

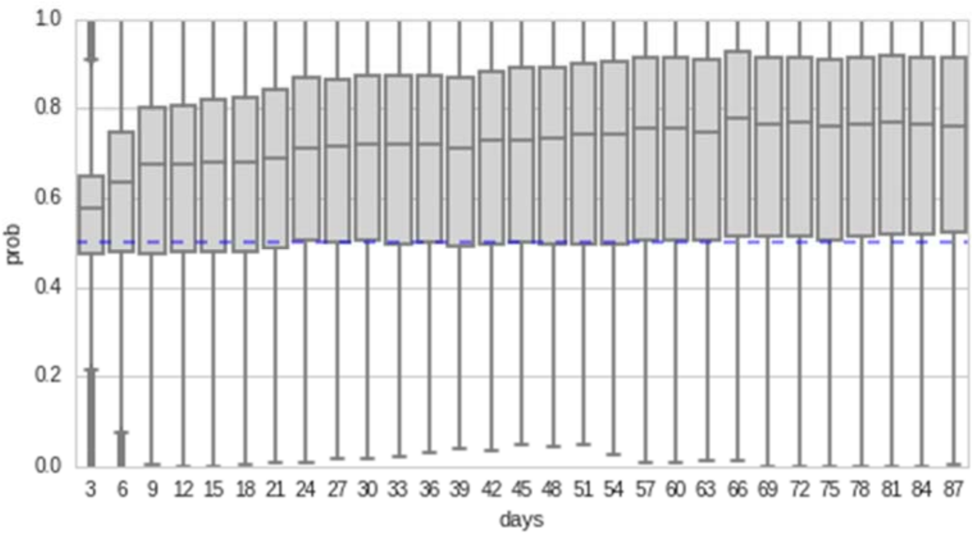

Figure B-8: The distribution of probabilities that the probit model assigns to the correct solution for each sample at different levels of temporal aggregation

B.2.3 Sub-sample of station data

Expanding on this approach, we can rephrase the question as*: What is the minimum level of temporal aggregation window needed to meet a chosen minimum skill requirement for a sub-sample of the stations in the data set that meet acceptable criteria of duration?*

Figure B-9 shows this result. Three interesting features can be interpreted from these results in Figure B-9:

- The variability of time aggregation for stations nearby to each other.
- The separation of the winter and summer rainfall regimes.
- The spatial cohesion, positioning and size of stations that require exceptionally high levels of temporal aggregation. This is particularly relevant as it informs on where the potential is best for developing skilful predictions at sub-seasonal time scales.

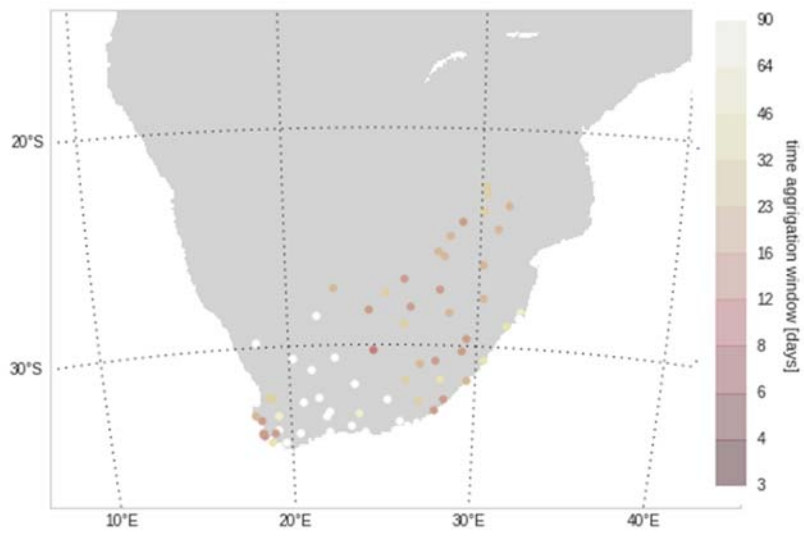

Figure B-9: Level of time aggregation required to meet skill level

Figure B-10 unpacks this further and poses the question as to which is the most weighted predictor for the different sites. Again, a strong separation appears. In this case, the south-western and eastern coastal regions share a dependency on the mean state of the moisture divergence, whereas the summer interior rainfall is better captured by the standard deviation of the moisture divergence.

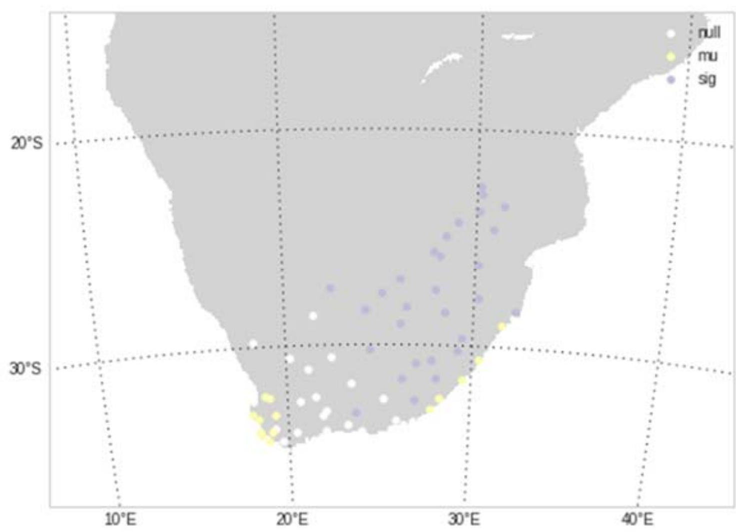

Figure B-10: Dependence of predictive skill as a function of the attributes of moisture divergence

B.2.4 Reanalysis results

As a last exploration of this approach to assess the predictive nature of the atmospheric dynamics, we extend the station analysis to gridded precipitation products. Figure B-11 to Figure B-14 show the same content to that station analysis above, but consider the relationship in terms of a spatially continuous field of precipitation. The results for the full span of the time period, then for El Niño, La Niña, and neutral ENSO years are presented. Each row in the figure shows the results for when one applies a spatial aggregation of zero, one, three, and five grid cells to explore the dependency on spatial scale. As in Figures B-9 and B-10, the left column of Figure B-11 to Figure B-14 show the temporal aggregation window needed to meet a chosen minimum skill, and the right-hand column shows leading predictor in terms of the attributes of the mean or the standard deviation.

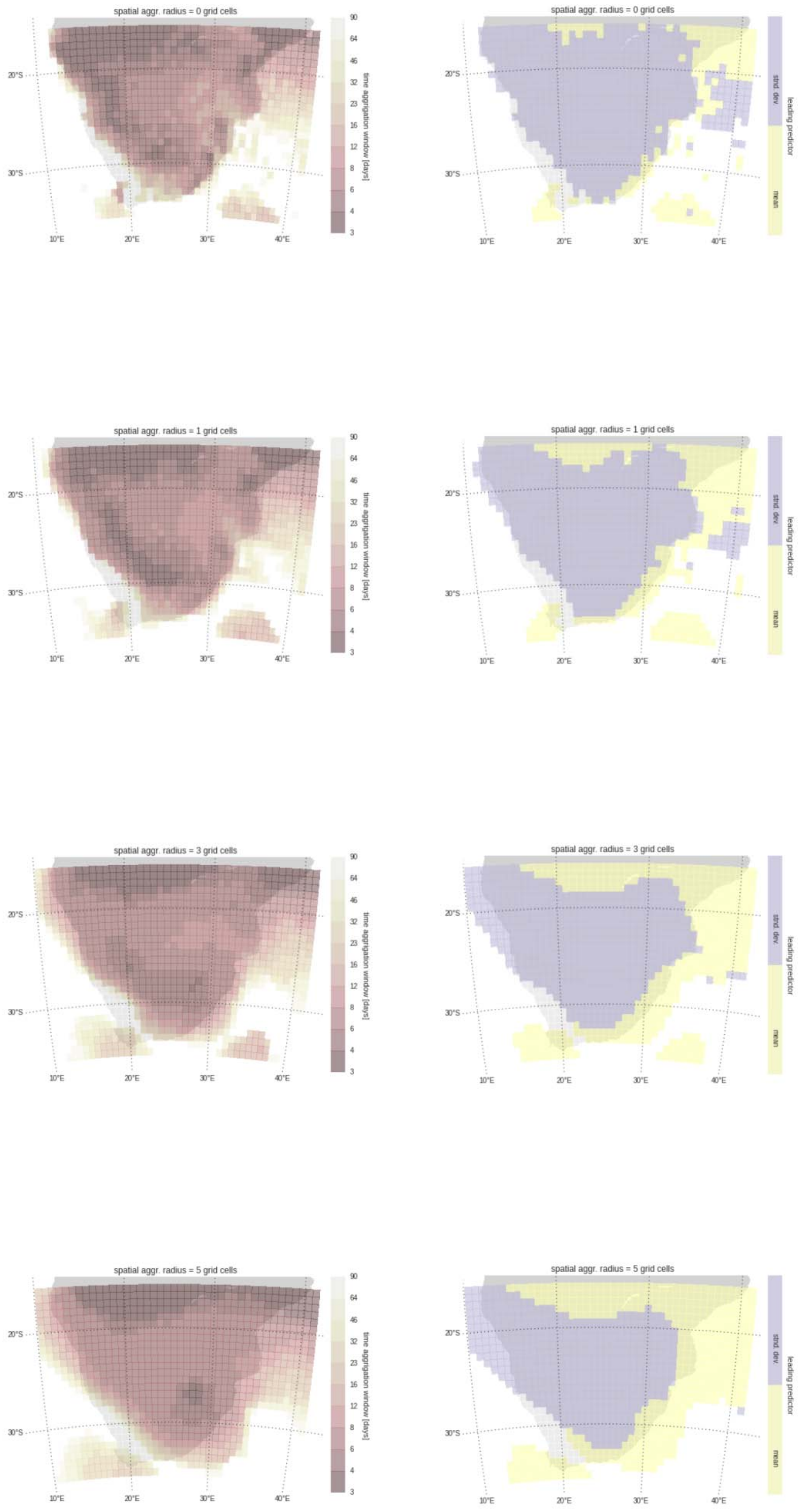

Figure B-11: Full time span of ERA Reanalysis atmospheric data with ERA Reanalysis precipitation

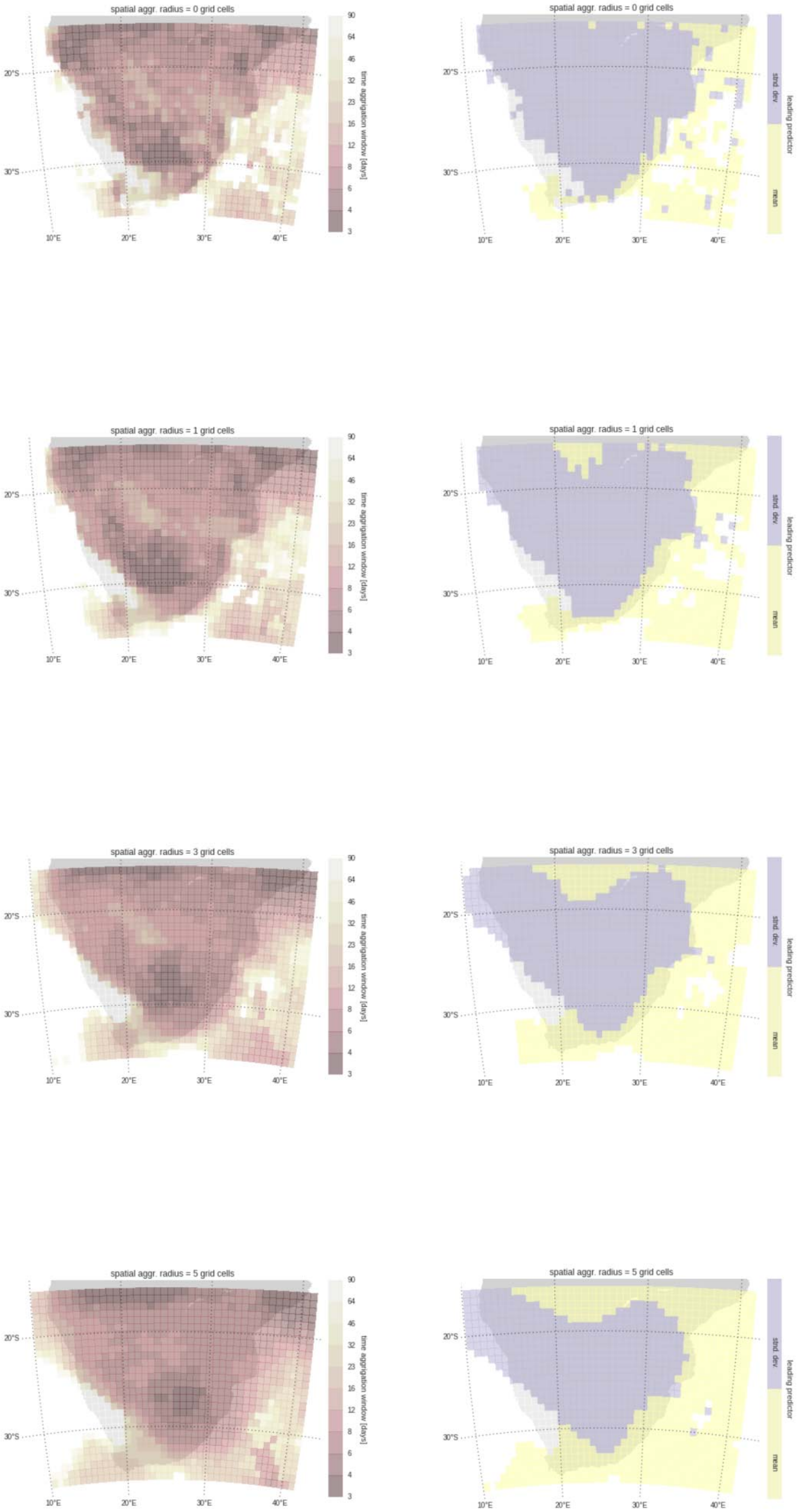

Figure B-12: El Niño years of ERA Reanalysis atmospheric data with ERA Reanalysis precipitation

