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Storylines of the Pilbara's future climate

A case study on constructing storylines of future water availability for western Pilbara aquifers in a warmer climate

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The Climate Systems Hub acknowledges the Tradition Custodians of the land across Australia where this work occurred. We pay our respects to Elders past, presents and future and recognise the important role traditional knowledge plays in understanding Australia’s climate.

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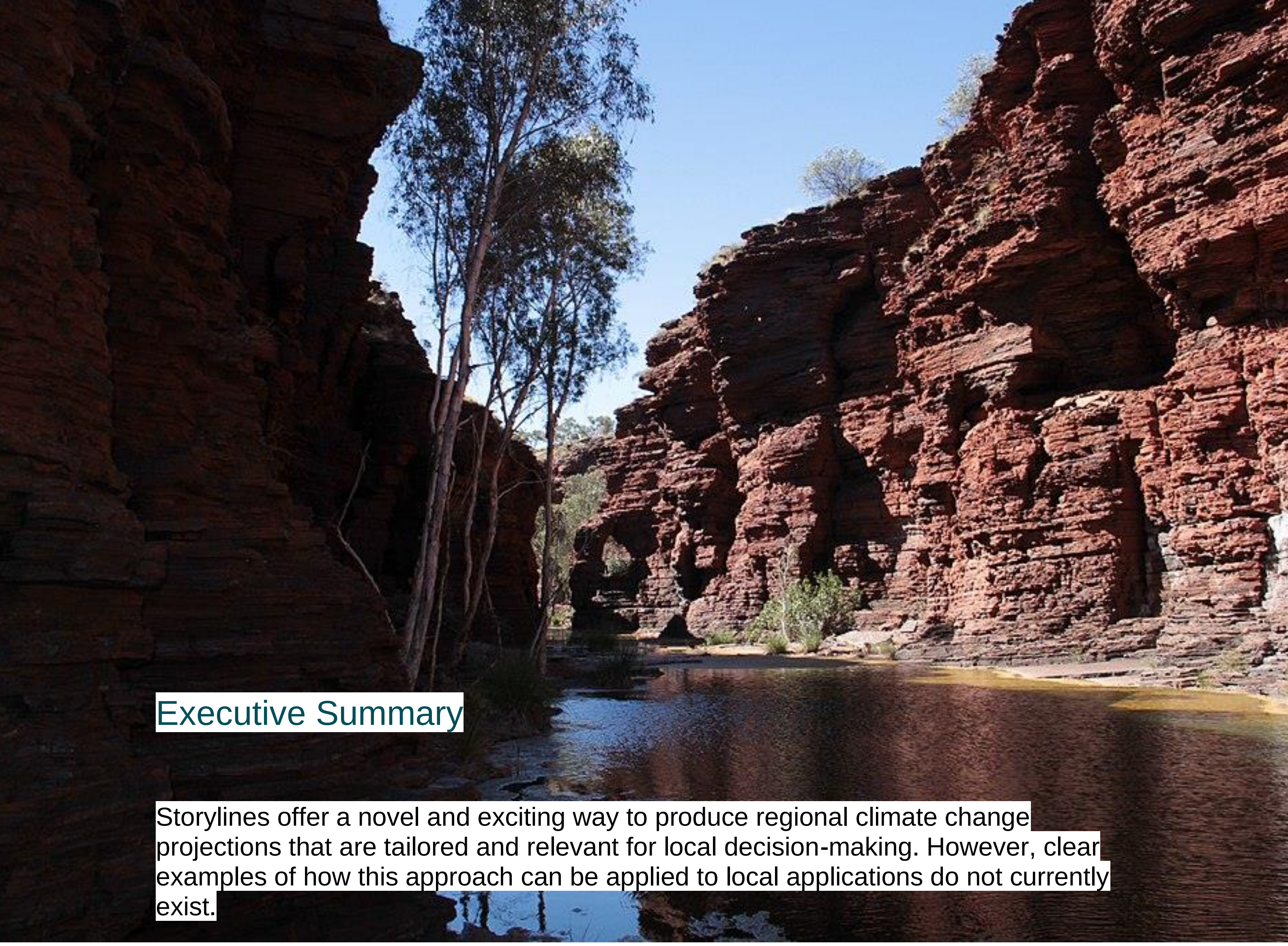

Executive Summary

Storylines offer a novel and exciting way to produce regional climate change projections that are tailored and relevant for local decision-making. However, clear examples of how this approach can be applied to local applications do not currently exist.

The aim of this project is to trial a storyline approach to support the process of future water availability planning at the catchment scale in a changing climate. The key findings of the present study are:

- Extreme wet and extreme dry future states are plausible for the western Pilbara catchments.
- Storylines can be constructed to exemplify these diverging narratives for highly localised purposes using available application-ready datasets, however care must be taken to ensure that the key storylines are represented in those datasets.
- We were able to approximate an extreme wet and a dry storyline using the National Hydrological Projections application-ready dataset. However, a plausible extreme drying storyline for these highly localised catchments may not be captured in this dataset.

Future work will consider novel methods to estimate missing plausible storylines using limited available information relevant at the decision-scale, as well as investigating the extension of storyline drivers to include more local and regional processes.

Introduction

The National Environmental Science Program Climate Systems Hub (the hub) provides scientific research and analysis that aims to help inform the climate change related decisions of our stakeholders. While a range of available sources provide climate change data and information, it is not always clear how to use this data to support decision-making processes. There are many reasons why this may be the case, including issues such as the availability of the relevant variables or time-periods, spatial and temporal resolution of the information, uncertainty or lack of confidence in the information presented, or a method of presentation that renders the information less usable. In the present report, we trial a case study on using a “storyline” approach to climate change projections to inform a stakeholders decision framework (Shepherd 2019). The general aim here is to describe the process by which we may be able to provide a coherent narrative-based exploration of the implications of climate change on a particular decision-point. We detail below the imperative, available resources, investigation process, and the outcomes of conducting this case study.

Why create climate change storylines when so many other sources of regional climate information already exist?

Although there are many trustworthy and useful existing avenues to acquire regional climate change information (such as Climate Change in Australia and the IPCC ATLAS- for more information see Project 2.2 report), these can pose several challenges for informing decisions. The vast quantity of climate projections data is non-trivial to analyse, involving multiple generations of climate models, multiple scenarios, and multiple ensemble members. In many cases the regional projections calculated from this vast source of information are highly uncertain due to model, scenario and internal variability uncertainty. The data from global climate models may not be relevant at the scale of every decision due to model resolution, and state-of-the-art dynamically downscaled projections available may suffer from small sample challenges due to the cost of production. In fact, even with a full ensemble of global climate models the issue of sampling remains - for example, how to create ensemble statistics for a set of models that are not independent? How should we adjust our sample statistics for important issues such as excessively high or low climate sensitivity of models?

It should be noted that the exercise conducted in this case study has some similarities to the projections produced for the Pilbara as part of the Western Australia CMIP3 future climate projections (Department of Water 2015). However, there are some key differences: here we use newer sources of information (CMIP5 models and NHP runoff estimates), we focus more on understanding and partitioning the relative sources of projection uncertainty through the use of large-scale drivers, and we attempt to connect our narratives of regional climate change directly to stakeholder decision-scale information (catchment runoff exceedances for estimating changes to water availability).

So what are climate change storylines?

A storyline can be defined as a physically self-consistent unfolding of events presented as a coherent narrative (Shepherd 2019). In our storyline approach we first define key climate change drivers and quantify their influence on impact variables. We then investigate the most salient plausible outcomes based on combinations of those drivers.

They must be plausible, therefore they should be based on evidence that establishes a causal pathway between physical climate conditions and a decision that is impacted by that pathway. While storylines can be either qualitative or quantitative an important aspect of storylines is that they emphasise the plausibility and usefulness of climate information for informing decisions, rather than focusing on the probability of a particular outcome. Often this leads to the consideration of multiple storylines. This may seem disappointing at first encounter since the ideal future-focused information is singular and definitive (for example, a decrease of 25% will occur by the year 2050). However, in the absence of certainty, which is typically the case in climate change projections, plural and conditional storylines may be more useful for making decisions than ensemble statistics (for example, an increase of up to 10%, as well as a decrease of up to 25% are both plausible future states by the year 2050, conditional on changes in our storyline indices). One key reason why plural and conditional storylines are useful is that they allow the consideration of correlated risk, which is difficult to assess using traditional ensemble statistical approaches. It also allows decision-makers to focus on the impact of particular actions on potential vulnerabilities and sensitivities in the system under a range of plausible futures.

Are climate change storylines arbitrary?

Climate change storylines are subjective in nature, however they are not arbitrary. Why is subjectivity appropriate here? They are subjective because ensemble statistics are combined with physical understanding, and a risk perspective that is subjective since it changes depending on use-case. Well-constructed storylines are conditioned based on changes to one or more features to make them as clearly relevant to an impact or decision as possible, exploring the bounds of plausible climate-related risk. They are one means of addressing the implications of uncertainty for a particular impact or decision.

Storylines are a versatile means of communicating causal pathways, and have been applied in several different contexts. A common aspect of each application is the emphasis on understanding the implications of one or more influences on a particular quantity of interest. Mindlin et al. (2020) explored storylines that relate Southern Hemisphere climatic changes to variations in the amount of tropical warming as well as variations in changes to the Southern Hemisphere stratospheric polar vortex. Narsey et al. (2022) explored storylines of precipitation change in the

South Pacific, conditioned on future changes in the position of the South Pacific Convergence Zone. Other applications of storylines include conditional climate change attribution of extreme events (for example, Van Garderen and Mindlin 2022).

In the present study, a causal network (adapted from Shepherd 2019) is established (shown in Figure 1 below) linking future water availability of local catchments in the Pilbara region of Western Australia to large-scale climate change due to human-induced global warming. The storylines developed here aim to explore the range of plausible impacts on water availability with global warming by the year 2050.