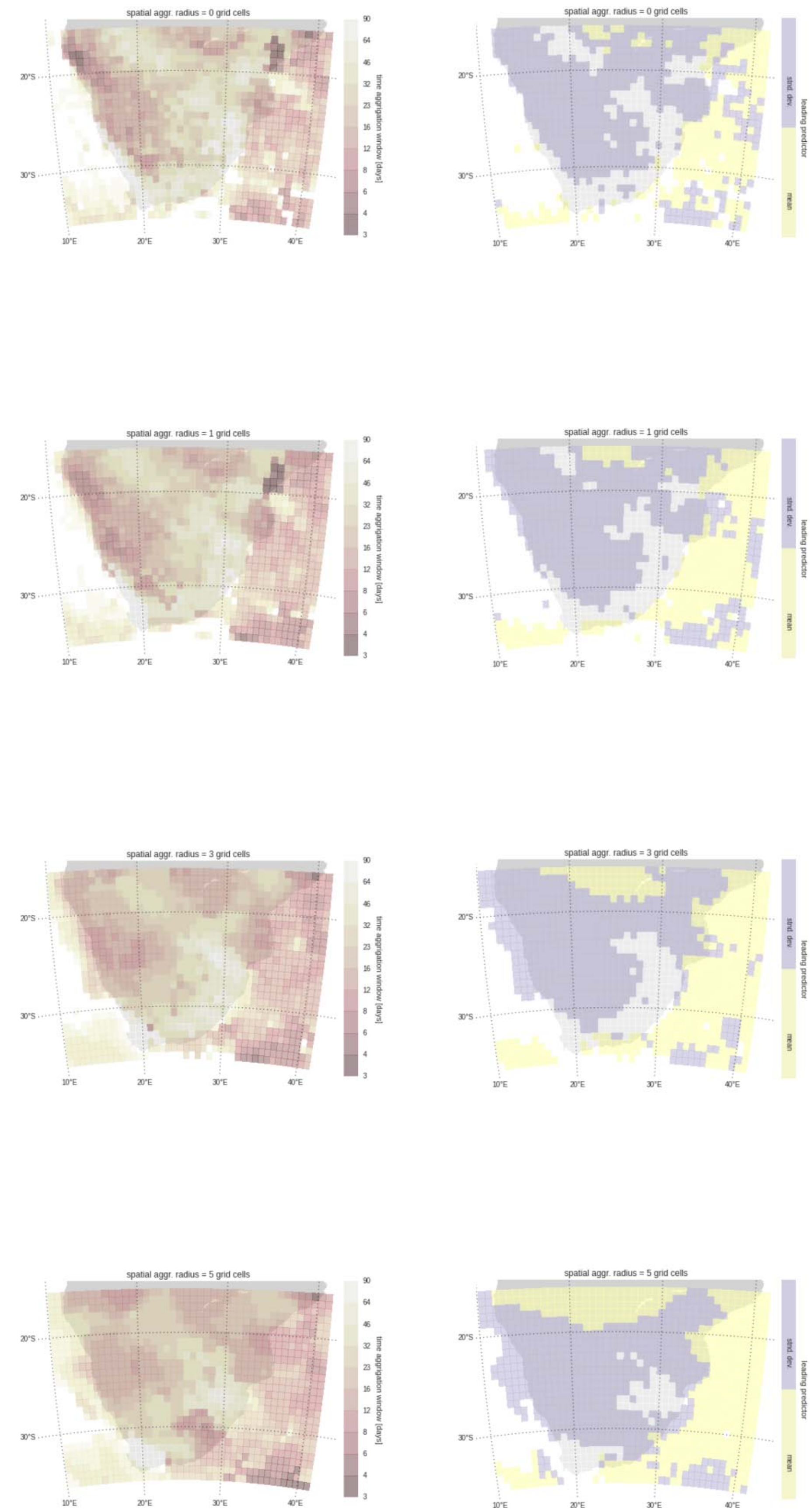

Figure B-13: La Niña years of ERA Reanalysis atmospheric data with ERA Reanalysis precipitation

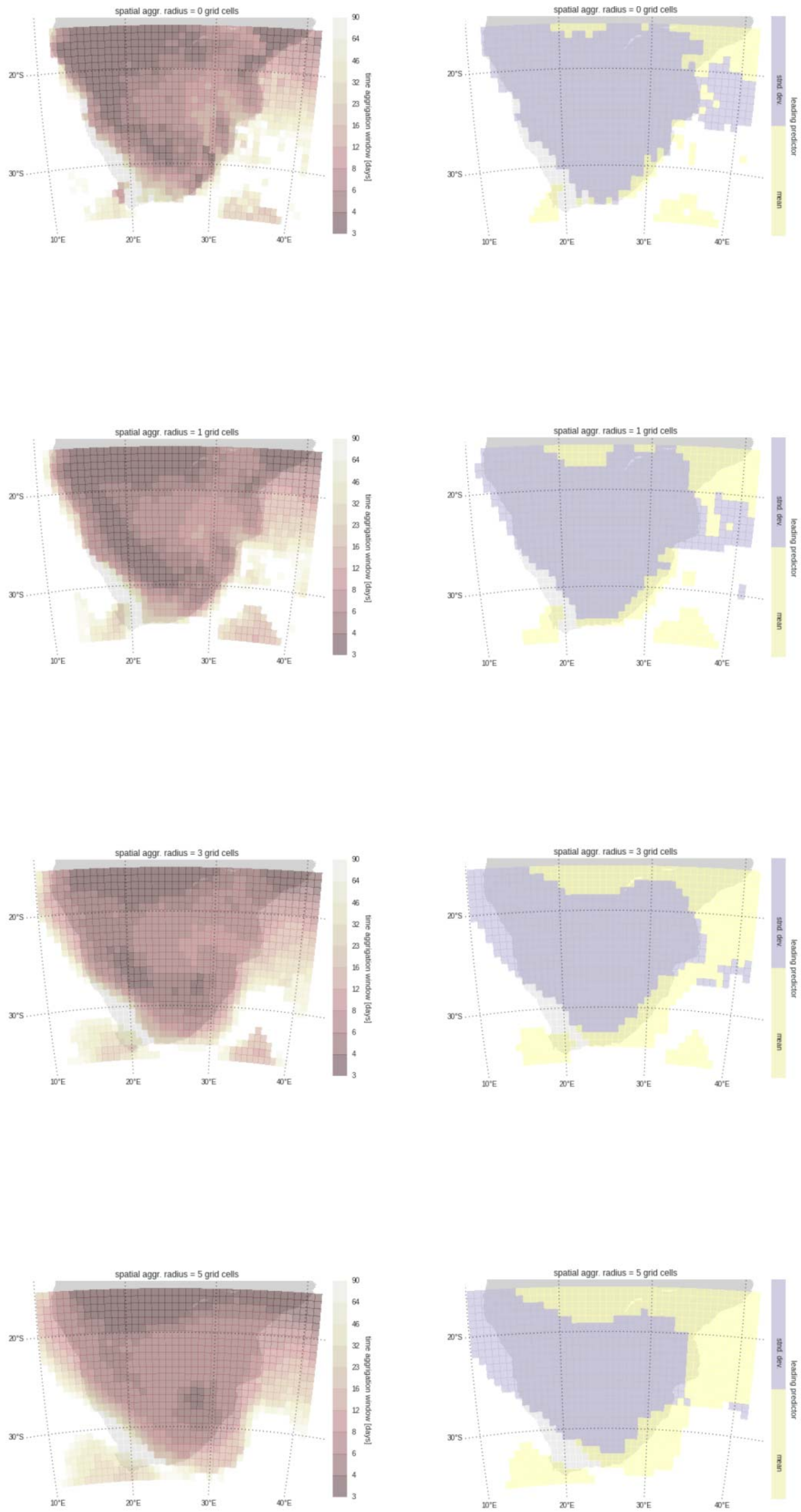

Figure B-14: Neutral years of ERA Reanalysis atmospheric data with ERA Reanalysis precipitation

B.3 Assessment of Relationship between Synoptic Circulation and Hydrological Responses

In the second exploration into local-scale response to atmospheric state, we investigate the role of land surface hydrological processes as exemplified through the generation of surface run-off as a basis for interrogating the level of predictability of climate at seasonal time scales within the framing akin to statistical downscaling, i.e. within a relationship between hydrological responses and synoptic forcing. We frame this objective through following questions:

- Do synoptic conditions differ between seasons/years with above and below average run-off?
- Do the differences in the run-off-synoptics relationship manifest regionally?
- Are the run-off-synoptics relationships scale-sensitive?

The above questions are answered using the innovative analytical tools and approaches developed earlier in the project. In particular, we use analyses based on seasonal trajectories through the SOM space and SOM node frequency ‘clouds’ that are the alternative way of schematizing the space-time evolution of synoptic conditions to the traditional compositing and empirical orthogonal function based approaches.

B.3.1 Context

From the point of view of forecasting practice where focus is often not on meteorological variables, but rather on impacts of those on particular elements of environment of economic relevance, using hydrological responses offers additional advantages. These relate to the bypassing of possible sources of uncertainty when deriving ‘intermediate’ meteorological variables. In particular, there is the possibility of bypassing model rainfall parameterizations with their known limitations.

The idea of using hydrological responses to interrogate predictability at seasonal time scales within the framework outlined above is akin to the process of statistical downscaling. Regional synoptic variables, generated by a forecast GCM, are used to infer local responses. In the context of forecasting a non-climate response (e.g. hydrological flux such as run-off), the downscaling typically involves a modelling chain illustrated in Figure B-15(a). In our approach, we adopt a similar setting to that illustrated in Figure B-15(b), where a direct relationship is hypothesized between the variables characterising atmospheric circulation and an integrative environmental response; in our case surface run-off.

B.3.2 Method

The general approach is to investigate how strongly the differences between hydrologically dry and wet years manifest in terms of differences in synoptic conditions, for locations across South Africa, and for different sizes of synoptic variables domain. The outline of the method is presented below, while its details are to be found in the Appendix.

The hydrological years (responses) are assessed based on surface run-off data obtained from the WR2012 (waterresourceswr2012.co.za) data set. The WR2012 naturalised run-off data set covers the period from 1920–2009 and provides monthly total surface run-off from each quaternary catchment within South African boundaries. We aggregated run-off from quaternary catchments to the level of a 0.5° × 0.5° grid.

The SOM of synoptic circulation types is established using monthly average fields of ERA-Interim wind (u;v), specific humidity (q), and air temperature (t) at 850 mb as these are the most generic variables reflecting the fundamental thermodynamic state of the regional climate system. The SOMs are developed for i) a single large domain, covering 0E-55E and 50S-10S, called here SAF; and ii) a number of small domains, covering the region of 8° × 8° centred over a number of points. These points are distributed every 2° (both E–W and N–S directions) covering the entire area of South Africa.

We use SOM space trajectories to visualise the seasonal progression of synoptic conditions, and differences in trajectories indicate differences in prevalent conditions. Apart from the SOM space trajectories, we use an index expressing similarity of frequency distribution of SOM nodes, or SOM node 'cloud'. We capture that similarity using the so-called Hellinger distance, which is a measure of relative overlap between two discrete frequency distributions.

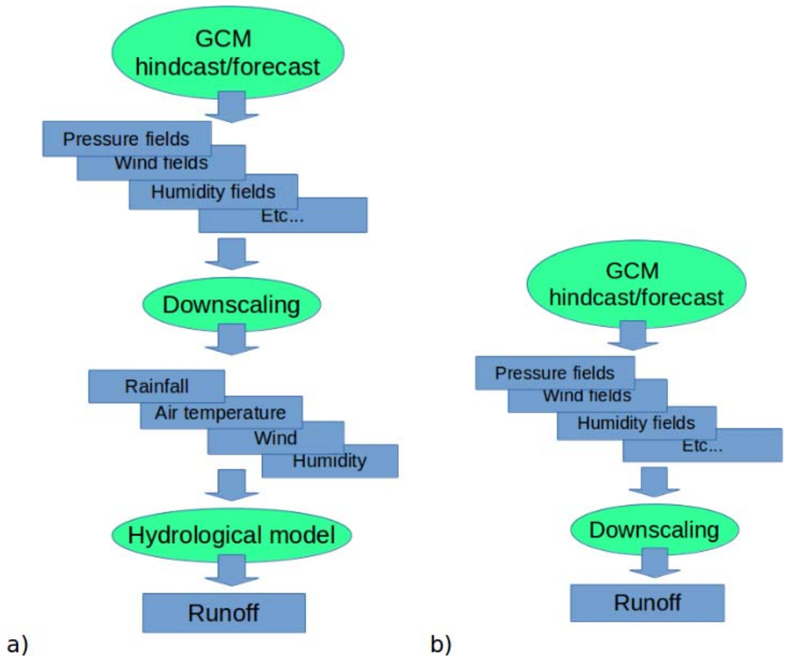

Figure B-15: Schematic representation of the process of a) hydrological model-based hydrological forecasting and b) direct downscaling-based hydrological forecasting

Results

A comprehensive set of results of the analyses are presented in the Appendix, while below we outline only the synthesis of the most significant findings. Figure B-16 summarises the differences between frequencies of synoptic circulation patterns in the SOM space, underpinning locally defined dry and wet DJF seasons. It illustrates a relatively coherent spatial heterogeneity in these differences and indicates that a good separation is present for locations in the Limpopo province and in parts of the Northern Cape and Eastern Cape provinces.

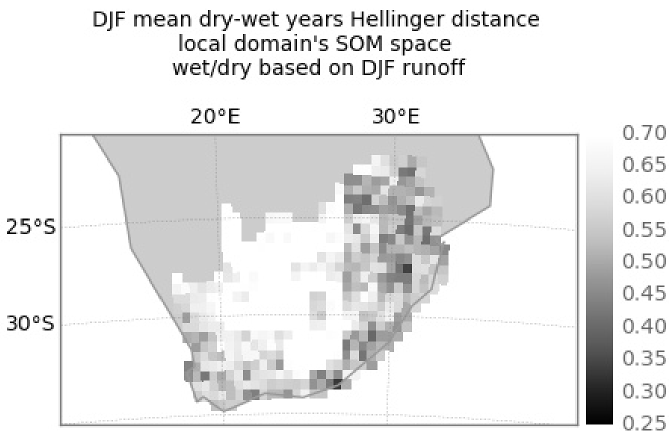

Figure B-16: Map showing Hellinger distance indicating separation between the frequencies distributions of ERA-Interim DJF synoptic states in the large (SAF) domain, between hydrologically dry and wet DJF seasons. The darker the colour, the less different synoptic states are

Figure B-17 presents similar results, but here, the synoptic variables domain is defined differently. The SOM space trajectories and distances are calculated for SOMs of synoptic variables over small, local domains centred over analysed location. This is meant to represent a different scale of the synoptic forcing-response relationship: instead of regional scale synoptic forcing, we consider sub-regional, meso-scale synoptics.

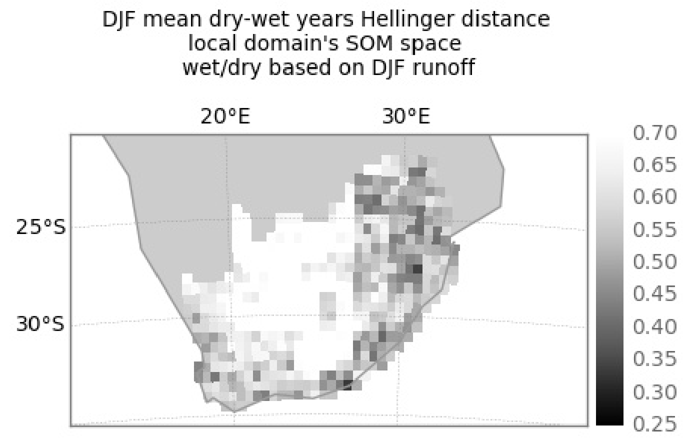

Figure B-17: Map showing Hellinger distance indicating separation between the frequencies distributions of ERA-Interim DJF synoptic states in the local 8° × 8° domains, between hydrologically dry and wet DJF season. The darker the colour, the less different synoptic states are

A comparison between Figure B-16 and Figure B-17 is particularly revealing. Figure B-15 illustrates the relationship between large-scale synoptic forcing and local responses – Limpopo and the Eastern Cape have relatively strong linkages. Figure B-17 illustrates the same but for local-scale synoptic forcing; the run-off-forcing relationship in Limpopo province is comparatively weaker, while the Eastern Cape region shows a very strong linkage. These differences are likely an expression of the role of scale of atmospheric circulation processes that affect the local rainfall (and thus hydrological) responses.

B.4 Conclusions

This chapter focuses on different characterisations of the local climate response to regional atmospheric state. It also explores different characterisations of the regional atmospheric state building on the conceptual explorations of the phase space analysis early on in the project.

Several key learnings and conclusions have emerged. The first is that there are strong spatial and temporal-scale dependencies on the strength of the linkages between regional atmospheric state and local-scale responses. While this is no real surprise, a quantitative objective result demonstrating the nature of these scale relationships is a significant step forward both methodologically and in our understanding of the regional climate dynamics. Related to this is the evidence that at a time scale longer than a few days, the variance of the regional atmospheric state is a better predictor of local response than the mean state. This is an important avenue to explore with respect to seasonal forecast skill where the focus is often on predicting changes in monthly or seasonal mean states; perhaps it should be shifted to understanding the global scale drivers of regional atmospheric state variance.

The second component of the work investigated how strongly the differences between hydrologically dry and wet years manifest in terms of seasonal synoptic conditions for locations across South Africa, and for different sizes of synoptic variables domain. As such, it is similar to the prior analysis in that it explores multiple spatial scales, but includes the added dynamic of the hydrological modelling as an integrator. We reveal that there is spatial heterogeneity in the relationship between synoptic forcing and hydrological responses. In the broader context of the project, these differences have implications to the statements about predictability of hydrological responses, but thus, likely, also predictability of meteorological responses. Additionally, we reveal that there are differences in terms of spatial scales at which the relationships manifest.

We presented three sets of analytical avenues that are based on hydrological responses and provide contextual information allowing interpretation of seasonal forecast data and seasonal forecast quality, and thus also seasonal forecast skill, particularly in the context of forecasting of 'impact' variables. Although the analyses are not exhaustive, i.e. they do not explore individual approaches at depth and comprehensively, the results show potential of these alternative approaches. We trust their details can be addressed in the future in the context of relevant practical applications.

The analyses reveal the following key learnings:

- There are spatial differences, likely related to hydrological processes and their parameterization in how well hydrological responses reflect the year-to-year (and by extension, also season-to-season) differences in evolution of climate forcings. This is likely attributed to the influence of the role of initial conditions, but also to the importance of threshold-dependent hydrological processes. This has implications to the assessment of forecast performance in terms of hydrological responses.
- There are spatial and seasonal differences in how hydrological processes constrain, or in other words, 'organise' noise in climate forcings. These differences are likely attributed to a specific combination of hydrological processes, including threshold-dependent ones, acting at local scale. These differences, again, have implications to the assessment of forecast performance in terms of hydrological responses.
- There are spatial differences that are additionally scale-sensitive, in predictability of hydrologically-relevant climate signal.

All these results serve one significant purpose: to identify new avenues of exploration that focus on the complexity and variability of local-scale responses to atmospheric states. Predicting local responses is highly dependent on spatial location, spatial scales and temporal aggregations scales. The quantitative results presented here contribute significantly toward identifying areas and scales where improved skill could be obtained and indications of the attributes of the regional atmospheric state that need to be targeted to improve skill.

The use of integrative models, such as hydrological models, have long been considered as possible avenues to reduce prediction spread or uncertainty. The results presented here indicate that this is indeed the case in some geographical areas, but it is not the case in others depending on the nature of the specific catchments and rainfall characterisations.

Appendix C: HYDROLOGICAL RESPONSES

C.1 Introduction

The analyses presented in this section are motivated by the fact that hydrological responses integrate several climate variables (rainfall and temperature, but also winds, humidities etc.), which offers an opportunity to look at aspects of forecast abstracting from errors and idiosyncrasies of individual climate variables. Additionally, hydrological analyses speak directly to one of the principal ways that seasonal forecast is interpreted by its users, which is through the implications to water resources and other hydrology-related indices such as surface run-off, streamflow, soil moisture, groundwater recharge, dam storage and flood susceptibility. Considering such context, a climate forcing-hydrological response framing is used here to explore synergies between individual seasonal climate forecast variables such as rainfall and air temperature (or alternatively, to identify discrepancies between them) that arise within the hydrological environment, and manifest through hydrological responses, and assess their implications to seasonal climate forecast skill.

We explore the following analytical avenues:

1. Assessment of surface run-off as an integrator of climate forcing. The approach is based on mapping correspondence between classes of seasonal evolution of forcing and responses, rather than on (what would be more typical) correlations. The question that is asked within this avenue is: *"Where, in which hydrological environments within South Africa, do we expect hydrological response (run-off) to reflect the principal elements of variability of climate forcing (rainfall and temperature) well?"*

The analyses consider a specific definition of "*principal elements of variability*" that focuses on the intra-annual evolution of forcings and responses. This index is more general than the typically used monthly, seasonal or annual totals. Rather than magnitude of response, it reflects the 'type' or year as manifested by annual progression of mean monthly states. Indirectly, this analytical avenue explores some modalities of derivation and use of this novel index.

2. Assessment of hydrological processes as a means to constrain uncertainty of climate forecast. The approach is based on mapping of relative magnitude of uncertainty in climate forcing compared to that in hydrological responses. This allows for assessing how climate forecast uncertainties propagate through the hydrological environment (or hydrological model) considering spatial, temporal and time scale context. The question that is asked is: *"When, where and at what temporal integration scales, does specific combination of hydrological processes make the hydrological forecast robust, i.e. insensitive to the uncertainty in climate forcing?"*

The analyses are carried out by framing climate variables uncertainty through a GCM ensemble spread.

Overall, the two avenues work across a set of spatial and temporal spaces that are typically involved and relevant in the context of seasonal forecasting. These are summarised in Figure C-1.

The analyses are based on observational and model data. In the analyses we use two hydrological models – VIC and PyTOPKAPI – with a dedicated setup allowing analyses at large-scale, countrywide scale. The two models are described below, and their configuration and results of initial testing are described in the Appendix.

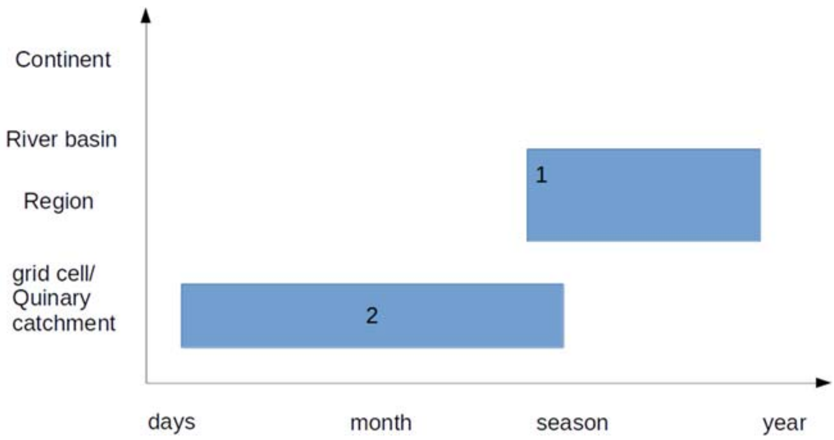

Figure C-1: Range of spatial and temporal scales covered by the explored analytical approaches; (1) is the assessment of surface run-off as an integrator of climate forcing, and (2) is the assessment of hydrological processes as a means to constrain uncertainty of climate forecast

C.2 Hydrological Models

Two models were implemented to simulate hydrological response over the domain covering South Africa. Both models were forced with the same climate data set, namely, WATCH WFDEI, which forms the basis for analysing the relationship between climate and hydrological variability. Both hydrological models used in the project – VIC and PyTOPKAPI – are grid-based and primarily concerned with vertical water balance in soil column. These water balance models can be linked with a routing model to generate streamflow. In fact, initial runs of the routing model of VIC model have been performed. However, results of the routing model simulations suggested that the standard parameterization and configuration of the routing model do not produce realistic streamflow. The fact that simulations of streamflow within the adopted modelling tools are deficient, does not, however, affect the usability of the two models in the context of the project. This is because the focus of the analyses is on the spatial heterogeneity of surface hydrological processes, which can be mapped through the outputs of the water balance model in a more consistent way than that obtained by mapping streamflow responses from a set of catchments of varying size and properties.

The two models are similar: they both rely on grid-based water balance calculations that consider only the vertical movement of water with the excess of water (surface and groundwater run-off) transferred through a channel network without further interaction with downstream cells. The models, however, represent two different approaches in addressing heterogeneity of the hydrological environment. In the PyTOPKAPI model, the heterogeneity is treated explicitly by using grid boxes that represent internally homogeneous units and are thus by necessity small – typically smaller than 1 km^2. In the VIC model, there is no requirement that the grid boxes are internally homogeneous as VIC handles internal heterogeneity with a sub-grid parameterization scheme (variable infiltration capacity scheme), using distributions of parameter values rather than a single parameter value and using tiles (i.e. sub-units that are not spatially explicit). Typical VIC grid sizes are larger than 100 km^2.

The simulations by both models seem realistic at the regional scale, although representation of hydrological responses at smaller scales remains somewhat deficient. Model results are relatively robust with respect to the forcing data sets. Initial tests of model performance indicate their ability to reflect spatial differences in the character of rainfall-run-off relationship.

C.3 Assessment of Surface Run-off as an Integrator of Climate Forcing

Exploratory analyses that were carried on the climate fields and hydrological modelling outcomes presented here were motivated by the need to inform development of robust indices of skill of seasonal forecast that move away from dependency on high-resolution time series of small-scale (rain gauge scale) responses.

C.3.1 Method

The analytical method developed here is based on schematizing forcings and responses in the form of broad classes describing their seasonal evolution. The index used to express the forcing-response relationship, i.e. a class based on similarity of month-to-month evolution of forcings and responses, captures the broadly defined 'type' of a season, which is independent on the high frequency characteristics of input or response time series.

We used two formulations of classes of forcing – one dependent on rainfall only; the other dependent on joint evolution of rainfall and mean temperature. The types of seasonal evolution of forcings and responses were derived for individual homogeneous climate zones. These zones were derived based on a nested clustering process capturing differences in seasonality and long-term variability of rainfall.

Since both sets of classes that are being compared (i.e. classes of climate forcings and classes of hydrological response) are categorical, and there is no a priori knowledge that class should map to which, we have used a chi-square contingency table test to analyse the correspondence between them, with p-value of the chi-square statistic used as a measure of the strength (significance) of the correspondence.

Hydrological responses to climate forcing based on regional hydrological modelling were obtained with VIC hydrological model forced with reanalysis (pseudo-observed) climate fields.

C.3.2 Results

The results for association between the climate (rainfall and temperature) anomaly classes and run-off anomaly classes are illustrated in Figure C-2 while Figure C-3 shows associations for anomaly classes derived from rainfall data only.

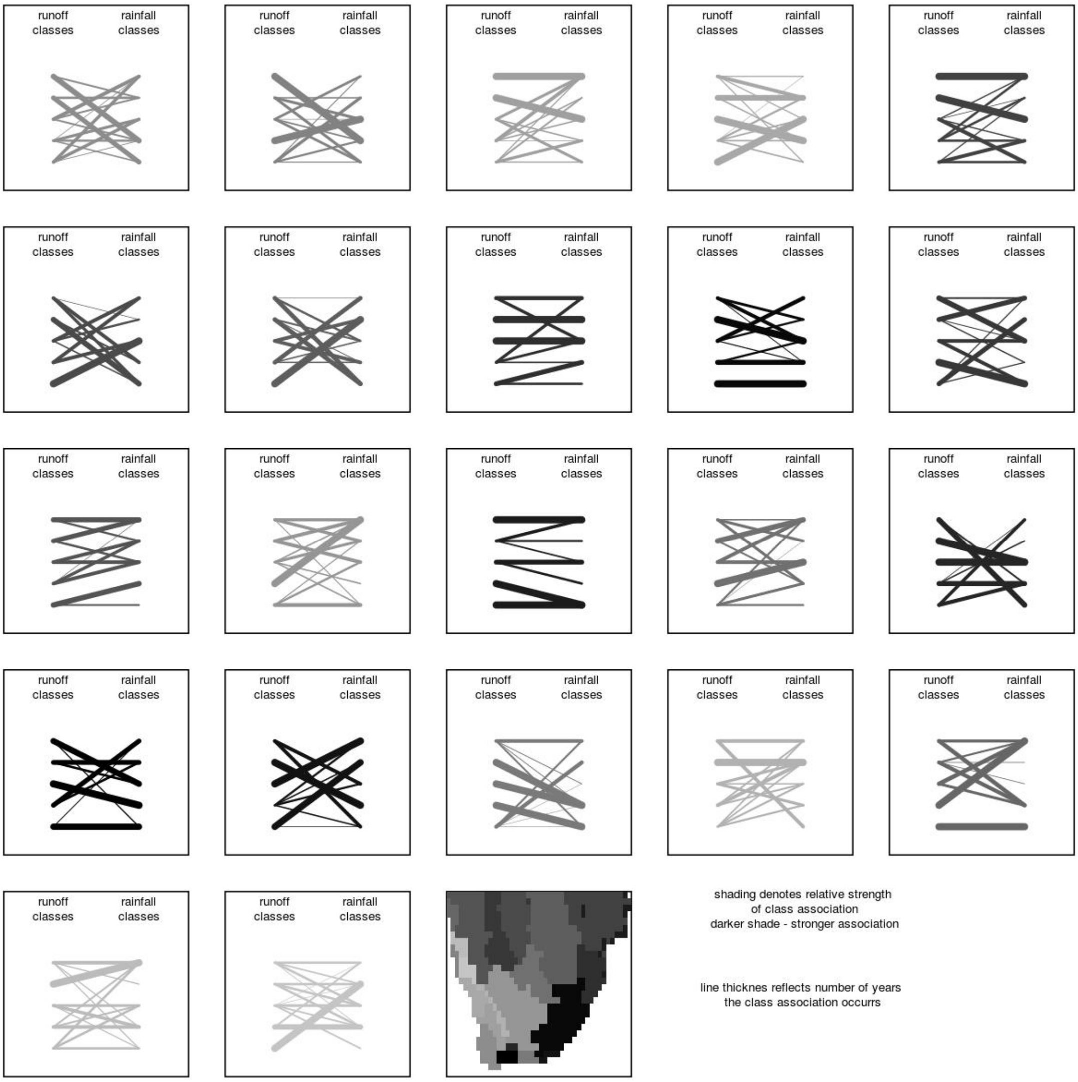

Figure C-2: Association between run-off seasonal anomaly classes and climate (rainfall and temperature) seasonal anomaly classes for each of the climate zones. Shading reflects strength of association measured by a ranked p-value of chi-square contingency table test. Line graphs illustrate linkages between forcing and response classes presented as a set of nodes. Line thickness proportional to the number of years when a particular forcing class maps on a particular response class. Here, the association is not statistically significant for six (lowest ranked, lightest in the figure) zones