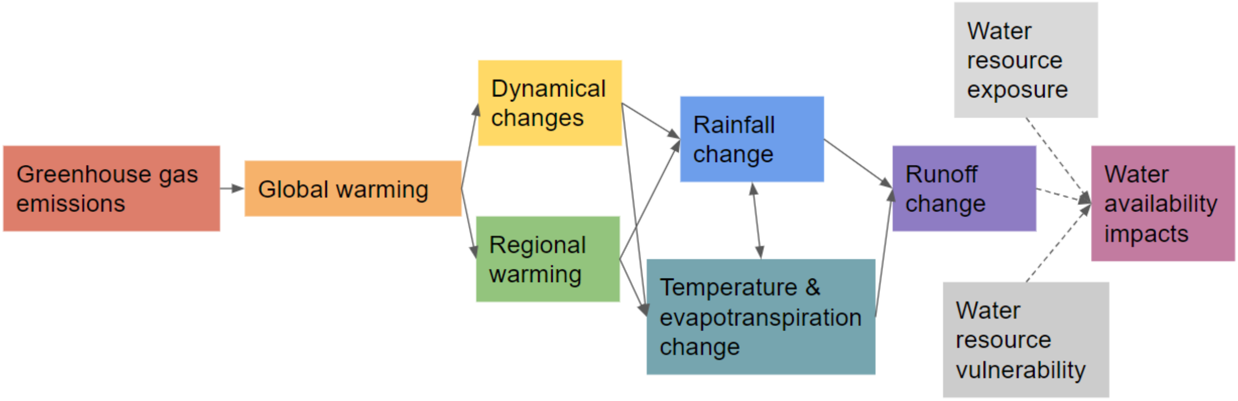

Figure 1: Causal network for runoff changes with global warming, adapted from Shepherd (2019).

What are the benefits of climate change storylines?

Storylines and other narrative-based methods can help us:

- distil the overwhelming amount of information into a few impactful narratives,
- quantify the implications of uncertainty on impacts through an event rather than probabilistic presentation,
- avoid improper statistical interpretation of available model ensembles,
- motivate action/decisions by relating plausible climate changes to real-world experiences,
- adapt climate information to a decision-framework rather than adapt a decision-framework to available climate information.

An in-depth description and discussion on the use of storylines can be found in Shepherd (2019).

Co-designing a case study on storyline projections

Following on from discussions with the hub Cross-Jurisdictional Community of Practice (CJ CoP CS) the Western Australia Department of Water and Environmental Regulation (DWER) was identified as a stakeholder with both an interest in exploring climate change storylines for informing decision-making, and also the capability to co-design a case study project within a relatively brief time-period. A clear opportunity was presented to leverage existing strong relationships between the Australian Bureau of Meteorology (BoM) and DWER through the National Hydrological Projections (NHP) activities.

The emphasis here is placed on the strength of those relationships, since the success of the case study will depend on the usefulness of the information produced to support their decision-making process in water resource planning, which in turn will hinge on the relationship between the climate data used and the impacts metrics needed for decisions by the end-user. Earlier work considering simple storyline scenarios for DWER assets in a warmer future climate had already been conducted (Department of Water 2015, Watterson et al 2015), which helped all involved parties understand the expectations of outcomes from the project. This work is an extension of a BoM, DWER and Western Australia Water Corporation demonstration case of applying the NHP to assess supply reliability in the Harding Dam (soon to be published).

The storyline approach is defined mostly by its intent rather than as a distinctive framework, and so a clear process has not previously been defined for the purpose of our project. Here we have taken the following steps, explained in more detail in the following sections, in attempting to construct our storyline narratives:

1. In collaboration with our stakeholder, define quantifiable climate-related metrics that are relevant to decision making.
2. In collaboration with our stakeholder, we chose analysis methods and relevant data sources for their intended purposes.
3. We then attempt to place the analysis in the context of other available sources of relevant information.
4. Assessing the information available to us, we attempt to construct storyline narratives of future water availability conditioned on relevant physical processes.

DWER was interested to see how storylines could provide a clear narrative for proponents, stakeholders and government departments to make water-related decisions in a region that is plausibly wetter and drier in the future. DWER selected a case study with a good understanding of water resource and environment system processes. This allowed us to explain the broad level of uncertainty in the physical change plausibility in the GCMs for the future climate projections. Identifying the climate processes known to exacerbate system sensitivities in the future climate projections, can help narrow down the projections to explore those of particular interest to the water resource system.

User needs

This case study will focus on the Yule, De Grey and Millstream aquifers that are covered by the Pilbara groundwater allocation plan (Department of Water 2013, see Figure 2 below for location).

- Water supply objective for Yule and De Grey is to provide a highly reliable (>95% annual supply with no failures) scheme to the Port Hedland Regional Water Supply. Both existing and new sources (groundwater, or desalination) and alternative supply options (demand management, wastewater recycling, managed aquifer recharge (MAR)) need to be assessed for climate risk. Where demand has the potential to exceed supply, significant investment may be required to ensure continued supply reliability. Ideally, the future supply needs to be robust under the full range of projected futures. This is a long-term decision with assessment out to 2050.
- Water Corporation licences to extract from the aquifers have an associated operating strategy to manage take in accordance with environmental objectives. In some instances, the condition of groundwater levels and how they impact the associated Groundwater Dependent vegetation and pools can constrain the yield for water supply.
- Environmental objective is to maintain the function, extent, and condition of groundwater-dependent ecosystems (through vegetation conditions) in the context of a naturally variable climate. A decision will need to be made into the future about what natural climate extent is managed to with regards to human-induced impacts on the vegetation (such as a historical dry 1970s or a recent wetter period). Current management assesses recharge as a function of historical river flows measured at gauging stations to indicate groundwater availability and ecosystem response of vegetation and pools. Wet season flows are categorised into drought, dry, and average to wet recharge classes (Appendix 1). To explore the natural variability in the future climate projections, it could be useful to understand the extent of time different recharge classes are projected to occur as linked to vegetation condition. For all three Aquifers, the duration of time below the average recharge class is the critical factor in regards to long term yield reliability and overall continued health of the Groundwater Dependent Ecosystems.

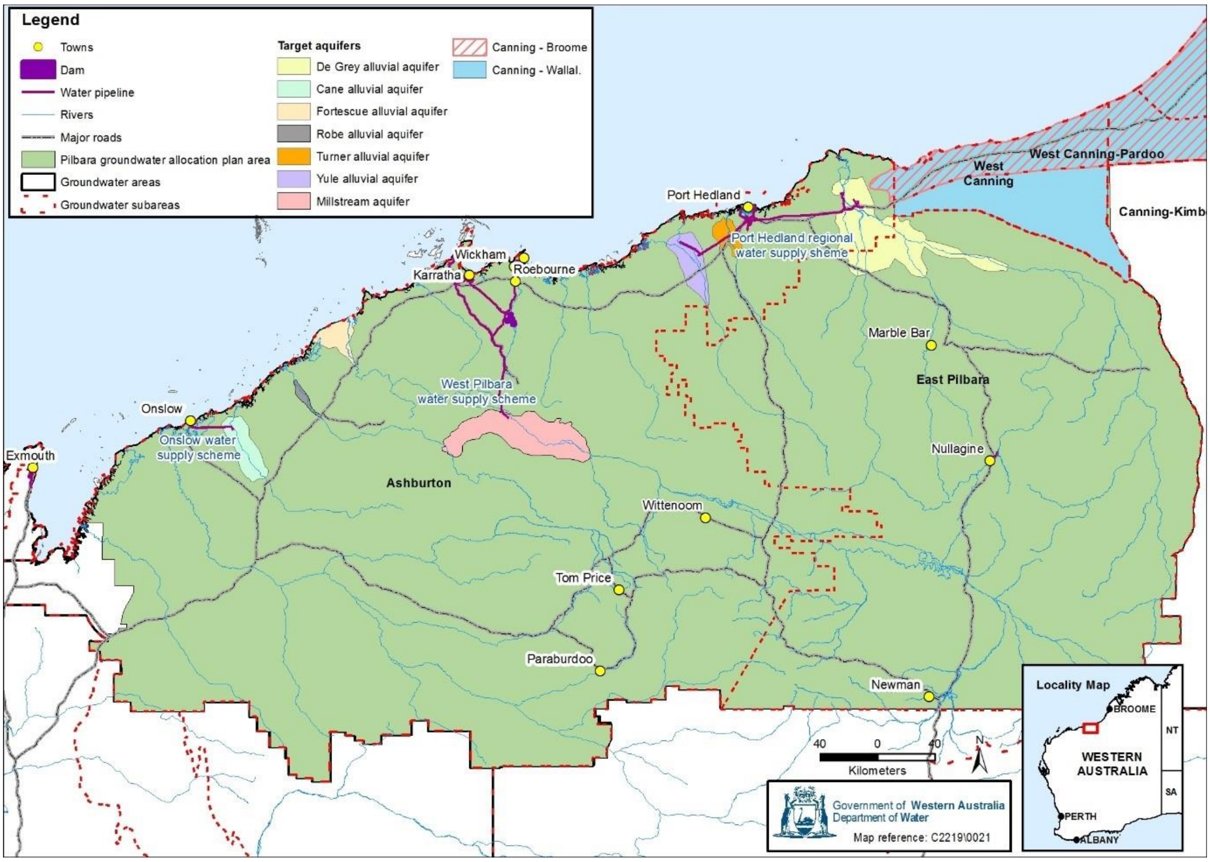

Figure 2: Target aquifers and water supply schemes (Figure 2 of the Pilbara groundwater allocation plan, Department of Water 2013).

The catchments from which runoff leads to recharge of the aquifers is shown in Figure 3.