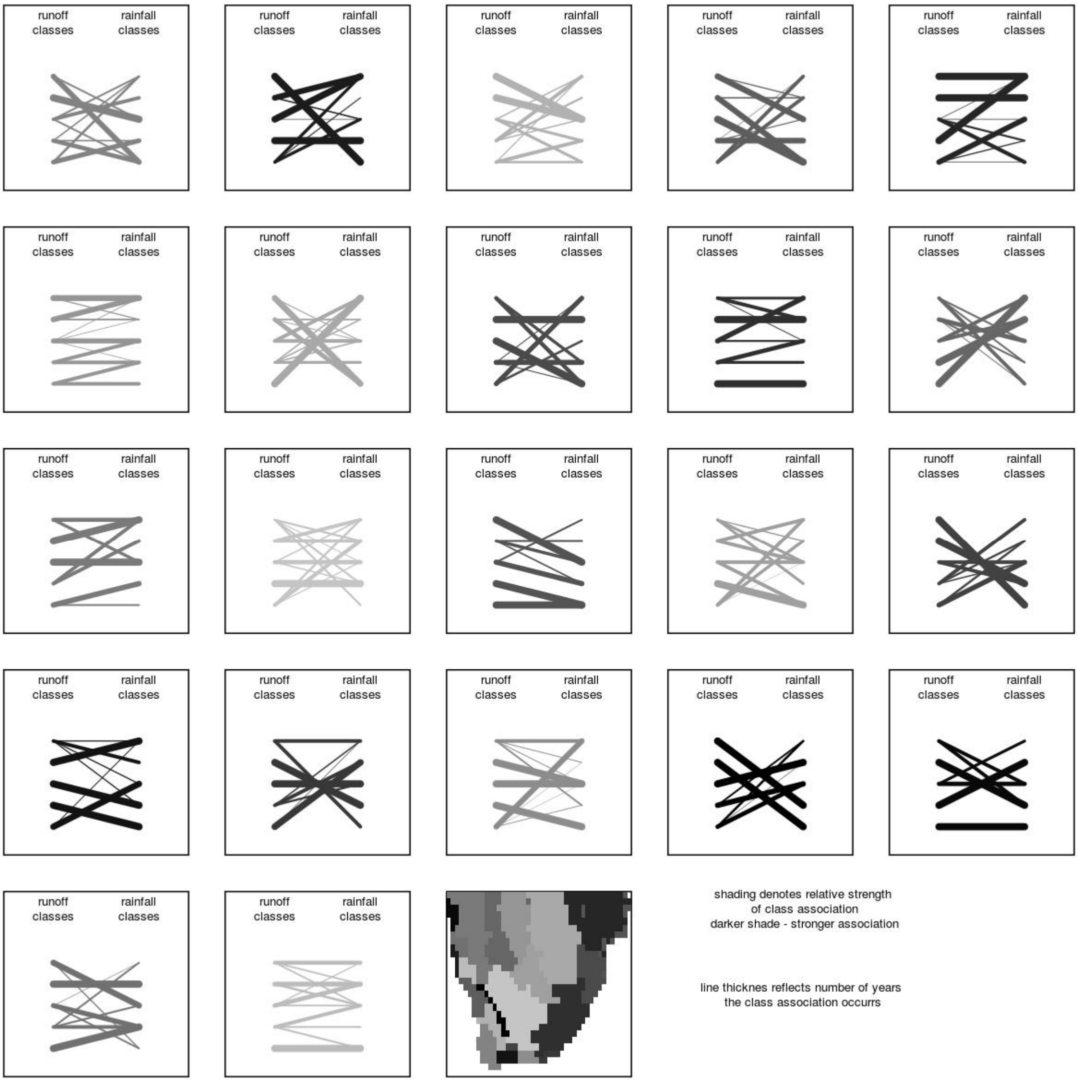

Figure C-3: Association between run-off seasonal anomaly classes and rainfall seasonal anomaly classes for each of the homogeneous climate zones. Here, the association is statistically significant in each homogeneous climate zone

C.3.3 Conclusions

The results of these analyses and experiences obtained while developing and testing modalities of the method can be summarised as follows:

Typical seasonal progressions of climate and hydrological responses

1. The process of derivation of classes in forcings and responses indicated presence of continuum of evolution types rather than distinct classes. This requires some level of arbitrary decisions to be involved in the process of class identification.

Association between rainfall-temperature and rainfall-only anomaly classes and run-off anomaly classes

2. Not surprisingly, strength of association between forcings and response classes varies in space and forms a regional gradient: it is somewhat stronger in the east of the country, and that strength reduces toward the west.

3. Surprisingly, however, the association between rainfall-only classes and run-off classes appears to be stronger than that between rainfall-temperature classes and run-off classes. This is perhaps because the rainfall-only classes are better defined than the rainfall-temperature classes. Also, there are differences between the two sets of classes in spatial patterns of association strength.

The overall conclusion is that there is a clear spatial heterogeneity in the way classes of seasonal climate evolutions translate into the hydrological response (surface run-off) evolutions. That translation is better in the eastern regions and along the south coast of South Africa, and worse in the inland and west coast regions. That relationship seems to generally correspond to the degree of wetness, i.e. it is better in the regions of higher rainfall, and worse in the arid zones.

Overall, we conclude that the method used here offers some potential opportunities in the context of formulating robust seasonal climate and hydrological responses that are not reliant on the traditionally used indices that focus on mean response calculated at a daily to monthly time scale.

C.4 Assessment of Hydrological Processes as Means to Constrain Uncertainty of Climate Forecast

C.4.1 Introduction

The focus of this avenue is to conduct and analyse model experiments to investigate the role of hydrological processes as represented by a land surface (hydrological) model, in transformation of uncertainty of climate forecasts (or simulations) into uncertainty of hydrological responses.

Specifically, we address the question of spatial and temporal differences in the propagation of uncertainties in the climate-hydrology modelling chain as determined by the hydrological processes and their parameterizations. We identify geographical regions where hydrological processes and parametrizations exert stronger influence on uncertainty of modelled responses, and where that influence is weaker. Similarly, we identify seasonal differences in the propagation of uncertainties. We do it with the outlook to identify geographical areas, seasons and characteristic integration times where hydrological forecasts can potentially improve weather forecasts.

C.4.2 Conceptual setting

This work builds on the concepts of uncertainty, reliability and predictability of climate simulations, and since these are often confused, we outline their understanding adopted in this work.

Uncertainty

Climate simulations uncertainty results from the chaotic nature of the climate system and is rooted in the sensitivity of the climate system’s response to the initial condition. It manifests through the spread of forecast states obtained with climate models initialised with various (perturbed) initial conditions (Figure C-4). In forecasting, the irreducible uncertainty present in the climate system at a time scale exceeding several days has led to the adoption of probabilistic rather than deterministic forecasting paradigm, where a distribution of possible system states is forecast rather than a particular system state. That distribution is obtained from the initial condition ensemble simulations.

Additional uncertainties arise in the climate modelling chain due to the necessary simplifications inherent to the modelling system. This source of uncertainty is addressed by multi-model or perturbed physics ensemble simulations. Within probabilistic forecasting, these are often used to prevent underdispersion of modelled results; i.e. inability of initial condition ensemble to generate climates covering the entire possibility space.

Reliability

Forecast reliability, within the probabilistic forecast paradigm, relates to how well the distribution of states simulated by the forecast ensemble maps onto the possibility space of the modelled system. The reliability captures such aspects of model simulations as the systematic model error (bias), non-systematic error, and under- or over-dispersion. It is worth mentioning that forecast reliability is quantifiable by a number of scores within formalised forecast verification routines. Here, however, we use term reliability in its broader, qualitative sense.

Predictability

Formally, predictability is the extent to which events/states can be known in advance. In the conceptual setting adopted here, predictability has deterministic meaning, and manifests by the size of the possibility space. Conditions that have large possibility space are less predictable than those for which possibility space is smaller. This pertains to the possibility space of the actual modelled system, which may be represented in the climate model space with various degrees of success, depending on model reliability. The concept of predictability can also be applied to probabilistic forecasts, where predictability becomes similar to model reliability.

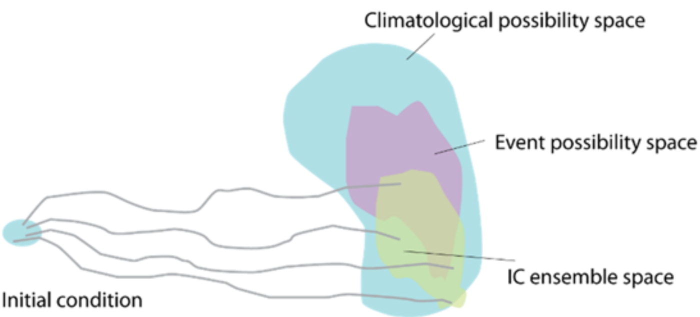

Figure C-4: Schematic illustrating concepts of uncertainty in climate simulations/forecasting. Climatological possibility space encompasses all possible system states. Event possibility space encompasses all possible system states conditional on a particular boundary forcing. Initial condition (IC) ensemble space encompasses model states obtained within initial condition ensemble simulations. Size of the event possibility space is equivalent to deterministic predictability. Overlap between initial condition ensemble space and event possibility space expresses forecast reliability

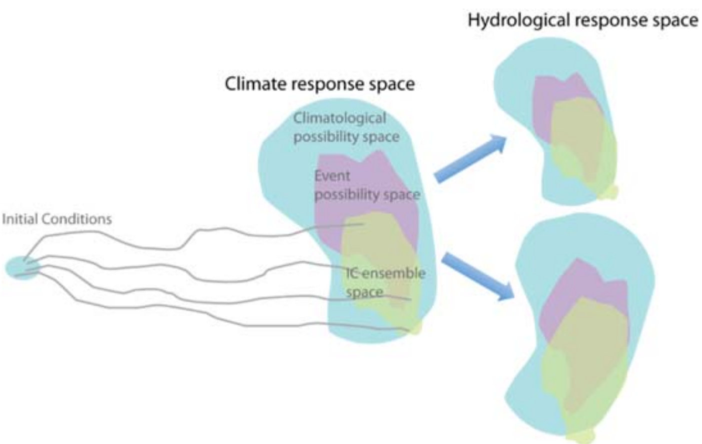

Figure C-5: Schematic illustrating transformation of climate uncertainties into uncertainties of hydrological responses. Hydrological environment, depending on feedbacks and role of water storages can have different influence on uncertainties of hydrological responses. Hydrological model uncertainty may expand the initial condition (IC) ensemble space

Uncertainties in the climate-hydrology modelling chain

The character of hydrological environment (land surface) is by nature different than that of the climate system. Because of the water and energy storages that act at a number of temporal and spatial scales, the hydrological environment usually dampens or integrates variations of fluxes at land surface, and that dampening is progressively stronger in three different contexts:

- Process context: integration increases from surface run-off to soil moisture fluxes to groundwater flows.
- Spatial context: the integration increases from soil pore scale to field scale, to hillslope scale, to the scale of subcatchments of increasingly higher order, to the basin scale.
- Temporal context: integration increases with the length of the integration period.

The degree of dampening within the hydrological system depends, obviously, on the characteristics of the land surface (soil properties, land cover, topography etc), and thus varies from location to location. One can picture this simply by considering that given the same climate forcings, different hydrological environments would generate different responses, or as illustrated in Figure C-5, different magnitude of hydrological response possibility space.

When climate fields are used to force hydrological model, climate field uncertainty propagates into the uncertainty of hydrological responses with an additional level of uncertainty added, that reflects hydrological model uncertainty, and the uncertainty of initial conditions in the hydrological system. This manifests by expansion of the initial condition ensemble space within the hydrological domain.

C.4.3 Method

The purpose of the analyses was to investigate relationships between the levels of uncertainties present in the ensemble simulations, expressed as ensemble spread, in drivers (rainfall) and responses (surface run-off and soil moisture in VIC, and soil moisture in PyTOPKAPI) to determine the spatial and temporal relationships between these uncertainties, that would ultimately allow for systematization of constraints the hydrological environment puts on forecast uncertainty. Details of the methods are presented in the Appendix, and below, we present only its general aspects.

In the design of model experiments, we focus on continuous model simulations under observed SSTs, rather than on forecasts. This allows the posed questions to be addressed without the unnecessary complications arising from the uncertainty in boundary (SST) forcing.

We conduct the experiments within a pseudo-reality paradigm – i.e. we relate modelled ensemble responses to model responses under reference conditions rather than to observations. Again, this allows for avoiding complications arising due to hydrological model uncertainties.

In the ensemble simulations, VIC and PyTOPKAPI are forced by Atmospheric Model Intercomparison Project (AMIP3) GCM data. The AMIP3 GCM data are atmospheric model simulations (hindcasts) conducted in the framework of AMIP3 initiative feeding into the IPCC AR4 assessment. The AMIP3 simulations include model runs performed with a number of AGCMs under prescribed observed SST.

This experiment is formally a multi-model ensemble experiment, which is not able to capture the initial condition uncertainty of a typical initialised forecast explicitly. This is because in AGCM model runs, simulations are started once at the beginning of the simulated period, and no atmospheric observations are assimilated during the simulated period. The prescribed SSTs, however, constitute the boundary forcing. At individual time steps, the experiment, therefore, simulates a situation analogous to a typical seasonal forecast, although likely with considerably inflated range of initial conditions, both within climate model and hydrological model, and without the uncertainty related to the forecast of SST forcing.

We use the PyTOPKAPI simulations to illustrate reduction in uncertainty of climate forcings within the hydrological environment by (qualitatively) comparing spread of climate forcings ensemble with that of hydrological responses on the daily time scale.

The analyses carried on the basis of VIC simulations address quantitative aspects of uncertainty reduction, as explained below. We analyse two hydrological responses obtained from the VIC model at grid level: surface run-off and soil moisture in the uppermost soil layer.

To account for the temporal context of factors affecting uncertainty, we perform analyses for various integration times. For that, we calculate running means for each analysed variable for each analysed integration time. That running mean allows for assessment and visualization of uncertainties (ensemble spread) for a selected integration time on a time-continuous basis.

Comparison of the role of hydrological processes in transformation of uncertainty, within such defined experimental framework, can be expressed as:

$$x_{VR} = \frac{x_{IQRstd}}{P_{IQRstd}}$$

Where

- P_{IQRstd} is standardised interquartile range (IQR) for rainfall.
- P_{IQRstd} is standardised IQR for the analysed variable.
- The standardised IQR is analogous to the coefficient of variation and is obtained by dividing ensemble's interquantile range by ensemble median.
- The x_{VR} is dubbed an uncertainty reduction factor.

C.4.4 Results

Qualitative illustration of uncertainty reduction within PyTOPKAPI simulations

Simulations by PyTOPKAPI hydrological model focused on daily time scales and on qualitative description of the uncertainty propagation as manifested by spread of the ensemble. Spatial distribution of forcing data sets for a selected day is shown in Figure C-6 and Figure C-7. These figures illustrate a clear spread of the AMIP5 forcing data, and differences between the ensemble members not just in magnitude, but also in the spatial pattern of climate variables.

The results of simulations expressed in terms of SSI are illustrated in Figure C-8. While the temporal evolution of SSI does display a considerable spread (not shown), the similar spatial patterns of SSI for the various ensemble members (Figure C-8), when juxtaposed against the differences in spatial pattern of rainfall/temperature/evaporation, clearly expresses that considerable narrowing of uncertainty takes place within the modelled hydrological environment.

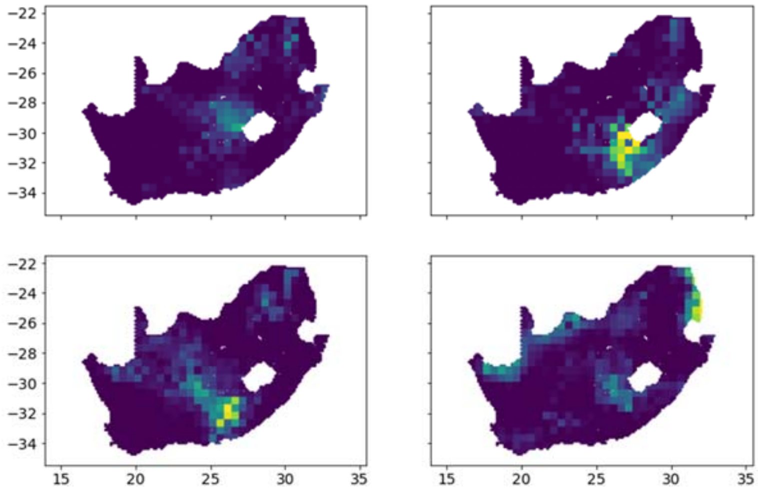

Figure C-6: Spatial distribution of rainfall on a day from four of the ensemble members. The colour scale ranges from dark blue (low) to yellow (high). Of note are the very different spatial patterns of rainfall on the day, but a similar range in the values (the colour scales in each panel are identical)

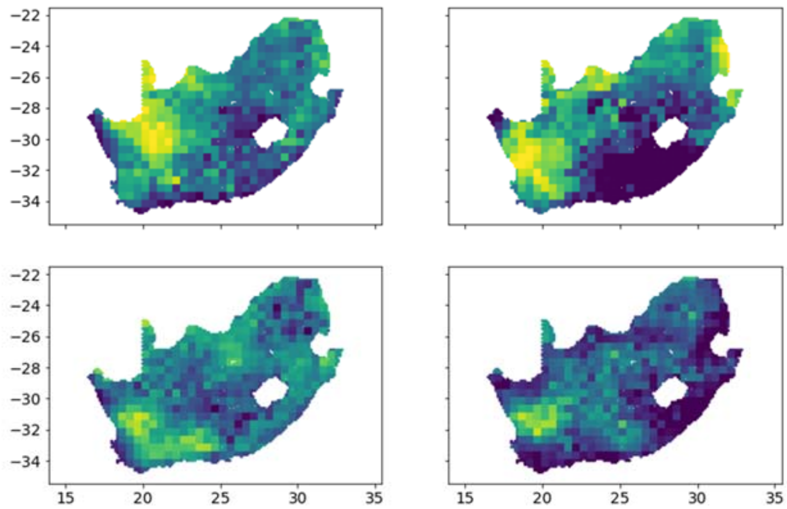

Figure C-7: Spatial distribution of ET_0 *on a day from four of the ensemble members. The colour scale ranges from dark blue (low) to yellow (high). Of note are the very different spatial patterns of* ET_0 *on the day, but a similar range in the values (the colour scales in each panel are identical)*

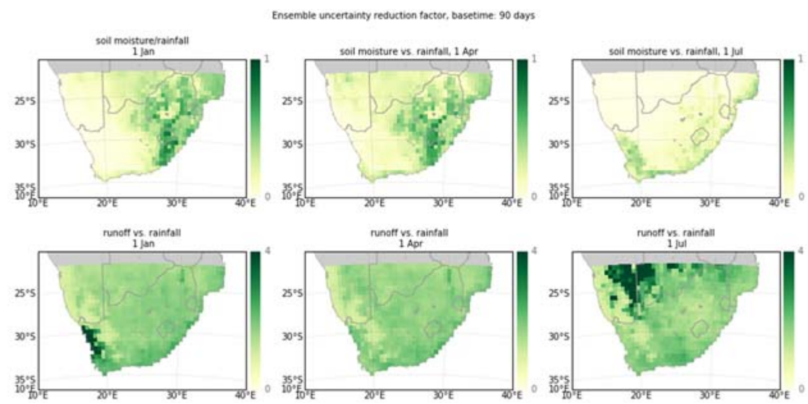

Figure C-8: Distribution of uncertainty reduction factor the considered variables and three seasons for 90-day integration periods. Soil moisture – top row, run-off – bottom row

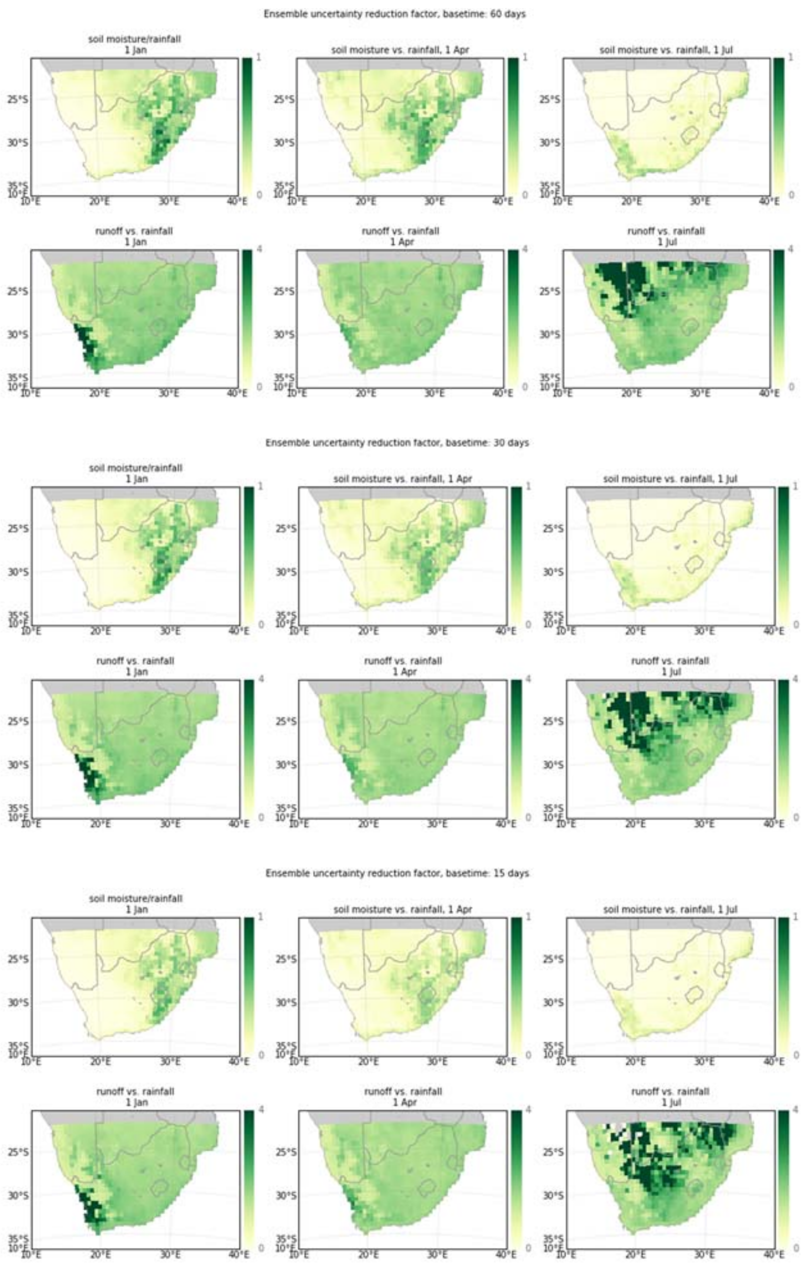

Figure C-9: As Figure C-8, but for different integration periods

Spatial aspects of ensemble spread and uncertainty reduction factor – VIC simulations under AMIP3 ensemble forcing

There is a considerable spatial heterogeneity in the uncertainty reduction factor throughout the modelled domain (Figure C-8, Figure C-9). Higher values (relative inflation of uncertainty) occur during the dry seasons (thus creating differences in seasonal signal between the summer and winter rainfall region. There is a general pattern of increase of uncertainty (somewhat unexpectedly) with shorter integration times. Run-off response generally inflates the relative ensemble spread, while soil moisture response generally reduces it.

For run-off, the lowest inflation of uncertainty is observed in the semi-arid region that is transitional between the winter and summer rainfall zone – stretching from Namaqualand toward western Namibia. The western part of the Western Cape and interior of South Africa (Karoo and Kalahari, as well as parts of Mpumalanga's Lowveld) display strong inflation of uncertainty. The east coast (KwaZulu-Natal and

Eastern Midlands) as well as southern Karoo have moderate levels of run-off uncertainty inflation, and these are stable throughout the year. The spatial patterns present in uncertainty of run-off response do not correspond to patterns of rainfall, run-off or soil moisture levels.

For soil moisture, the eastern part of South Africa is characterised by weaker reduction of uncertainty, and that reduction is stronger in the dry wester part. This spatial pattern is relatively consistent with the overall wetness as expressed by mean annual rainfall, although there is clearly a considerable level of intricacies in smaller-scale spatial patterns present within wetter eastern part of the country.

A more comprehensive and detailed set of results can be found in the Appendix.

C.4.5 Conclusions

The analyses performed here allowed for understanding how climate forcing uncertainty as expressed by the spread of a multi-model ensemble propagates through the hydrological system. Although qualitative assessment performed based on the simulations with PyTOPKAPI suggests that the reduction of uncertainty occurs throughout the analysed domain, the quantitative analyses performed with VIC simulations suggest that the picture is more nuanced. We have identified regions and seasons when there is relative inflation of uncertainty and relative reduction of uncertainty in responses as compared to the levels of uncertainty in climate forcing (rainfall).

Overall, the approach appears informative in the intended purpose, i.e. for understanding of spatial and temporal aspects of propagation of signal uncertainty within hydrological environment. However, it appears that its applicability is limited to assessment of relative effects between various locations, or between various seasons. Considering this limitation, the approach is still useful to differentiate between the regions (or the seasons) where hydrological responses are likely strongly sensitive to the forecast variables, and where they are less sensitive. This knowledge does inform about the robustness of a hydrological forecast.

C.5 Synthesis of Results of Hydrology-based Analyses

We presented three sets of analytical avenues that are based on hydrological responses and provide contextual information allowing interpretation of seasonal forecast data and seasonal forecast quality, and thus also seasonal forecast skill, particularly in the context of forecasting of ‘impact’ variables. Although the analyses are not exhaustive, i.e. they do not explore individual approaches at depth and comprehensively, the results show potential of these alternative approaches, and we trust their details can be addressed in the future in the context of relevant practical applications.

Generalising, the analyses reveal the following:

- That there are spatial differences, which are likely related to hydrological processes and their parameterization, in how well hydrological responses reflect the year-to-year (and by extension also season-to-season) differences in evolution of climate forcings. This is likely attributed to the influence of the role of initial conditions, but also to the importance of threshold-dependent hydrological processes. This has implications to the assessment of forecast performance in terms of hydrological responses.
- That there are spatial and seasonal differences in how hydrological processes constrain, or in other words, ‘organise’ noise in climate forcings. These differences are likely attributed to a specific combination of hydrological processes, including threshold-dependent ones, acting at local scale. These differences, again, have implications to the assessment of forecast performance in terms of hydrological responses.

Appendix D: FORMULATING AN INTEGRATED METHODOLOGICAL APPROACH OF SOM TRAJECTORIES AND THEIR APPLICATION IN SEASONAL FORECASTING

D.1 Context

The climate system is inherently coupled across scales of time and space with significant interdependencies, and the global modes of variability reflect the underpinning processes that condition regional climate. The strength of this conditioning is variable, non-linear, and may be a function of a given mode of global processes. As such it is important to understand these conditioning modes not only in their individual nature, but also in how they work together to affect the region of interest.

For South Africa, the classically accepted conditioning mode is the ENSO, and much is made of the dominance of ENSO when determining summer rains for South Africa. However, it is equally apparent that ENSO is only one among multiple processes of interest; that ENSO is not consistently influential as a function of the state of ENSO; and that the influence varies in nature between years. This is indicative of the fact that the southern Africa region can, in large part, be considered a 'climate receiver', which means that the collection of global modes are together the conditioning factor on the regional seasonal climate. For example, it is known that the TTTs are strongly influential in the intra-seasonal rains, but that TTTs are in turn sensitive to the positioning of the mid-latitude westerly waves, the seasonal positioning of the hemispheric Antarctic Oscillation, and the intra-seasonally varying Madden–Julian Oscillation.

In considering skill of the GCMs for seasonal forecasting, the ability of a GCM to reflect these global modes of variability is essential; not all modes are critical for southern Africa, but at the same time the interaction of the modes can be as important as each mode by itself. Again, the cross-scale interactions in time and space of the climate system make this of deep importance to the forecast skill. While in isolation a mode may or may not be of key importance to the region, nonetheless all modes influence other modes and hence are indirectly important. The short perspective is this: it is not sufficient that a GCM can capture the climatology of a region, nor that a GCM captures each of the global modes independently, but that a GCM credibly reflects the interconnected cross-scale behaviour of the dominant modes of variability that are relevant drivers of local climate responses.

There is a long history in the scientific literature of considering the global modes in their independent nature, and in many cases, this is reduced to an index (e.g. ENSO). These indices are useful in that help characterise key modes of variability, but the indices are nonetheless imperfect representations and assume a measure of spatial stationarity. Furthermore, the lead-lag interrelationship of these modes is notably non-stationary and introduces a multi-dimensional complexity that is reflective of the chaos basis of the climate systems variability. The simplicity of indices is appealing, and De Viron et al. (2013) is one example that lists and characterises indices, constructs a set of relationships between indices, considers their teleconnection in context of SST fields, and examines the lead-lag differences and spectral behaviour of the indices.

From this perspective, it is clearly possible to analyse firstly, to what extent the individual indices, or their combination, explains the variance in rainfall/temperature or any other variable relevant from the point of view of impact at seasonal time scale. It is also possible to assess the ability of a GCM to replicate these indices. At one level this is useful, and such approaches are helpful for assessing the deterministic predictability and evaluating the relative performance of different models (e.g. see the GCM chapters of WG1 in the IPCC assessment reports). However, such an approach is limited as it relies on a set of variables, or indices that are defined a priori, and do not necessary take cognizance of cross-scale behaviour of processes within the climate system.

The exploration of the literature indicates a strong need to consider the problem differently, in particular by taking an approach that views the holistic interaction of the modes and atmospheric dynamics at a range of scales as the system semi-deterministically evolves through the seasonal cycles. While others have taken approaches such as eigenvector decomposition (e.g. Messié & Chavez, 2011), here we choose to use a method that makes as few assumptions as possible of linearity and temporal relationships. The method is based on schematizing the complex, multi-dimensional state of the atmospheric system in the form of two-dimensional array of states represented by SOM nodes.

D.2 SOM Patterns of Variation

With a view to assess the processes that underlay predictability of climate, and to evaluate their representation in the model and forecasts, there are two avenues: assessment of processes/modes independently, or consideration of the cohesive whole of the climate system. For the reasons outlined above, we approach this from the view of the cohesive whole. For this purpose, SOMs offer a number of methodological advantages.

SOMs are a well-established methodology; initially introduced to the climate community by Hewitson and Crane (2002) it has since received wide adoption. Some advantages of the technique are the minimal assumptions about the data, robustness in the presence of noise, ability to handle complex multi-dimensional data, and facilitating helpful visualisation of the generalised data. The technique identifies a user-determined number of exemplar states that represent the span of the continuum of data.