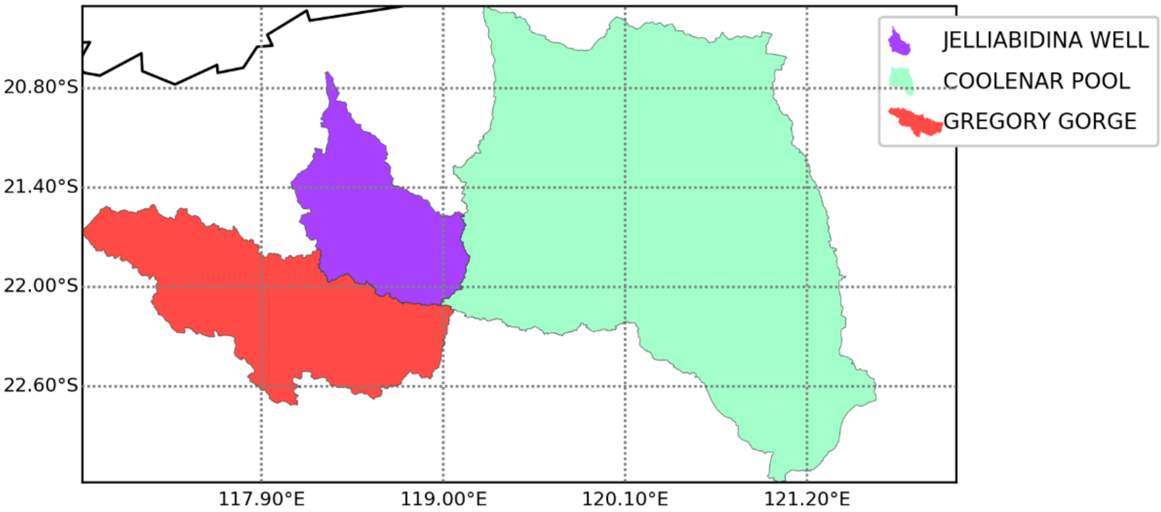

Figure 3: Three catchments used to explore the storyline concept for future water availability planning in the Pilbara using NHP runoff dataset: De Grey (as represented by the Coolenar Pool streamflow gauge), Yule (as represented by the Jelliabidina Well streamflow gauge) and lower Fortescue (as represented by Gregory Gorge streamflow gauge) including the Millstream aquifer

Available data

DWER provided drought, dry and average-wet classes for groundwater aquifer recharge, as a function of observed streamflow, that align with groundwater availability and defined triggers for environmental objectives (Appendix 1). Certain streamflow classes are indicative of drought conditions and are used to assess modelled runoff from the NHP datasets. The De Grey catchment runoff is estimated at the Coolenar Pool streamflow gauge, the Yule catchment runoff is estimated at the Jelliabidina Well streamflow gauge, and the lower Fortescue catchment runoff is estimated at the Gregory Gorge streamflow gauge as a surrogate for recharge to the Millstream Aquifer.

The hydrological information for assessing future climate change used in the present study was obtained from the NHP readily available dataset. A more detailed description of the NHP dataset can be found in Section 3.1.

The source of climate change information for the present study originates from global climate models made available through the Coupled Model Intercomparison Project Phase 5 (CMIP5, Taylor et al 2012). These global climate models incorporate our best understanding of how the climate system works and have been extensively evaluated for global and regional purposes (see Christensen et al. 2013 and references therein). Three scenarios are considered here: a historical scenario representing recent climate conditions, a medium emissions scenario (RCP4.5) and a high emissions scenario (RCP8.5). Global climate model experiments are typically run multiple times with slightly different initial conditions to help account for natural variations internal to each models simulated climate. Here we only use one (i.e. the first) ensemble member for each model. For brevity we only present some analyses for the high emissions scenario. We note here that a new ensemble of GCMs is now available (CMIP6, Eyring et al 2016), however we choose not to include CMIP6 analyses here since the impacts modelling (runoff) has thus far only been applied to CMIP5 models. A careful comparison of the two ensembles (CMIP5 and CMIP6) for our study region has not been conducted, however at larger scales (over northern Australia) they project similar ranges of uncertainty in future projections (for example, Narsey et al., 2020).

The Global Precipitation Climatology Project (GPCP) rainfall dataset (Adler et al 2003), the Australian Water Availability Project (AWAP) rainfall dataset (Jones et al, 2009), and the Hadley Centre Sea Ice and Sea Surface Temperature (HadISST) surface temperature datasets are used to compare the global climate models against the real world (Rayner et al 2003). We did not test the sensitivity of results to the choice of reference datasets; however we expect the results to not be sensitive to this choice.

Decision metrics for storylines

What climate parameters drive water supply and vegetation conditions in the Pilbara?

Groundwater availability for water supply and to maintain vegetation condition is a function of aquifer recharge from rainfall events. Most aquifers are recharged by water infiltrating through streambeds during large rainfall events. River flow from these events is the major source of aquifer recharge for the Yule and De Grey aquifers whereas direct rainfall, and runoff infiltration from the Hamersley Range is also a source of recharge for the Millstream aquifer in addition to seasonal flows from the lower Fortescue River.

The total wet season flow (October – April and December – April) is the best indicator for recharge to the alluvial aquifers. Due to rainfall also having an influence on recharge for the Millstream aquifer, and the location of the gauging station downstream of the Millstream aquifer, both river flow and a target mean aquifer level (MAL), are useful as indicators for aquifer recharge.

River flow is the result of rainfall (as well as noting other contributing factors to catchment hydrology such as soil moisture) but events can occur quite a way upstream of the aquifer and still prompt a flow event (and hence recharge). There may be some correlation between the upstream rainfall events and resultant river flow but there are limited pluviometer and streamflow gauging networks to explore this.

River flow (as represented by runoff) can be estimated from BoMs national landscape model AWRA-L, which is the model used to estimate runoff for climate model projections in the NHP dataset. Water Corporation has a rainfall-runoff model for the Lower Fortescue River so this could be a good test of AWRA-L applicability to the Pilbara region. Water Corporation also have a combination of numerical and lumped parameter groundwater models for the aquifer systems. We note here that comparison of BoMs regional landscape model and Water Corporations local scale models have not been undertaken in this study.

Categories for recharge as a function of river flow have been developed that align with groundwater availability and set triggers for environmental objectives (see Table 1, 2 and 3 in Appendix 1). For more information see Department of Water (2010, 2011, 2012, 2013, 2015).

Considering the information provided by DWER and after preliminary discussions, it was determined to explore storylines that considered the extremes of future water resources using the changes in drought frequency against changes in the frequency of excessive wet season runoff for each catchment, as defined above.

Assessing the evidence available

Rainfall and runoff from the National Hydrological Projections Dataset

The National Hydrological Projections (NHP) dataset consists of future climate information that is at a high enough spatial scale to be considered relevant for informing catchment-scale decisions by DWER. It consists of bias-corrected variables from coarse global climate models such as rainfall and temperature, that have then been used to estimate hydrological variables using a water balance model. Since bias correction involves subjective choices and different methods do not agree on corrections, the NHP approach is to provide climate information using multiple methods.

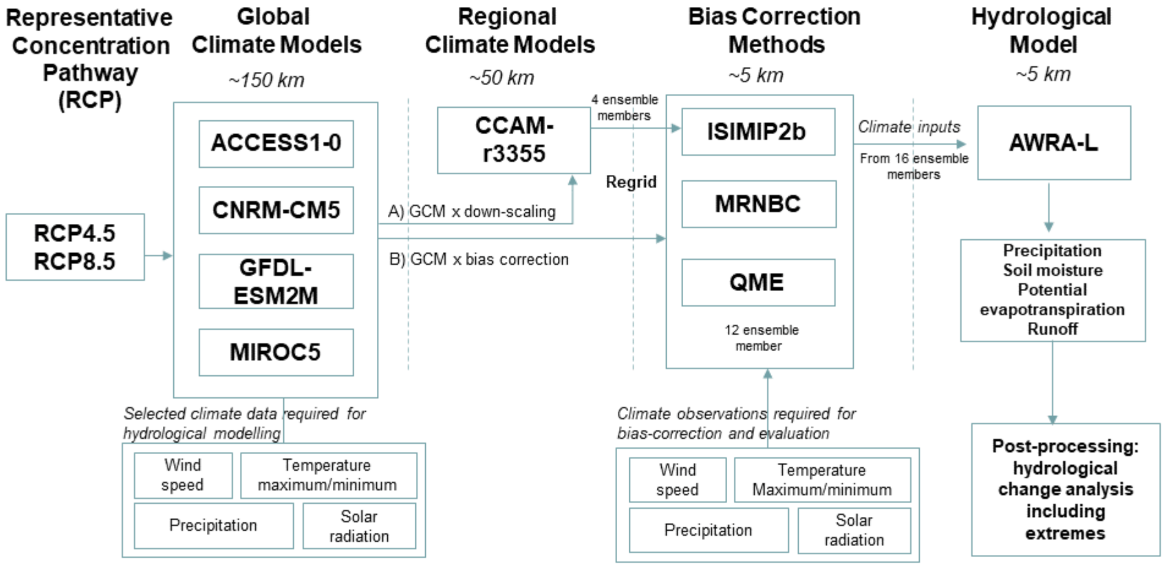

Figure 4: National Hydrological Projections showing details of the processing steps: i) 2 representative concentration pathways (RCP4.5 as medium and RCP8.5 as high) are selected, ii) 4 CMIP5 global climate models (GCMs) are selected, iii) path A – each GCM is downscaled by a regional climate model (RCM) to a 50km (0.5°) scale and then re-gridded to a 5 km (0.05°) scale. The RCM uses one bias-correction method (ISIMIP2b) that corrects the necessary climate inputs (precipitation, temperature, wind and solar radiation) against observations, iv) path B – each GCM is re-gridded to a 5 km (0.5°) scale and corrected directly using one of 3 bias-correction methods) climate data from the 16-member ensemble is used to run the hydrological Australian Water Balance Model (AWRA-L) to produce hydroclimate change information for precipitation, soil moisture, runoff and evapotranspiration. These hydroclimatic variables are processed to understand future changes on the Australian water cycle components, including extremes.

Due to limited resources only a subset of 4 climate models were selected for analysis in NHP. However, the 4 models broadly capture the range of expected temperature changes and expected wetter and drier future rainfall changes at a national scale, across the full set of 42 GCMs reported in the World Climate Research Programme's Coupled Model Intercomparison Project 5. Below we detail some relevant information for this case study.