The approach in this context is to map out the exemplar states of the observed global system, and then to map the forecast model's representation of these states onto this distribution of modes. By examining the differences between the observed and modelled climate states, and with examination of the underlying differences in the atmospheric variables, the SOM can help assess, firstly, whether climate predictability arises within the part of the atmospheric system that is resolved by a GCM, and secondly, where and how the models are weak in their representation of drivers of climate variability.

The SOM represents the continuum of the data space by a matrix of exemplar nodes; adjacent nodes are marginally dissimilar and represent the progression of change in state. Likewise, nodes widely separate are markedly dissimilar and represent fundamentally different modes. The SOM output is analogous to cluster analysis in that it is possible to associate any one-time slice in the data with an exemplar node, and likewise analogous to eigenvector analysis in that it identifies the fundamental axes in the data around which the variability occurs.

For applying the data to the SOM we undertake a number of pre-processing decisions/steps.

1. Select appropriate variables. For this analysis, we are looking at coarse resolution global patterns indicative of the fundamental thermodynamic state. Here we initially use the wind (u;v), specific humidity (q), and air temperature (t) all at 77 hPa.
2. Select reanalysis data. For a coarse scale global analysis, any of the contemporary reanalysis data sets is probably adequate. As we have most experience with the ERA-Interim data, we choose this and span the period 1979–2012. As we are interested in the general state of the climate system, we use monthly averages.
3. Select model forecast data. For this stage of the analysis we focus on the Hadley unified model (HadAM3P) as used in operational seasonal forecast by Climate System Analysis Group (CSAG) at the University of Cape Town. The data is selected initially from forecasts for the DJF season for the 7 years.
4. Interpolate to a coarse common grid. As the reanalysis and model data are on different grids, it is necessary to interpolate to a common grid. Further, since the coarse global patterns are the focus, we interpolate to a relatively coarse grid of 5° latitude by 7° longitude, which introduces a measure of smoothing to the data.

5. Standardise the data. As multiple variables of different numerical range are combined in the SOM, and as SOMs respond to the variance structure of the data, it is necessary to scale the different variables to place them on an equal footing in the SOM. The standardisation is done by time for each grid cell.
6. Latitudinal weighting of the data. As noted above, the SOM responds to variance, and with the convergence of longitude toward the poles, this would artificially weight the variance of the poles in influencing the SOM mapping. To compensate for this, we weight the data by the square root of the cosine of latitude to ensure that each grid point is weighted by the area it represents.

Training a SOM begins by setting up a matrix of nodes where each node has an associated data vector (initially randomised) with the same dimension at the input data. The reference data, in this case the reanalysis data, is presented to the SOM algorithm one time step at a time. The data is matched to the node with the most similar node vector (the winning node), which is incrementally nudged toward the values of the presented data. Surrounding nodes are likewise nudged, but to a lesser degree as a function of the distance from the winning node. The next data time step is then presented, and the process repeated. This is iterated for many thousands of passes through the data (it is not possible to overfit as with regression processes) until an acceptable stability of the nodes is achieved. At this point, the node matrix is considered to be trained, and each node represents an exemplar state in the continuum of the data.

The reanalysis data are first used to train the SOM. Here, SOM of 7 × 11 nodes is used, giving the possibility for a relatively nuanced representation across 77 possible exemplar states. From the trained SOMs, the exemplar states of the global patterns on each node, the frequency of occurrence of these states, the mean seasonal cycle across the node matrix, and the comparative set of seasonal cycles for the individual years are plotted.

Following this, the unified model hindcast and seasonal forecast data are mapped to the SOM and evaluated where the model positions the seasonal modes relative to the reanalysis data. Lastly, we consider the differences between the model and reanalysis in terms of how the mode is deviating from the observed seasonal evolution. The following sections describe the initial results.

D.3 SOM Reanalysis Assessment

The first step in evaluating the SOM results is to consider the patterns of each variable associated with the trained SOM. Figure D-1 to Figure D-8 show the node maps from the SOM for the 7 × 11 node array, each representing an exemplar state of the climate system for the 700 hPa variables of temperature, specific humidity, and wind. Figure D-9 and Figure D-10 show the frequency of occurrence.

Figure D-1 and Figure D-2 for the air temperature most clearly show a classic split of the fundamental seasonal cycle from southern hemisphere summer states dominating on the lower right section of the array, complemented by southern hemisphere winter in the upper left quadrant. Across the secondary axis from the top right to lower left are the variation around the seasonal fundamental, including the transition seasons and natural variability. Matching this are the maps for the specific humidity (Figure D-3 and Figure D-4) and wind (Figure D-5 and Figure D-6). In the specific humidity maps, the strong positive anomaly over South Africa in the summer is clearly apparent, which is the source of the summer rainfall. A key driver for this is in the wind field, which shows the summer pattern of positive moisture flux from the east over the sub-continent. This result reflects the ability of the SOM to allocate discriminating power where the variability is dominant, a very positive attribute in the context of the objectives here.

These patterns over the sub-continent are central to summer rainfall. If the climate for the season is dominated by modes other than these, the impact on rainfall will be notable. However, a key point here is to not focus on the sub-continent itself, but to realise that these key patterns are part of a global system, and responsive to a global state.

In terms of the frequency of occurrence of each node's representative state, Figure D-7 and Figure D-8 most clearly show the summer/winter dichotomy of the system, and how the shoulder seasons fall into the patterns. Figure D-7 is the total frequency of occurrence of each node, and Figure D-8 breaks this down by season.

Figure D-9 represents a very important diagnostic and shows the time evolution of monthly states within the space defined by SOM nodes. That evolution is constructed and visualised as follows: The analysed atmospheric conditions are schematised within the SOM procedure so that each time step, month in our case, falls onto one of the SOM grid nodes. The temporal evolution of climate system's state can thus be mapped as a vector traversing from node to node – that is a trajectory through the SOM space. A climatological progression is then determined by considering the SOM space to be a Euclidean space, and averaging positions of nodes from a given month. Importantly, climatological trajectory coordinates take up continuous values (in the case of SOM analysed here in the range of 0–7 for × and 0–11 for Y), unlike the SOM nodes coordinates which are discrete.

Considering the objectives of the analysis, the SOM space trajectory becomes a useful way to visualise what is expected in terms of atmospheric conditions (i.e. climatology) as well as the effects of natural variability that manifest through deviations in climate system's state approached holistically. We can also relatively easily visualise how a GCM matches this behaviour. However, one must be very careful to not overinterpret this.

A few overarching messages can be drawn from Figure D-9:

- The SOM captures a clear seasonal cycle as represented by the reanalysis data.
- The HadAM3P model simulates a credible representation of the seasonal cycle.
- The forecasts are credibly within the domain of the observed climatology.

However, there are also suggestions of more information. First, that December and to certain extent also September in both the hindcasts and the forecasts are where the greatest separation lies between the reanalysis climatology and the model's representation of this. The suggestion is that the model is suffering most in the ability to represent the onset of the southern hemisphere summer. Second, is that with the greater resolving of states by the larger SOM, it is clear that the northern hemisphere summer has an enhanced range of climate states than is seen in the southern hemisphere summer. This is evident by the SOM allocating a greater portion of the SOM array to distinguishing these differences.

It is tempting to interpret this at the regional scale, but here we are particularly interested in how the global patterns differ as a step toward understanding where and why the models are deviating from expected behaviour. In the case of the December deviation, the clearest distinction (Figure D-2) is that the model has anomalously high polar temperatures compared to the reanalysis data. For the southern Africa domain there are suggestions that this translates to December in the model having weaker moisture transport into the region from the east (Figure D-6) than is seen in reanalysis data. An analysis if only undertaken on the regional domain of southern Africa would have shown this, but not revealed that from a global view one can see this is tied to, and perhaps dependent on a bigger picture of process state.

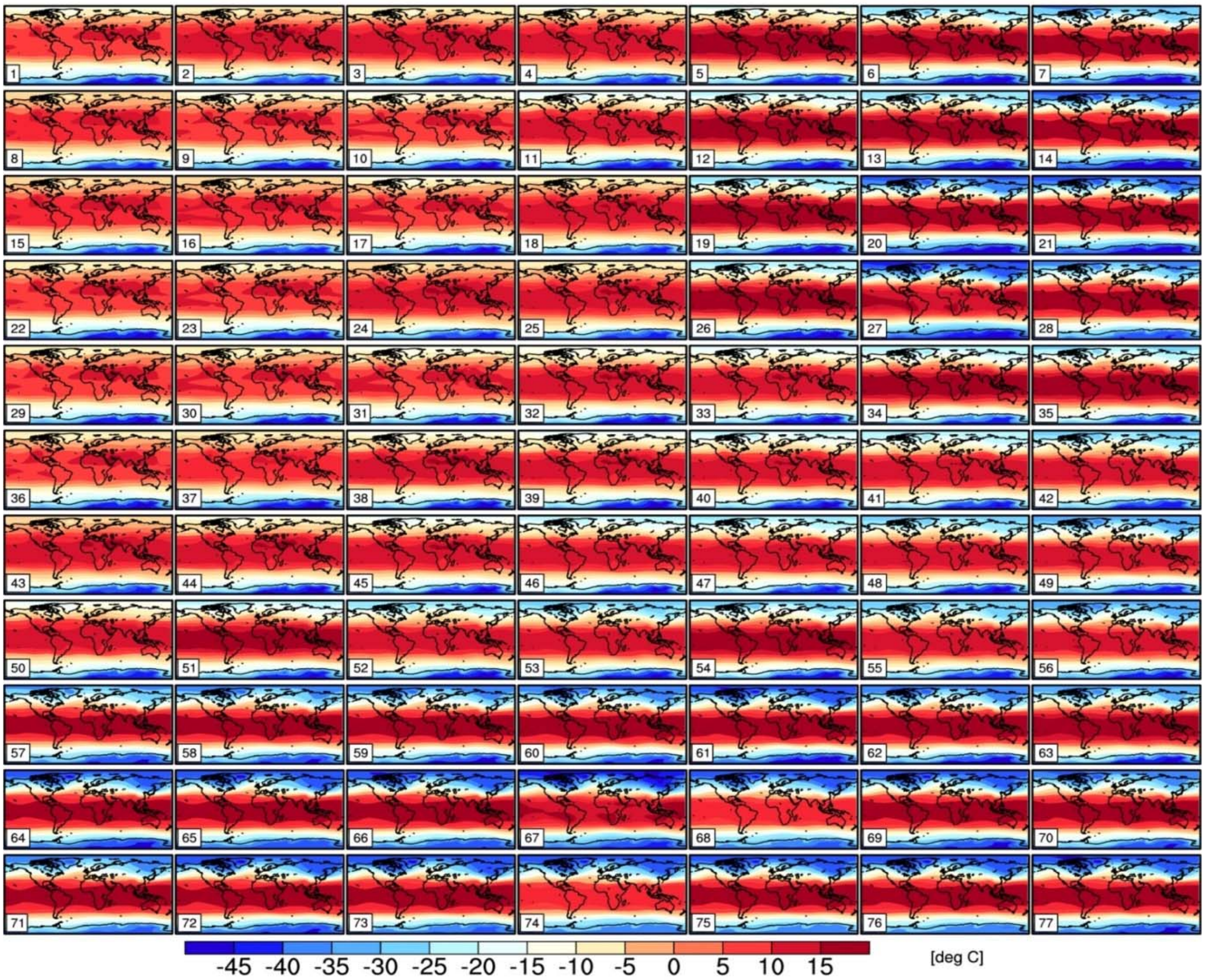

Figure D-1: The monthly air temperature at 700 hPa for a SOM with a 7 × 11 array of nodes trained on the collective of air temperature, specific humidity, and winds for 1972–2012 from the ERA-Interim reanalysis

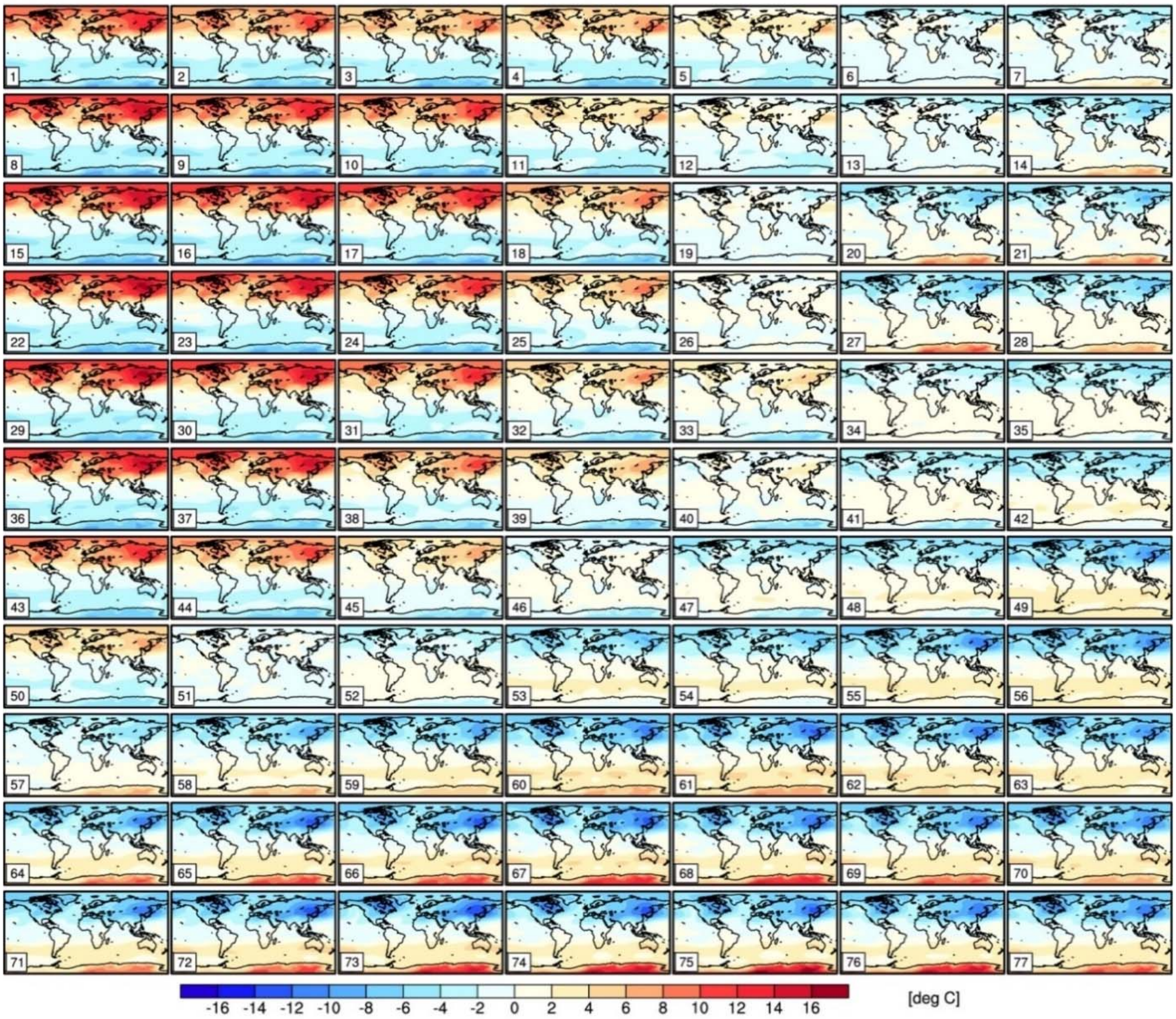

Figure D-2: Anomalies of the monthly air temperature (departure from the mean) at 700 hPa for a SOM with a 5 × 7 array of nodes trained on the collective of air temperature, specific humidity, and winds for 1972–2012 from the ERA-Interim reanalysis

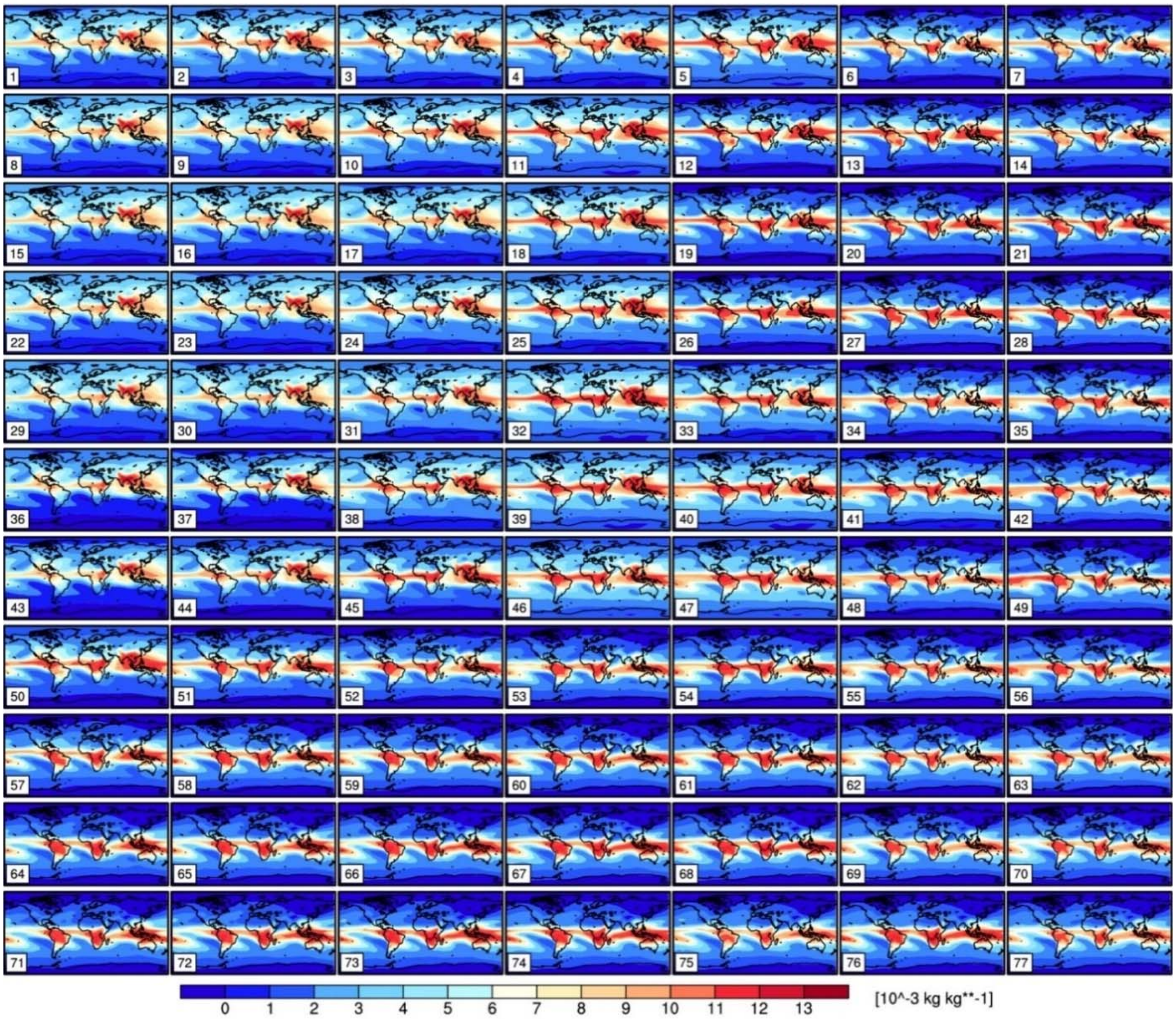

Figure D-3: The specific humidity at 700 hPa for a SOM with a 7 × 11 array of nodes trained on the collective of air temperature, specific humidity, and winds for 1972–2012 from the ERA-Interim reanalysis

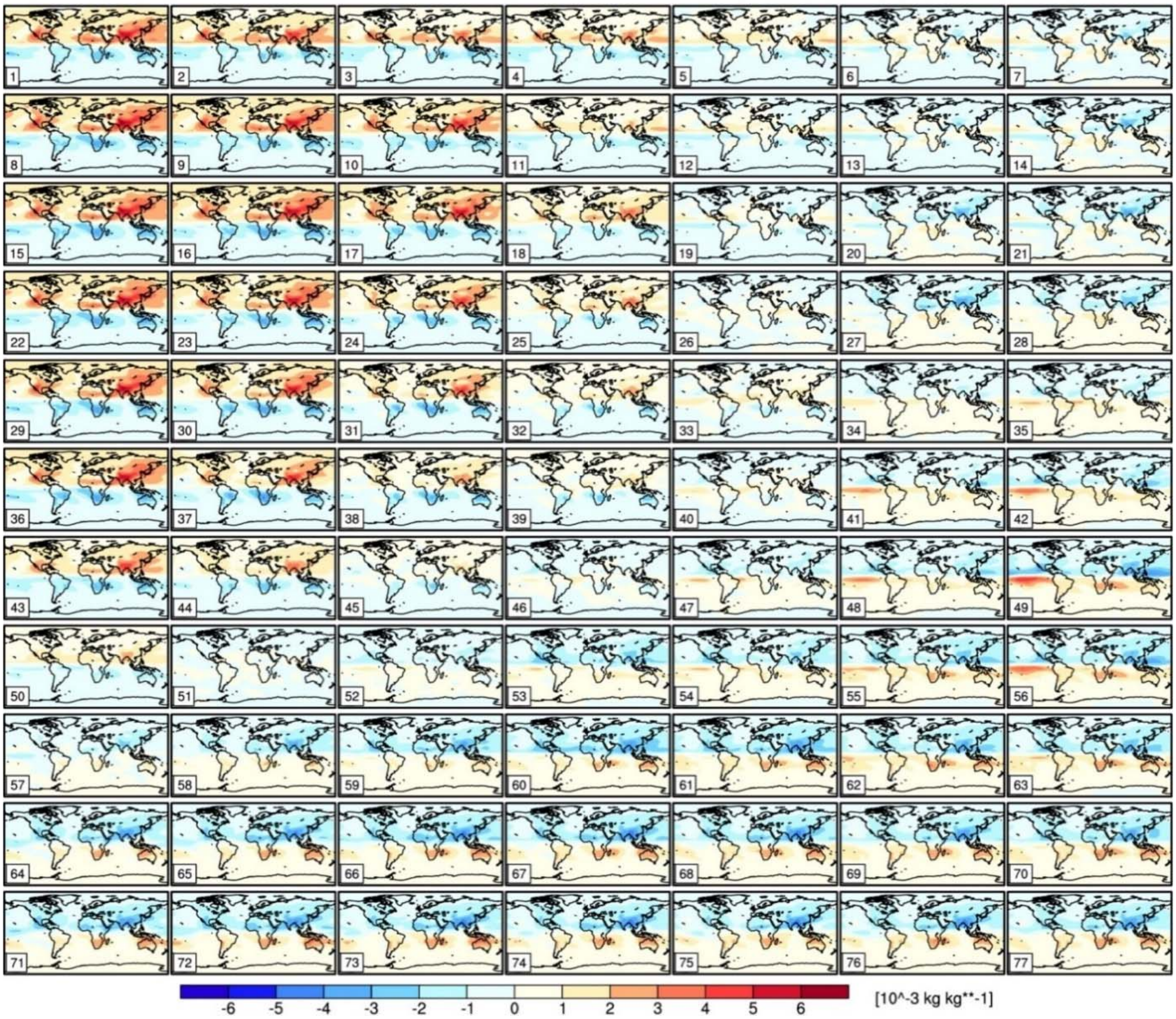

Figure D-4: Anomalies of specific humidity (departure from the mean) at 700 hPa for a SOM with a 7 × 11 array of nodes trained on the collective of air temperature, specific humidity, and winds for 1972–2012 from the ERA-Interim reanalysis

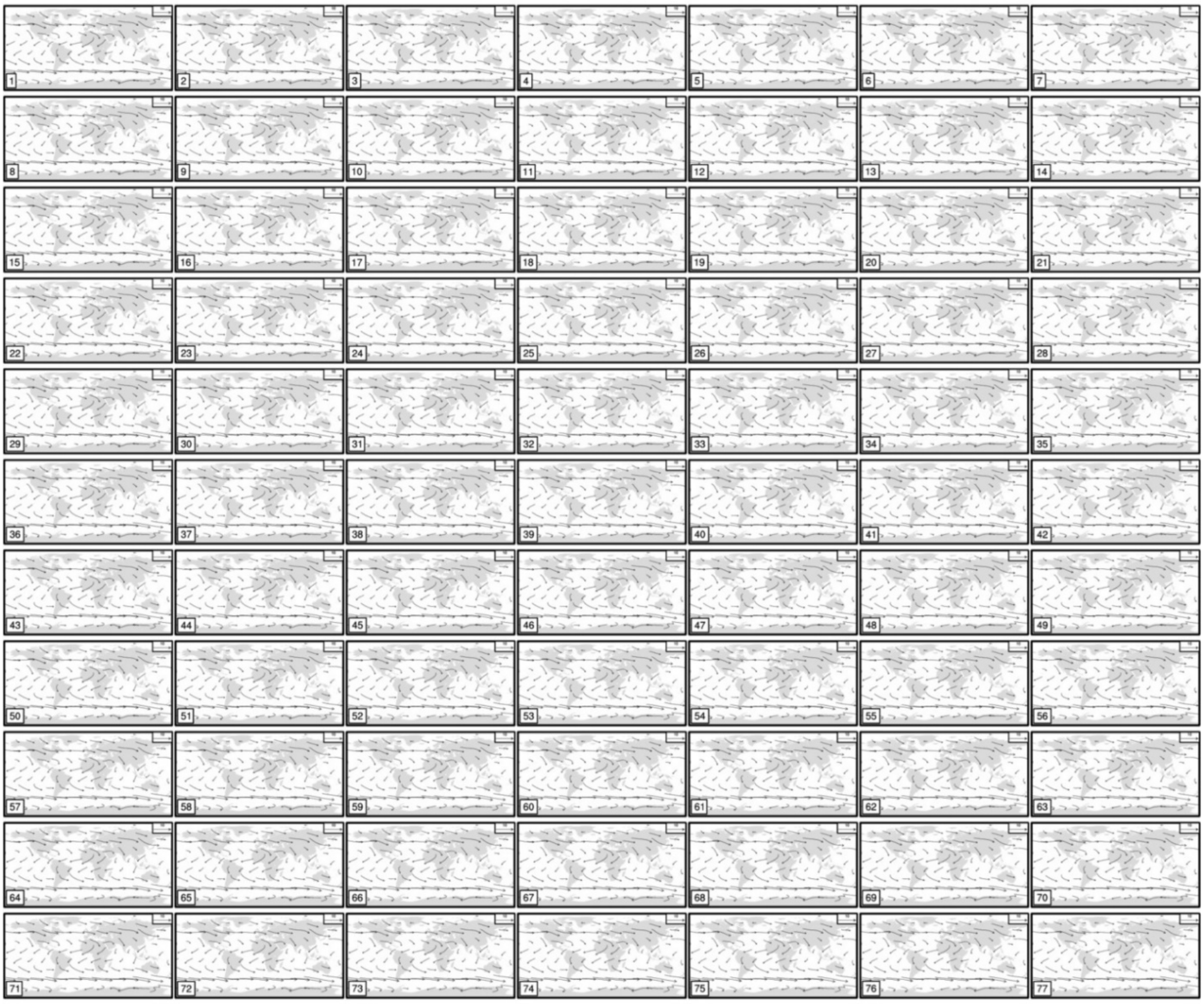

Figure D-5: The winds at 700 hPa for a SOM with a 7 × 11 array of nodes trained on the collective of air temperature, specific humidity, and winds for 1972–2012 from the ERA-Interim reanalysis

Figure D-6: Anomalies of wind (departure from the mean) at 700 hPa for a SOM with a 7 × 11 array of nodes trained on the collective of air temperature, specific humidity, and winds for 1972–2012 from the ERA-Interim reanalysis

	0	1	2	3	4	5	6
10	2.21	0.74	1.23	1.23	1.72	1.47	1.72
9	1.23	0.98	0.49	1.72	1.23	0.49	1.72
8	0.74	1.47	0.98	0.98	1.23	0.98	0.98
7	0.98	0.74	0.98	0.98	0.74	1.23	0.74
6	2.21	0.74	0.98	0.25	2.94	0.25	1.72
5	1.23	0.98	0.74	2.21	0.00	1.47	0.49
4	2.45	0.98	2.70	0.74	2.45	0.49	2.21
3	2.21	1.47	1.47	1.72	0.00	2.21	0.25
2	1.47	0.74	1.96	0.74	0.74	2.45	1.96
1	2.21	0.25	0.00	0.25	3.68	0.49	1.47
0	1.23	1.72	1.23	3.92	0.49	2.21	1.47

Figure D-7: Frequency of occurrence of climate states across each node

SA nodes Freq. dist. 1960–2010

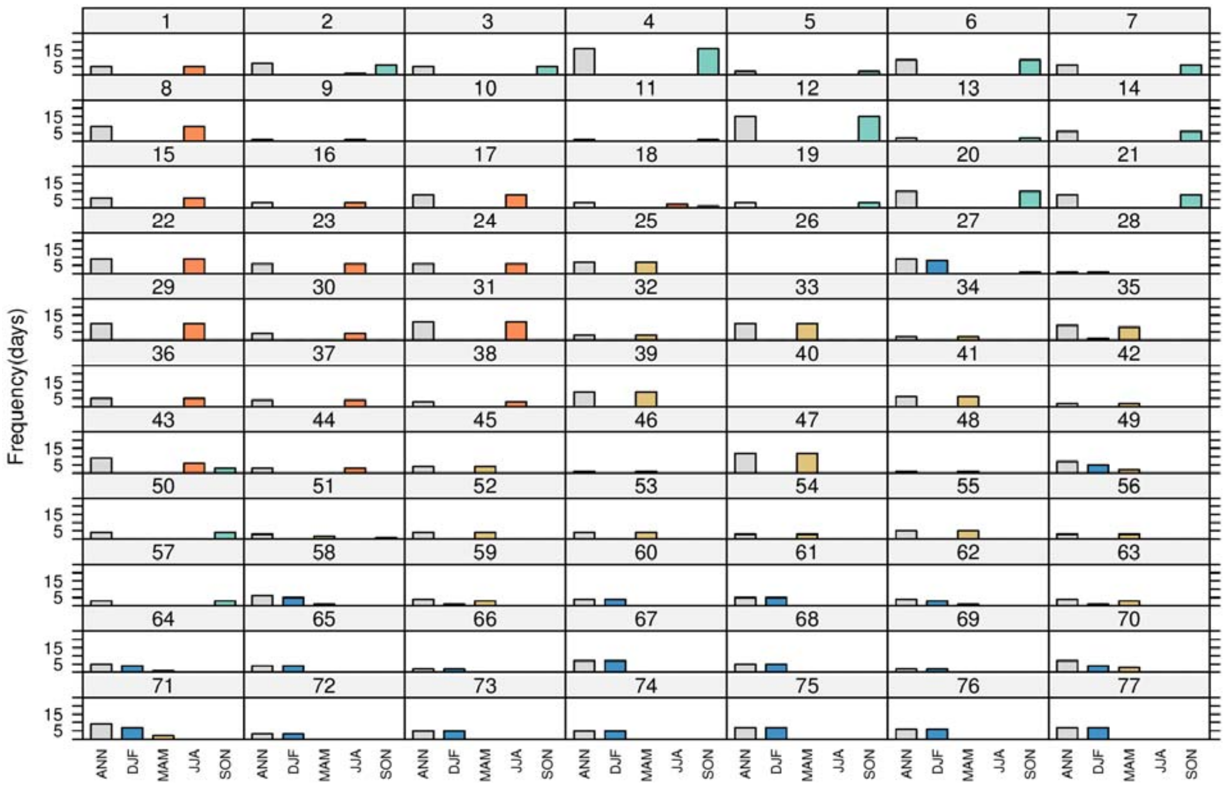

Figure D-8: Frequency of occurrence (reanalysis data) of climate states across each node, expressed in absolute numbers of months mapping to each node, and broken down as the annual and seasonal totals