The role of bias correction in projected signal

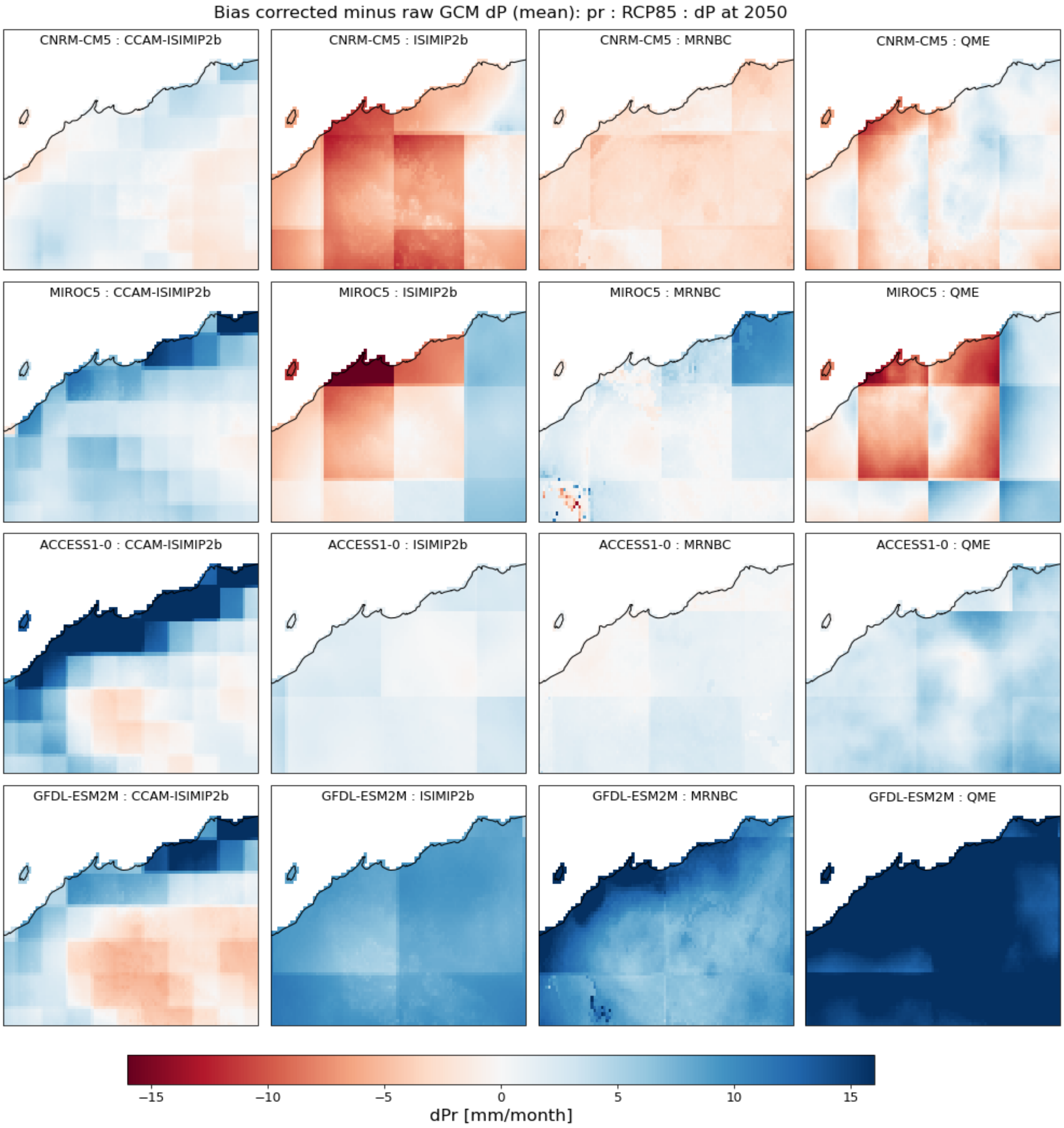

Figure 5: The influence of bias correction on the local precipitation change signal is shown here for the 4 climate models (rows) and the 4 bias correction methods (columns). Change signal is defined as the difference between 2035-2065 (RCP8.5 high emissions scenario) and 1975-2005 November to April average rainfall. Colours represent the difference in change signal between the bias-corrected data and the raw GCM data.

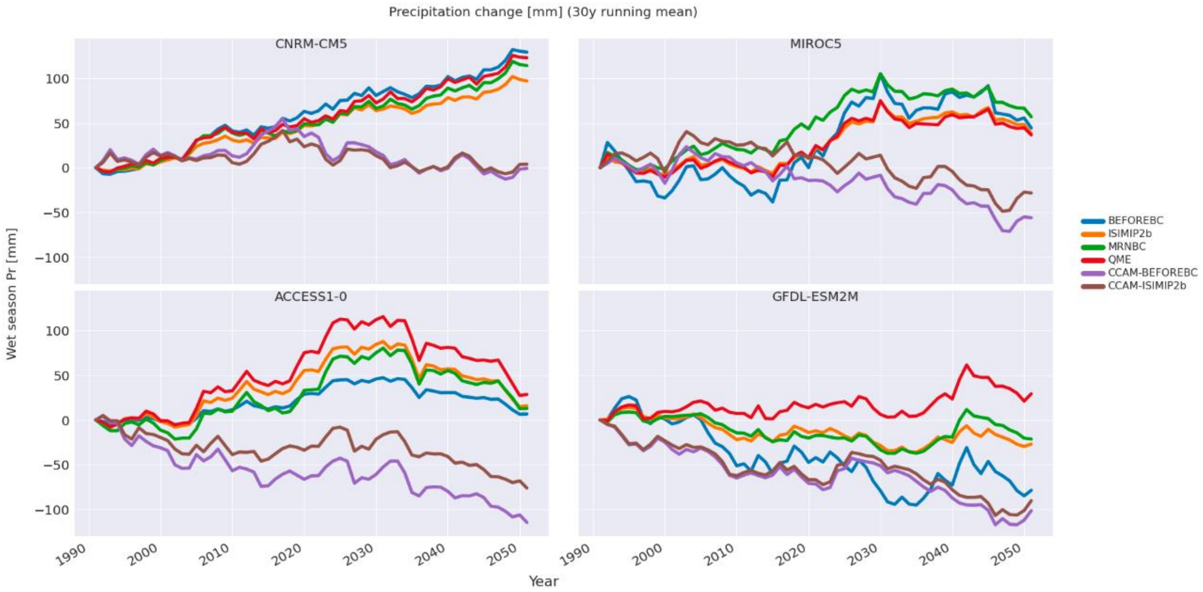

Figure 6: The influence of bias correction on the local precipitation change signal is shown here for the 4 climate models (panels, blue lines) and the 4 bias correction methods (other colours). Changes are shown for the high emissions scenario (RCP8.5) for the November to April total rainfall. Each timeseries is smoothed using a 30-year running mean, and presented as a change-quantity compared to the November-April total rainfall for the historical period (1975-2005).

The bias-corrected change signal minus the raw GCM change signal for wet season (NDJFMA) is shown in Figures 5 and 6 (above). Clearly the bias correction method has an influence on the precipitation change signal projected by each climate model. We consider each of the bias correction methods to have merit, and therefore are plausible here. One note of caution that is important to note is the different approach taken for producing the CCAM-ISIMIP2b data. Unlike the other data, the CCAM-ISIMIP2b information is taken from dynamically downscaled simulations. These experiments are run using bias-corrected GCM inputs for the four NHP models. Whilst these downscaled experiments share some qualities with the original driving GCMs, due to the nature of the downscaling experiment set-up the CCAM-ISIMIP2b projections can diverge quite significantly from the original GCM projections. We do not investigate this further here but note for all following analysis that the GCM-based estimates of storyline drivers may not be relevant for the CCAM-ISIMIP2b projections. This does not serve as evidence for rejecting these models, but it precludes any interpretation of the original GCM based storyline drivers to explain regional projections without further analysis of the CCAM-ISIMIP2b projections. However, it is clear that the CCAM-ISIMIP2b projections represent a severely drier future.

Further information on the bias correction methods can be found in Appendix 2.

Assessing modelled runoff for the three test catchments

Before assessing changes in future drought using the NHP dataset we first evaluate the NHP estimates of runoff for the three catchments (Appendix 3). While biases exist in the NHP dataset for all three catchments, we find that the NHP dataset is acceptable for water availability assessment using the DWER-provided runoff categories for two out of the three catchments (Yule and De Grey catchments). While modelled NHP runoff dynamics matched the streamflow observations for the lower Fortescue catchment, runoff amounts were largely biased, resulting in seasonal water availability categorisation that was overestimated (such as permanently higher water availability found in the NHP runoff estimates when compared to observations). The Millstream area, located on the bottom end of the Lower Fortescue Catchment (within the Millstream Chichester National Park), is a complex system of alluvial aquifers, permanent pools and wetlands, predominantly fed by spring discharge from the bordering Millstream Dolomite (an unconfined highly transmissive aquifer), along with seasonal flows in the Fortescue River. Such regional hydrological complexities, as well as influences from direct water usage in the river and aquifer are difficult to model with nationally-calibrated hydrological models and require additional locally parameterised and calibrated models, such as the inclusion of rainfall-runoff and groundwater models. The effectiveness of the Numerical groundwater models for Yule, De Grey and Millstream in particular are highly dependent on the appropriate characterisation of the runoff contributions as well as rainfall and PET. Similarly, the lumped parameter groundwater model for Millstream is strongly dependent on runoff and rainfall.

Further investigation is on-going, however for the purpose of the present case-study we discontinue analyses of the Millstream aquifer water availability, focusing instead on storylines for the Yule and De Grey aquifers.

Water availability information for the selected storyline catchments

We consider here the runoff estimated for the Yule and De Grey catchments in the NHP dataset. This runoff estimate is based on a water balance model (AWRA-L) with bias-corrected inputs as described above and in the NHP documentation (Srikanthan et al., 2022). The drought categories for each catchment were defined in consultation with water managers and can be found in Appendix 1.

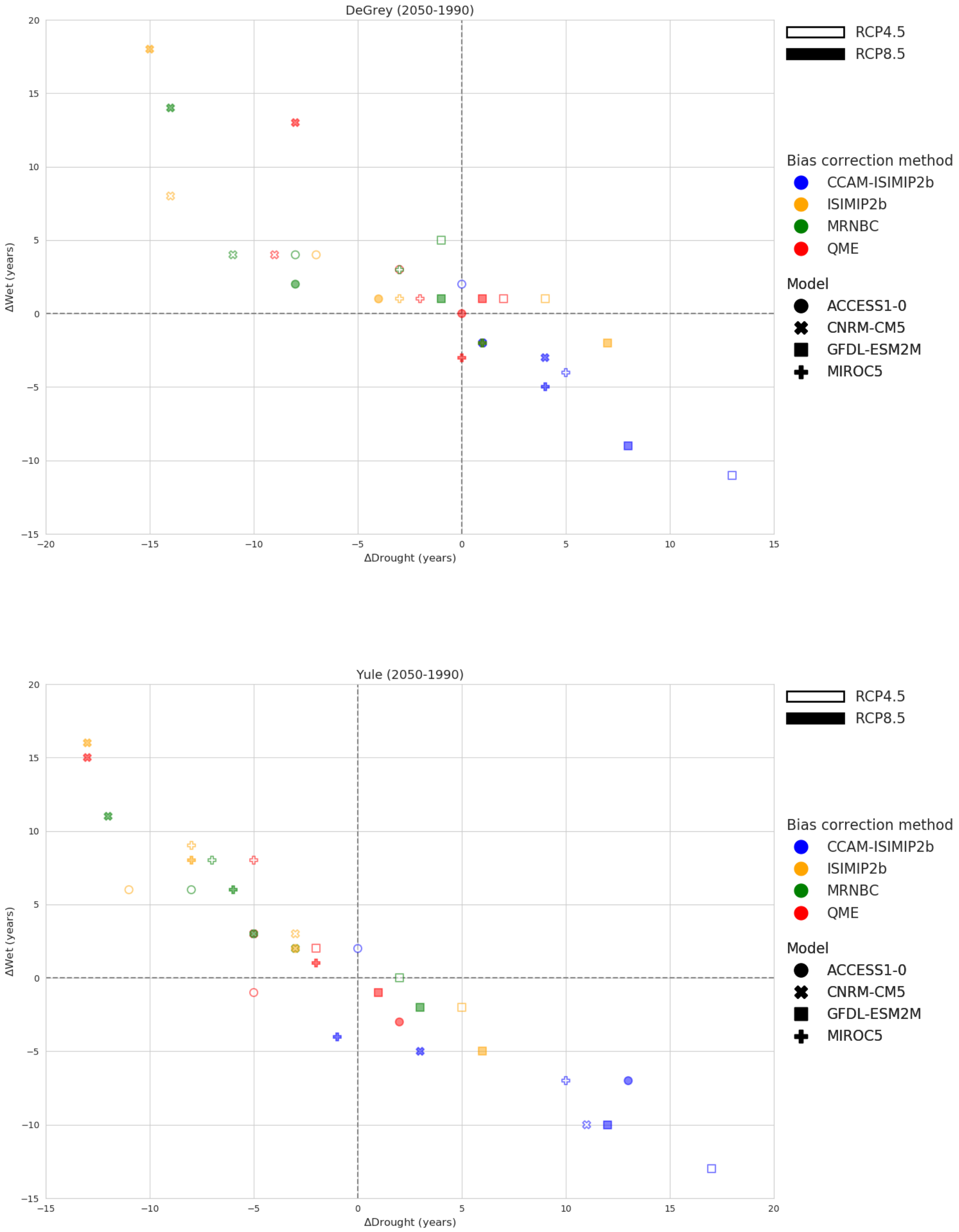

Figure 7: The NHP based assessment of change in drought frequency vs change in wet year frequency for each model (markers), bias correction method (colours), and emissions pathway (marker fill) by 2050 for the De Grey catchment (top) and the Yule catchment (bottom).

In Figure 7 we show that changes in drought frequency and changes in wet year frequency are highly correlated at the catchment scale. It is important that selected storylines are able to adequately describe the range of projected changes to runoff.

Further details on catchment runoff and changes in drought frequency for each catchment based on NHP data can be found in Appendix 4.

Large scale changes from global climate models

The western Pilbara region is located on the north-west coast of Australia, on the southern edge of the Australian monsoon region. In this section we discuss the evaluation of the large-scale historical climate features relevant to the Pilbara region in the NHP global climate models, as well as investigate the large-scale climate changes in those models with global warming (using the high emissions scenario).

We have evaluated the large-scale conditions relevant to the western Pilbara (defined here as the box average 23ºS-18ºS, 115ºE-120ºE), and found that the climate models analysed in the NHP dataset are broadly appropriate for use in regional projections, although some regional biases should be corrected for. Specifically, the Australian summer monsoon to the north of the study region displays a seasonal cycle similar to that observed albeit with some biases in the seasonality and extent of monsoon rainfall (Appendix 5).

Next, we considered the projected changes to the western Pilbara region in the full CMIP5 ensemble as well as the four NHP models (Figure 7). We found that changes to the western Pilbara region are broadly consistent with previous studies investigating the projected changes to the Australian summer monsoon, with models disagreeing on both the direction and magnitude of rainfall change with global warming (Brown et al. 2016, Narsey et al. 2020).

The NHP models capture parts of the CMIP5 projected range in wet season rainfall over the western Pilbara, but do not sample the lower end of the range in changes by 2050 under a high emissions scenario (Figure 8). However the four NHP models do reasonably span the range of year-to-year variability (standard deviation) of wet season rainfall in CMIP5 models, and they also adequately span the range in temperature changes projected for the western Pilbara in CMIP5 models (Appendix 5).

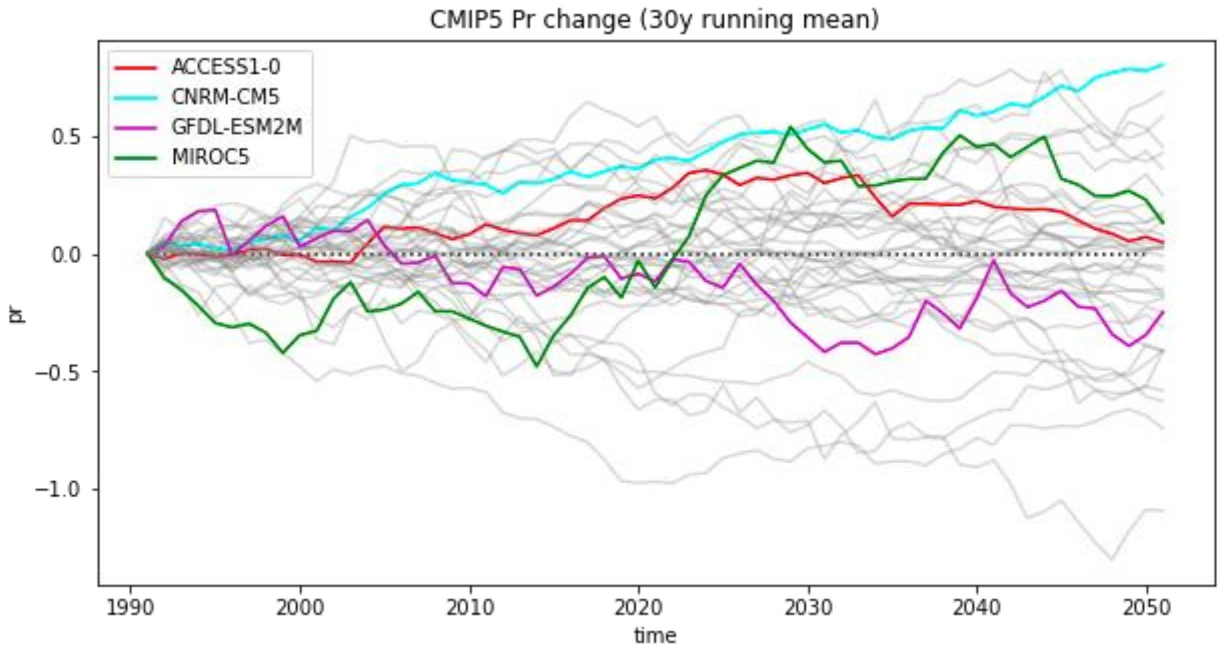

Figure 8: The projected changes in precipitation (mm/day) by 2050 (RCP8.5 high emissions scenario) for individual CMIP5 GCM ensemble members (grey), and the NHP-selected GCMs (colours) are presented after applying a 30-year centred running mean.

Physical process conditions for storylines

A key step in defining regional storylines is the choice of conditions upon which to base them. Ideally these conditions are able to explain much of the variance in projected changes between climate models and are based on physically plausible changes to drivers of regional climate under global warming. Mindlin et al (2020) constructed storylines for Southern Hemisphere mid-latitude changes based on two key factors for the Southern Hemisphere summer. Firstly, they conditioned future changes based on the strength of tropical upper tropospheric warming in response to greenhouse forcing (hereafter TW). Their second condition was the response to the delayed breakdown of the stratospheric polar vortex (hereafter VB). While these factors were selected in the Mindlin study to explain changes in the mid-latitude regions, they also are seen to explain some of the variance in projected rainfall in tropical locations. The processes involved in these teleconnections are not investigated here, and the ability of models to simulate the past variability of the Antarctic Stratospheric polar vortex or the tropical upper troposphere is also not evaluated in this study. What we attempt here is to relate the projected changes in the NHP dataset to the context of the Mindlin et al. storylines. We note for clarity that these two factors are relevant at the hemispheric scale, but other regional drivers are likely to also be important for rainfall change in the western Pilbara region (e.g. see Charles et al 2013). In this study we did not investigate other drivers, and this is a suggested topic of future research.