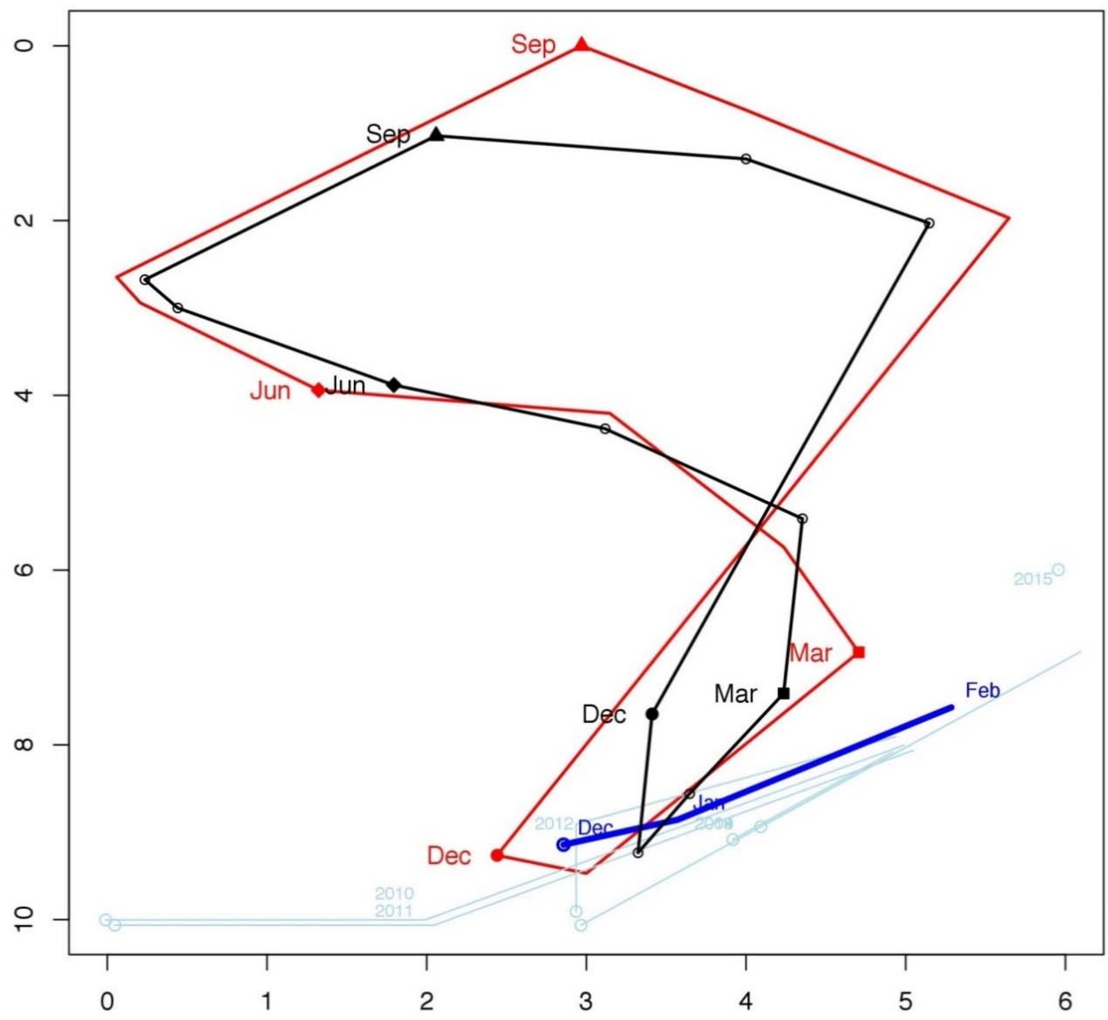

Figure D-9: Trajectories on the 7 × 11 SOM node array

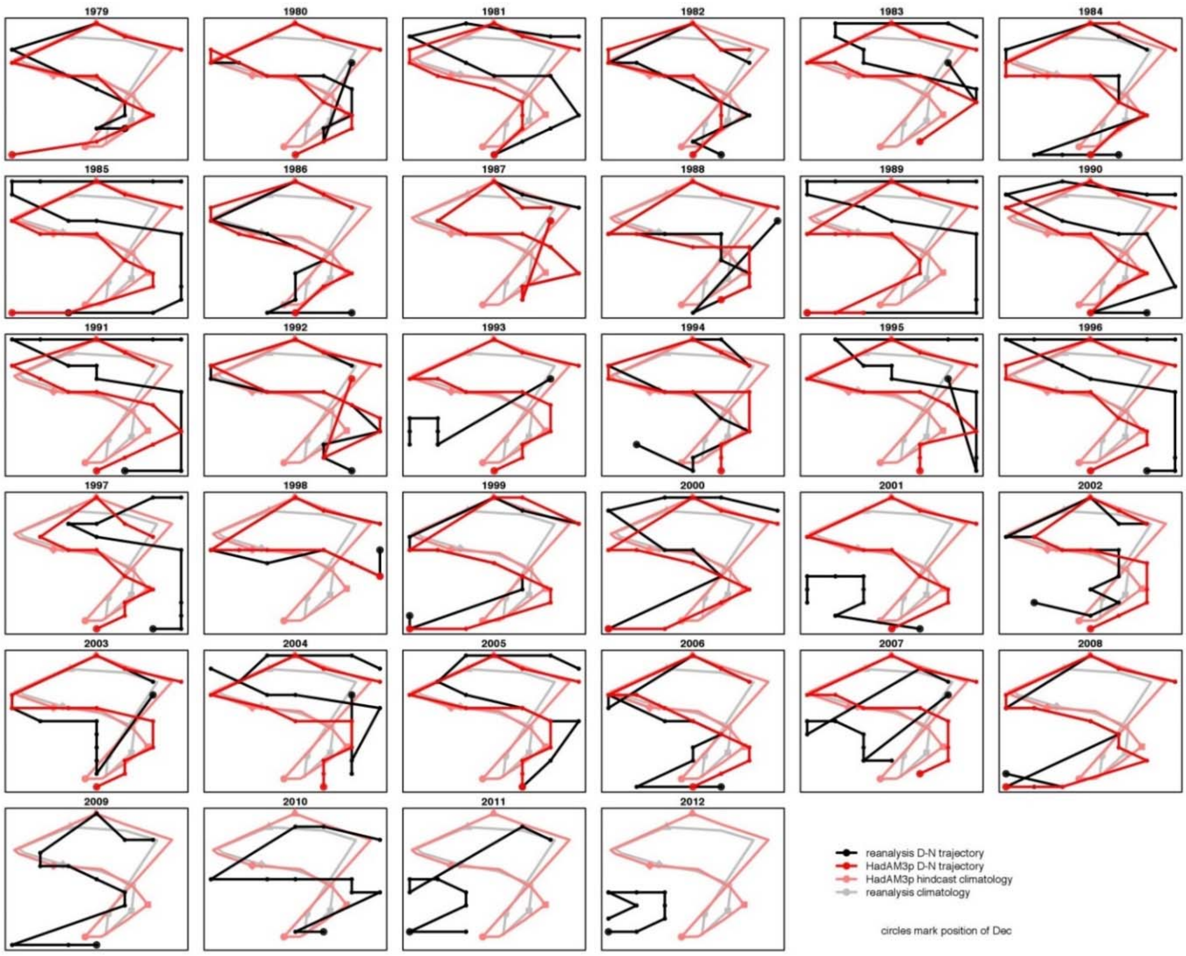

Figure D-10: Seasonal trajectories of all years used in the analysis

reanalysis D-N trajectory
HadAM3p D-N trajectory
HadAM3p hindcast climatology
reanalysis climatology

circles mark position of Dec

First, consider the individual years and how their trajectories display substantial interannual variability. In each of the years shown in Figure D-10, the climatological trajectory of the reanalysis and the hindcast from HadAM3P are shown in the light colour. For each year, the actual year's trajectory as characterised by the reanalysis data and by the HadAM3P hindcast are shown in the bold colour. Three key messages may be drawn from this:

- As represented by the reanalysis data, the global modes of variability display substantial interannual variation in all seasons – at times with large departures from the climatological average seasonal cycle. This indicates that the conditioning global state for the sub-continent is subject to strong differences from year to year, which suggests that if a model cannot capture this interaction of global modes, then the credibility of the regional responses is likely to be significantly undermined in any simulation.
- In each year, the HadAM3P model's trajectory lies close to the model's climatology – itself a credible representation of the climatology. However, the implication of this is that the HadAM3P has a significantly low measure of interannual variability. In turn, this suggests that the model is not responding to the interannual SST forcing with appropriate magnitude, and/or the model's internal sources of variance are supressed – likely a combination of both – and hence raises critical questions of where the model is failing and the applicability in forecasting a season. This does not mean that the model fails with all interannual modes, and it is possible that under certain states the model is credible, but at the very least there is clear indication that the model needs further examination for

the relevant sources of shortcoming, and the implications for the skill in forecasting the African sub-continent.

- Where the HadAM3P model does show the most interannual variation is in the December month, where for some years the model places this portion of the seasonal cycles in the lower left of the SOM array.

This assessment provides perspective on the model, and the basis for subsequent intermodel comparisons and of the models' ensemble simulations. At this stage of the work, we conclude with one additional view, that of the seasonal DJF forecasts (Figure D-11).

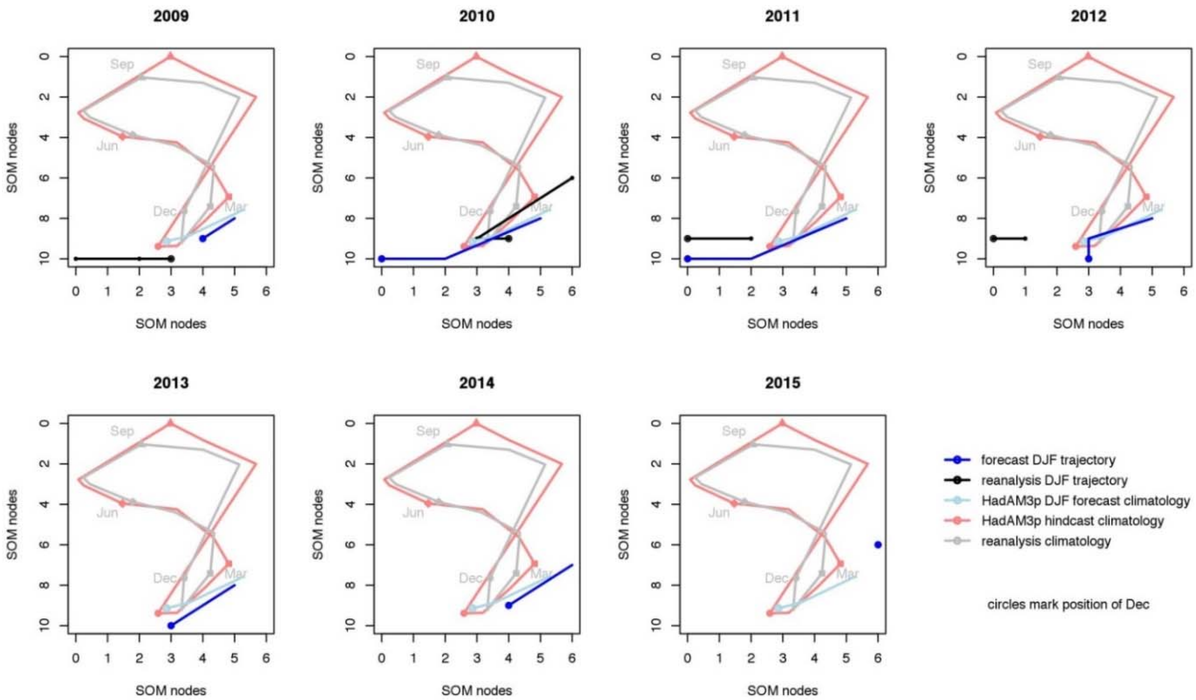

Figure D-11: HadAM3P model performance in forecast mode for DJF and related reanalysis trajectories

Figure D-11 shows the climatological trajectories are again shown in pale colours as a reference. In addition, we show in pale blue the climatology of past seasonal forecasts for the DJF period. In bold colours are the forecast trajectories for DJF over the last 7 years by the HadAM3P model, and the reanalysis representation of what actually occurred. From this, we draw some provisional key messages about the models' representation of the DJF period in forecast mode.

- The model displays low interannual variability.
- December is a problem month and struggles to capture the season's onset state.
- The model has a systematic bias in the evolving trajectory; a bias that seems to be related to stronger gradients and more intense features of the anomaly patterns for the global modes.
- The representation of the tail of the season is relatively stable, with the onset of the season indicating the main problem. The degree to which the tail of the season is predicated on the onset is unclear, but the relationship does not appear to be strong.

D.4 Conclusions

We presented an approach to evaluate the role of the global atmospheric conditions as the conditioning state of the regional sub-continental response. The method adopted approaches with the explicit view of treating the global atmospheric system holistically rather than by singling out individual modes of global variability, or particular, narrowly-defined indices of atmospheric state. The method allows for examining the agreement between model and (pseudo-) reality through a lens of the evolution of the global state in time.

The results present a robust framework for evaluating the attributes of multiple models and ensemble members to perform a diagnostic of the models and identify key attributes of concern for consideration in the further development of models. Furthermore, it provides a means to identify where in the seasonal forecast the skill is most limited.

While the analyses presented above were carried out at the global spatial scale with a monthly time step, the method can be extended to perform similar analyses at smaller spatial scales and at higher temporal resolution in a framework similar to that used in the section on regional multi-scale responses. In there, we illustrated an example extension of the method to analyse and identify deterministic predictability of local climate responses integrated within hydrological system. We mapped differences in predictability in space and across spatial scales.

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