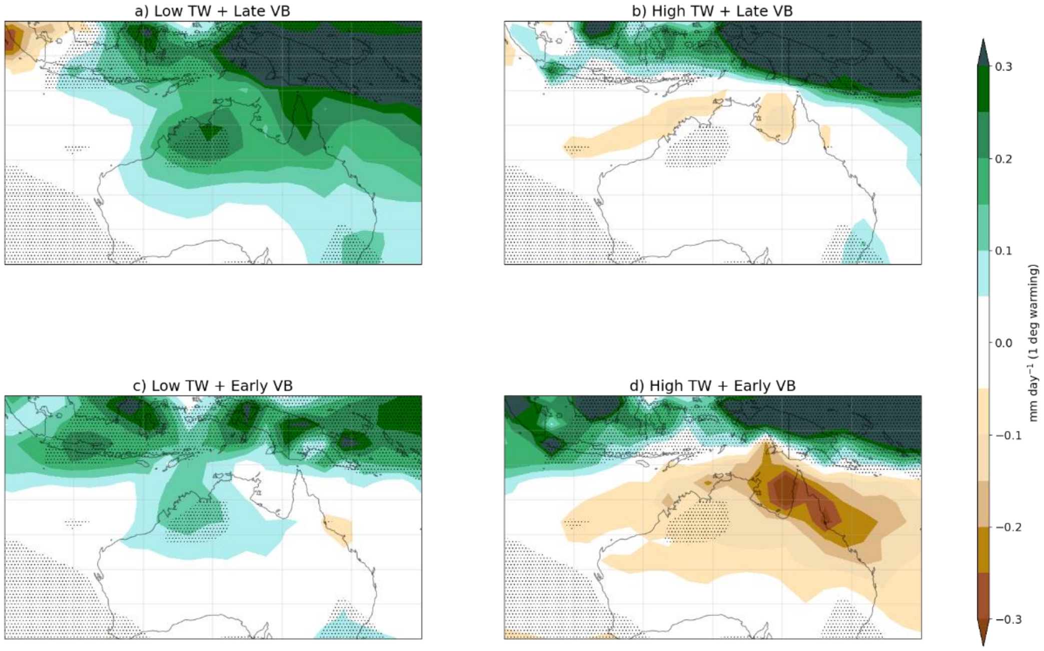

Figure 9: Storyline composites of November to April rainfall change per degree of global warming, adapted based on Mindlin et al 2020 analysis (credit: Julia Mindlin, 2022).

The combinations of these conditions are a continuum, however for our purposes the storylines that are sampled in the NHP dataset are:

- Low tropical warming. This storyline results in wetting over north-western Australia. The CNRM-CM5 model is an expression of this storyline. Late vortex breakdown would predict even greater wetting over much of northern Australia, however a delayed vortex breakdown does not strongly moderate rainfall increases for the local catchments in western Pilbara considered here.
- Moderate tropical warming, and moderately delayed vortex breakdown. This storyline results in little rainfall change over north-western Australia. The ACCESS1-0 and MIROC5 models are close expressions of this storyline.

The western Pilbara region projected change for the GFDL-ESM2M model is found to be inconsistent with the Mindlin storyline drivers, predicting a moderate drying. We suggest that this may be related to other regional climate driver storylines (not yet identified) that lead to moderate drying. This implies other regional drivers that may be important for the Pilbara region. Preliminary analysis (Appendix 5) indicates that regional processes, for example local SST changes or asymmetry in tropical Pacific SST change, are indeed important for the western Pilbara precipitation response to global warming. Since there are drier projections in NHP (from the CCAM runs described below) we do not further analyse the direct GCM-based GFDL-ESM2M projections for this study.

Although the NHP dataset provides a sample of the wettest GCM projections and the wettest storyline for the western Pilbara region, unfortunately the NHP dataset does not sample the driest GCM projection for the region, nor does it sample the driest storyline based on the Mindlin et al storyline drivers:

- High tropical warming and early vortex breakdown. This storyline results in the strongest drying over north-western Australia. **None of the global climate models sampled in the NHP dataset represents the combination of drivers that lead to this storyline**.

However, **there are in fact strong drying future states projected in the NHP dataset**. This may seem like a contradiction at first. If the NHP dataset does not include global climate models with severe drying at this location, then how is it that the NHP dataset contains severe drying projections for the western Pilbara region?

The answer is that the NHP dataset also includes dynamically downscaled projections (the CCAM-ISIMIP2b dynamically downscaled runs), and in those experiments the downscaling model has diverged quite significantly from the original GCM projections for the western Pilbara region. Although these are driven using the GCM data as inputs, the GCM projections are bias corrected prior to running the downscaling simulations. The downscaling model CCAM is different to many other models used for dynamical downscaling, which are typically regional limited area models. CCAM is a global model, and the experiment set-up used for the NHP project allows significant deviation from the original GCM inputs. It is therefore not straightforward to define the storyline drivers for the CCAM-ISIMIP2b projections without further analysis. This was out of scope for the present study and is proposed for future research.

For the purpose of the present study we propose to use the CCAM-ISIMIP2b projections as an example of strong drying, while noting that we were not able to associate this with storyline drivers. One key caveat though is that there is no CCAM-ISIMIP2b simulation available for a GCM that predicted strong drying over the western Pilbara. In that case **it is possible that the worst-case projected drying could be even more severe than the driest projections in the NHP dataset**.

Based on the available information we will construct scenarios based on storylines that account for much wetter, little change, and much drier future climates over the western Pilbara.

Describing storylines of future water availability for the Yule and De Grey aquifers in a warmer climate

We have consulted our relevant stakeholder (DWER) in order to determine the key decision metrics of interest to them, in this case the metric of interest being seasonal runoff exceedance categories in a warmer future climate. We then identified available resources, the National Hydrological Projections dataset, from which we could estimate the climate change impacts on runoff. Further inspection of the available NHP dataset in the context of the full climate model ensemble revealed that for our location of interest the NHP dataset would likely fail to capture the full range of plausible climate change responses. Specifically, the driest plausible future is not represented in the NHP dataset, posing a challenge here for constructing a useful set of storylines for the western Pilbara.

However, given the available evidence we are able to describe future water availability in the western Pilbara with global warming for the following scenarios based wherever possible on storylines:

1. **A much wetter future**, quantified using the NHP GCM-based runoff estimates for the CNRM-CM5 model. This storyline is well understood here through large-scale drivers.
2. **A future with little change**, quantified using the NHP GCM-based runoff estimates for the MIROC5 model for the de Grey catchment, and ACCESS1-0 model for the Yule catchment. This storyline is reasonably explained using large-scale drivers.
3. **A severely drier future**, quantified using the NHP dynamically downscaled CCAM-ISIMIP2b GFDL-ESM2M model based runoff estimates. A key caveat is that the storyline drivers are not known, and further research is needed to contextualise these. **We note that the impact of western Pilbara region severe drying in the CCAM-ISIMIP2b projections is qualitatively consistent with our missing storyline, however it is currently unknown whether an even more extreme drying outcome is plausible**. To test this would require analysing the storyline drivers in the existing CCAM-ISIMIP2b experiments, as well as running the CCAM-ISIMIP2b experiment using a GCM that represents a severe drying storyline (for example, high tropical warming and early vortex breakdown). If the influence of downscaling on local precipitation change is linear then to first order we might expect an even drier plausible future than is presented here.

For simplicity we focus on the projections that are bias-corrected using the ISIMIP2b method for the high emissions scenario (RCP8.5). We note that these choices are subjective. ISIMIP2b is a trend-preserving bias correction method, which is advantageous for climate change studies. However, the other methods have relative merits discussed in Section 3.1.1 as well as in Appendix 2. Regardless, the choice of bias correction method is less impactful than the role of dynamical downscaling. We note here that the severe drying scenario, although employing ISIMIP2b bias correction, is different from the data used for the other scenarios in that the dynamical downscaling may significantly change the regional climate compared to the original global model. Data used in the storyline narratives is recorded in Appendix 6.

Future water availability in the De Grey catchment

A much wetter future

We approximate this storyline using the CNRM-CM5 model ISIMIP2b bias-corrected NHP runoff estimates for the RCP8.5 high emissions scenario by the year 2050 (2035-2065) relative to 1990 (1975-2005).

In this storyline increased greenhouse gases will lead to a warmer global climate by the year 2050. The tropical upper troposphere will only warm weakly, leading to a regional pattern of circulation change that results in a much wetter climate over the western Pilbara. Changes to other regional drivers are also likely to contribute to the wetting trend. Runoff in the De Grey catchment will increase as a result of these human-induced causes. In combination with natural variations in the region's climate we estimate that wet season runoff for the De Grey catchment could increase by around 150% on average by the year 2050. Relative to present-day conditions this corresponds to an increase of 225% in the frequency of very wet years, and a reduction in the frequency of drought conditions of nearly 90%.

A future with little change

We approximate this storyline using the MIROC5 model ISIMIP2b bias-corrected NHP runoff estimates for the RCP8.5 high emissions scenario by the year 2050 (2035-2065) relative to 1990 (1975-2005).

In this storyline increased greenhouse gases will lead to a warmer global climate by the year 2050. The tropical upper troposphere will be moderately warmed which will have a drying influence over the western Pilbara, however this influence will be partly compensated for by a moderately delayed breakdown of the Southern Hemisphere polar stratospheric vortex. Runoff in the De Grey catchment will decrease as a result of these human-induced causes. In combination with natural variations in the region's climate we estimate that wet season runoff for the De Grey catchment may be reduced by nearly 10% on average by the year 2050. Relative to present-day conditions this corresponds to a 20% decrease in the frequency of very wet years, and an increase in the frequency of drought conditions of around 5%.

A severely drier future

In this storyline increased greenhouse gases will lead to a warmer global climate by the year 2050. The regional pattern of circulation change will result in a severely drier climate over the western Pilbara. The tropical upper troposphere will warm considerably which has a drying influence over the western Pilbara, and this drying is exacerbated by an earlier breakdown of the Southern Hemisphere polar stratospheric vortex. Changes to other regional drivers are also likely to contribute to the severe drying trend. Runoff in the De Grey catchment will decrease as a result of these human-induced causes. In combination with natural variations in the region’s climate we estimate that wet season runoff for the De Grey catchment may be drastically reduced by the year 2050.

We are unable to quantitatively estimate this storyline using runoff from the NHP dataset, however we know that this storyline is plausible based on the CMIP5 global climate model simulations. Instead, **we approximate the impacts of the severe drying storyline** using the dynamically downscaled (CCAM-ISIMIP2b) GFDL-ESM2M model runoff estimates for the RCP8.5 high emissions scenario by the year 2050 (2035-2065) relative to 1990 (1975-2005). The drivers of this severe drying in the downscaled projections are a topic of future research.

In combination with natural variations in the region's climate we estimate that wet season runoff for the De Grey catchment may be reduced by nearly 60% on average by the year 2050. Relative to present-day conditions this corresponds to a 75% decrease in the frequency of very wet years, and an increase in the frequency of drought conditions of nearly 70%. Based on the storyline drivers presented in this study it is possible that future drying could be even more severe.

Future water availability in the Yule catchment

A much wetter future

We approximate this storyline using the CNRM-CM5 model ISIMIP2b bias-corrected NHP runoff estimates for the RCP8.5 high emissions scenario by the year 2050 (2035-2065) relative to 1990 (1975-2005).

In this storyline increased greenhouse gases will lead to a warmer global climate by the year 2050. The tropical upper troposphere will only warm weakly, leading to a regional pattern of circulation change that results in a much wetter climate over the western Pilbara. Changes to other regional drivers are also likely to contribute to the wetting trend. Runoff in the Yule catchment will increase as a result of these human-induced causes. In combination with natural variations in the region's climate we estimate that wet season runoff for the Yule catchment could increase by nearly

120% on average by the year 2050. Relative to present-day conditions this corresponds to an increase of more than 120% in the frequency of very wet years, and a reduction in the frequency of drought conditions of up to 100%.

A future with little change

We approximate this storyline using the ACCESS1-0 model ISIMIP2b bias-corrected NHP runoff estimates for the RCP8.5 high emissions scenario by the year 2050 (2035-2065) relative to 1990 (1975-2005).

In this storyline increased greenhouse gases will lead to a warmer global climate by the year 2050. The tropical upper troposphere has moderately warmed which has a drying influence over the western Pilbara, however this influence is partly compensated by a moderately delayed breakdown of the Southern Hemisphere polar stratospheric vortex. Runoff in the Yule catchment will increase as a result of these human-induced causes. In combination with natural variations in the region's climate we estimate that wet season runoff for the Yule catchment may increase by nearly 50% on average by the year 2050. Relative to present-day conditions this corresponds to an increase of 20% in the frequency of very wet years, and a reduction in the frequency of drought conditions of 20%.

A severely drier future

In this storyline increased greenhouse gases will lead to a warmer global climate by the year 2050. The regional pattern of circulation change will result in a severely drier climate over the western Pilbara. The tropical upper troposphere will warm considerably which has a drying influence over the western Pilbara, and this drying is exacerbated by an earlier breakdown of the Southern Hemisphere polar stratospheric vortex. Changes to other regional drivers are also likely to contribute to the severe drying trend. Runoff in the Yule catchment will decrease as a result of these human-induced causes. In combination with natural variations in the region’s climate we estimate that wet season runoff for the Yule catchment may be drastically reduced by the year 2050.

We are unable to quantitatively estimate this storyline using runoff from the NHP dataset, however we know that this storyline is plausible based on the CMIP5 global climate model simulations. Instead, **we approximate the impacts of the severe drying storyline** using the dynamically downscaled (CCAM-ISIMIP2b) GFDL-ESM2M model runoff estimates for the RCP8.5 high emissions scenario by the year 2050 (2035-2065) relative to 1990 (1975-2005). The drivers of this severe drying in the downscaled projections are a topic of future research.

In combination with natural variations in the region's climate we estimate that wet season runoff for the De Grey catchment may be reduced by nearly 70% on average by the year 2050. Relative to present-day conditions this corresponds to a 75% decrease in the frequency of very wet years, and an increase in the frequency of drought conditions of 100%. Based on the storyline drivers presented in this study it is possible that future drying could be even more severe.

Final remarks

In the present report we have outlined the rationale, process, and initial attempts at constructing storylines of future water availability for local-scale catchment runoff in the western Pilbara in a warmer climate. Through a process of co-design with our stakeholder (DWER) we determined appropriate data sources relevant to decision-making, and adopted their preferred decision metrics for use in describing the impacts of individual storylines. Their central concern for the purpose of this case study was providing clear climate change information relevant to water resource planning for a mid-21st century time horizon (2050).

After an initial evaluation of the impact-scale application-ready dataset chosen, the National Hydrological Projections, we found that the dataset was not able to adequately represent runoff for the Millstream catchment which is known to have complex hydrology in the real world. We therefore chose to focus our analysis on the Yule and de Grey catchments.

We were able to quantify scenarios of a much wetter future storyline, and a future storyline with little change. We qualitatively described a storyline for a much drier future, and we then provided a quantitative example scenario of a much drier future, described in Section 4 above.

Key lessons were learned through this trial case study approach:

- Due to limited information at the impact-scale (that is, runoff only estimated at catchment scale for 4 out of nearly 40 CMIP5 climate models), storylines could not be directly quantified in relation to the explained variance of runoff. Instead, we adopted storylines that explained variance in the projections of a proxy variable (rainfall), which could be calculated for the full climate model ensemble. We then treated individual climate model-based runoff estimates as “expressions” or “scenarios” of key storylines. *An important caveat here is that our runoff changes for each storyline expression is not purely a function of our storyline drivers. Instead, they include influences from other drivers (that we did not investigate here) as well as internal variability, and added uncertainty due to impacts modelling and bias correction.* Future work should focus on addressing this issue: How can we quantify storylines to maximise explained variance at the impact scale when the available information relevant at that scale is limited?

- We found that the driest plausible future state (and storyline) seen in the CMIP5 ensemble was not sampled in the NHP dataset, meaning that we could not provide an expression of runoff changes for the driest storyline. Although this issue could be countered by larger samples at the impact scale, in practice this is limited due to the large costs involved in creating information relevant at decision scale for a national or global domain (either through downscaling and/or impacts modelling). One possibility would be to only estimate impacts such as runoff after describing and quantifying storylines for a proxy variable such as rainfall which is available from a larger sample such as the CMIP ensembles. However this approach would be highly bespoke to each location (depending on chosen drivers or storyline conditions), and would require significant expertise in multiple disciplines. Additionally, the calibration of these impact models (for example, rainfall-runoff models) for a future climate is highly problematic since they may implicitly assume stationarity of the climate (for example, Fowler et al 2020). An alternative approach may be to approximate the missing storylines at the impact scale by relating the available scale-relevant data to the larger climate model ensemble-based information in a predictive model (for example, multiple linear regression). This may be difficult due to sample size at the impact scale.

- The NHP dataset is mostly based on global climate models, which may not accurately simulate important processes relevant to extreme wet year rainfall at the catchment scale, such as local land-atmosphere feedbacks, and severe storms such as tropical cyclones. High resolution regional climate models are better able to capture these features, and future work should consider maximising the use of available regional climate model projections.

- Although the runoff estimates from the NHP dataset are bias-corrected, they remain quantitatively different to observed runoff in the historical period. For more information on the hydrological model biases see https://awo.bom.gov.au/about/overview/historical and references therein. They are also distinct from each other in both the historical and future periods. This leads to some level of disagreement in terms of runoff categorisation for both the historical period as well as for the change signal, especially when presented as percent-changes as has been done in this case study. As mentioned above, perhaps the use of calibrated local scale impact models may help with this issue, although this comes with its own challenges, also described above.

- The storylines used here were based on conditions relevant at the hemispheric scale (Mindlin et al., 2020), however it became clear through our analysis that the range of climate model projections for the western Pilbara region also relates in part to other influences. We did not attempt to quantify those here, but initial analyses indicate that other remote drivers may be important for future changes over the western Pilbara, including tropical Pacific SST asymmetry and nearby coastal SST changes.

- The regional influence of the selected drivers differs between models and may also differ compared to their patterns of regional influence in the real world. For example, while polar vortex weakening is associated with drying over much of Australia, it appears to have a very localised relationship with Pilbara rainfall in the real world (Lim et al, 2019) which is different to that found in climate model projections with global warming (Mindlin et al, 2020). We note this here as a caveat, however the significance of this difference is unclear; in part because the effect is highly localised, but also because the sample of years in the observed real world for which vortex weakening occurs is small (9 out of 38 years) compared to that from models (tens of models, with multiple hundreds of years of simulation). Additionally, it is unclear if the regional effects due to internal variability of features like the stratospheric polar vortex (for example, year-to-year vortex weakening) should be identical to the regional influence of mean state changes in those features (such as systematic earlier breakdown of the vortex) since they may occur against quite different background states.

With the afore-mentioned caveats in mind, we emphasise that **the storyline projections presented here based on runoff from the NHP dataset are considered to be plausible, reliable, and relevant for planning future water resources for the western Pilbara case-study catchments that influence the Yule and de Grey aquifers**.

Future efforts should focus on addressing the known issues described above, however, several other fruitful avenues may also be pursued. The role of bias correction was shown here to be significant for estimating the runoff changes, and indeed can even influence the direction of change at some locations. This requires further investigation to determine locally which method is most fit-for-purpose. The role of climate variability is central in extreme seasonal runoff, yet here we have only managed to provide an exploratory evaluation of key processes influencing local climate variability. Further evaluation and analysis would help clarify the validity of individual storylines. The impacts in this case study are estimated from one source of information with limited ability to address model uncertainty. Future work could incorporate other sources of information with evidence relevant at the decision scale, including dynamical downscaling and high-resolution global climate simulations. Finally, other climate variables may be of relevance and interest to decisions rather than focusing on narratives of runoff change. Water availability is both a function of supply and demand, so including some estimate of demand would be useful (for example, potential evapotranspiration, usage demand, soil moisture or temperature).

Although the exercise described in this report has not fully quantified a complete set of climate change storylines for western Pilbara water availability, it represents a useful first step in that direction. Crucially we have established the plausibility of extreme future states of water availability and identified that future water-resource planning based on existing application-ready hydrological data may significantly under-estimate future risk if a plausible drier future eventuates.

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Appendices

Appendix 1: DWER triggers for runoff-recharge categories

Table 1: De Grey aquifer recharge classes

Recharge Class	Water availability conditions	Total wet season flow (Oct-Apr ML) measured at Coolenar Pool gauging station (AWRC Ref 710003)
1	Drought	<200 000 or two consecutive dry periods
2	Dry	200 000 – 1 000 000
3	Average to wet	> 1 000 000

Table 2: Yule aquifer recharge classes

Recharge class	Water availability conditions	Total wet season flow (Oct-Apr ML) measured at Jelliabidina Well gauging station (AWRC Ref 709005)
1	Drought	<3 000 or 2 consecutive dry years
2	Dry	3 000 to 150 000
3	Average to wet	>150 000

Table 3: Millstream aquifer revised recharge classes

Recharge class	Water availability condition	Total wet season flows (Dec–April ML) measured at Gregory Gorge gauging station (AWRC Ref 708002)
1	Drought	< 43,000 for previous 3 or more years.
2	Dry	< 43,000 for previous 1 or 2 years.
3	Average to wet	> 43,000 (if the mean aquifer level is < 294.00 mAHD at the beginning of the water year, recharge class 2 should be applied).

What is the impact?

Table 4 below shows the link between the aquifer recharge categories and the ecosystem response for Millstream aquifer.

Table 4: Ecological water requirements in the form of percentiles used to set flows and groundwater criteria and predicted ecosystem response

Water availability*	Percentile based on historical monitoring data (groundwater or flow)	Predicted ecosystem response	
		Aquifer ecosystems supported by MAL8	Riverine and Delta ecosystems supported by Deep Reach Pool and Chinderwarriner Pool flows
Average to wet	> 50th percentile	Recovery and recruitment.	High surface water expression and connectivity between wetlands.
Dry	>20th percentile	Riparian vegetation using proportionally more groundwater and minor large-scale decline in percentage foliage cover	Drying out of intermittent and semi-permanent wetlands.
Drought	>5th percentile	Riparian vegetation dependent on groundwater as other water sources become restricted. Minimal recruitment and more significant decline in percentage foliage cover	Permanent pools and habitat below Livistona Pool contracting.
Excluded	< 5th percentile.	Groundwater level declining below root zone of some vegetation resulting in tree health declines and death.	Permanent pools disconnecting from hydrology, large reduction in aquatic habitat and disconnected flow to Livistona Pool.

Lower Fortescue groundwater allocation limit report, Method used to set an allocation limit and licensing rules for the Lower Fortescue alluvial aquifer
https://www.water.wa.gov.au/__data/assets/pdf_file/0008/4301/96734.pdf

Yule River – ecological values and issues, Oct 2010 Yule River - ecological values and issues (water.wa.gov.au)

Appendix 2: Overview of the bias correction techniques

For the National Hydrological Projections (NHP), three bias correction techniques were implemented. They are all variants of quantile mapping, whereby the quantiles of the GCM-modelled field at a location are matched to observations. For NHP, the observations were provided by the Bureau's 5 km gridded AWAP data set (Jones et al., 2009). Although all of the bias correction methods used quantile mapping they have fundamental differences as to their implementation, most notably in the timescales on which the quantile matching is performed. Here we give a brief outline of each of the NHP bias correction methods.

ISIMIP2b method

The Inter Sectoral Impact Model Intercomparison Project (ISIMIP) (https://www.isimip.org/) was designed to offer a consistent framework for projecting climate change impacts across different sectors and spatial scales. It is a parametric quantile matching method as it describes variables of interest by a parametric distribution. This is different from the other methods which use only quantiles rather than fitting a distribution to the variable; temperature is assumed to be modelled by a Gaussian (normal) distribution, while precipitation is represented by a Gamma distribution. The ISIMIP2b method is comprised of the following steps: (1) correction of the monthly mean, (2) correction of the daily variability, (3) correction for the frequency of dry days and (4) correction for the intensity of wet days (Hempel et al., 2013; Piani et al., 2010a, 2010b). Steps (1) and (2) have different implementations depending on whether the correction to be applied is additive (temperature) or multiplicative (precipitation, winds and solar radiation). These steps are performed at a monthly time scale.

QME method

The quantile matching of extremes method was developed at the Bureau to match the extremes of the probability distribution (Dowdy, 2020). In the normal quantile matching method, a simulated value, a quantile of the simulated distribution, is replaced by the quantile of the observed distribution corresponding to the same probability. As an additional step, the QME method uses the 5 most extreme values to calculate the mean difference between the projected and the observed data. The mean difference is then used to bias-correct the values outside of the range of historical values. The mean difference is calculated separately for the 5 extreme high values, as well as for the 5 extreme low values. This approach allows extreme values outside the range of historical values to be represented in the simulated data after bias correction. The QME method also removes a 40-yr moving average prior to calculating the calibration factors for daily maximum and minimum temperatures, with that moving average then added back into the calibrated temperature data, thereby reducing the potential for statistical artefacts relating to large shifts in the future temperature distribution. For the National Hydrological Projections, the QME approach was applied to the seasonal time scale.

MRNBC method

The nested bias correction (NBC) method corrects the distributional (first two order moments) and persistence (lag 1 autocorrelation coefficient) at monthly, seasonal and annual time scales (Johnson and Sharma, 2012). The recursive nested bias correction (RNBC) method is an extension of the above NBC method. In this method, the above NBC method is applied three to five times repeatedly so that it significantly reduces the biases in mean, variability and persistence related attributes in GCM/RCM simulations (Mehrotra and Sharma, 2012). The Multivariate Recursive Nesting Bias Correction (MRNBC) method is a multivariate version of the above RNBC method. It simultaneously corrects many GCM/RCM variables at different time scales to impart observed distributional and persistence properties, preserving both the relationship between variables and time dependence attributes (Mehrotra and Sharma, 2016).

The effect of the bias correction on the climate change signal is shown in Figure 5. The climate change signal is constructed as the difference between the temporal mean of a future period minus the historical period. In this case, the future period is the 30-yr period centred on 2050 and the historical period is 30-years centred on 1990. Figure 5 displays the bias-corrected change signal minus the raw GCM change signal and therefore indicates the effect that bias correction has had on the climate change signal. The GCMs are displayed across rows and the bias correction methods along columns. The models are ordered from wettest to driest, shown in previous analysis (Figure 8), to be CNRM-CM5, MIROC5, ACCESS1-0 and GFDL-ESM2M. The bias correction methods have all imposed a drying on the wettest model (CNRM-CM5) and a wetting signal on the driest model (GFDL-ESM2M). Both ISIMIP2b and QME have imparted a drying signal on the MIROC5 model while MRNBC has increased the precipitation. This difference is most likely because the MRNBC applies the bias correction on multiple timescales which enables it to better represent the low-frequency variability of precipitation. However, the multivariate capability of MRNBC may also contribute to this opposite signal compared to the other bias correction methods. The QME method has enhanced rainfall for the driest model (GFDL-ESM2M). The QME is applied on a four season timescale which does not correspond with the wet season shown here (November to April), requiring the bias correction to apply a greater wetting signal during the Spring (SON) and Autumn (MAM) which straddle the wet season. The MRNBC method has also resulted in some coastal precipitation being imposed on the GCM signal, which is most likely due to the multivariate component of the bias correction being able to modify the GCM signal and incorporate a coastal (seabreeze) precipitation signal.

What is different about the CCAM information?

The left column of Figure 5 displays the ISIMIP2b method applied to the CCAM output (forced by the individual GCMs). The CCAM model tends to produce a drier signal than each of the host GCMs which is evident as a general wetting signal being imposed on all models by the ISIMIP2b. The increased resolution (and subsequent added value) of CCAM (~50 km) enables it to represent coastal circulations, however, the ISIMIP2b has made large increases to the raw CCAM output. This signal is only captured by the MRNBC method indicating that it may provide better bias correction where local-scale circulations are important, for instance near the coast or in regions of complex topography. Finally, we note that the climate change signal generally relaxes back to the spatial scale of the host GCM, such that the model scale is evident in the rectangular features displayed. However, all the bias correction methods, most notably MRNBC, have imposed extra information on the climate change signal that is not present in the host GCM and therefore "added value" to the GCM output.

Appendix 3: NHP runoff evaluation by catchment

Below we present a comparison between Yule, DeGrey and Millstream flow volumes against drought requirements as prepared by DWER.

Method:

The volume from the models is calculated by masking the model data with the associated shapefile (provided by DWER) for each of the three regions, then summing all the streamflow amounts within the shapefile. The total is multiplied by the shapefile area (which is calculated using a gdal package, 14,629.370523 km^2) to create a volume metric, and changing to appropriate units. The same methodology was applied to all three regions. In addition, gridded streamflow based on AWAP gridded observed climate data as inputs to the awra model, was used as an estimate of observed streamflow for Millstream.

Outcomes:

The three figures below show the results for the catchments DeGrey, Yule, and Millstream for (a) the CMIP5 model data, and (b) "observed" streamflow from gridded awra data. The streamflow accumulation during December to April over the Millstream region is found to be significantly larger than the nearby observed streamflow gauge Gregory gorge (Figure A3.1)

To check that the methods we used to generate the time series did not have obvious systematic errors, time series plots of the CMIP5 model ensemble data was produced for all three regions: DeGrey, Yule, and Millstream. Dashed lines were added to the plots to indicate threshold values for three water deficit classes – Drought, Dry, and Wet.

The results for DeGrey and Yule show there is a reasonable spread of values across all three classes, although in the case for Yule, there are no values below the first threshold of 3GL. However, this does not prevent cases of drought occurring since there are cases of two consecutive dry periods, which is classed as drought.

The CMIP5 (Fig. A3.3a) and AWRA (Fig. A3.3b) results for Millstream show that in the historical period, there is no event less than 43GL during December to April. In comparison, the streamflow gauge (Gregory gorge) regularly shows volumes below 43GL (Fig. A3.4a), and the associated cumulative probability distribution shows at least 40% of the data is below 43GL (Fig. A3.4b).

Gregory gorge is plotted with the AWRA time series (Fig. A3.5a), which shows there is reasonable agreement, however it appears the peak values are significantly overestimate, as well as near-zero observed flows. Figure A3.5b also confirms this due a significant scattering of positive AWRA values when the observed is close to zero.

The last figure (A3.6) shows the spatial map of Millstream, and part of the other two regions. It shows the distribution of rainfall stations across the regions. There appears to be a good spread of stations across Millstream, and similarly for the other two regions. This shows it is not a lack of rainfall stations that is causing the AWRA gridded streamflow to over-estimate the streamflow.

There appear to be disconnected rivers in the Millstream region, so it is not clear to us if the flow from these rivers contributes to the streamflow at Gregory gorge. The AWRA model does not do routing of flow, so it simply accumulates the flow value at each pixel that lies within the shapefile. It is possible that this is the reason that AWRA is over-estimating the streamflow, since it is assuming that all flow values within the shapefile are contributing to Gregory gorge.

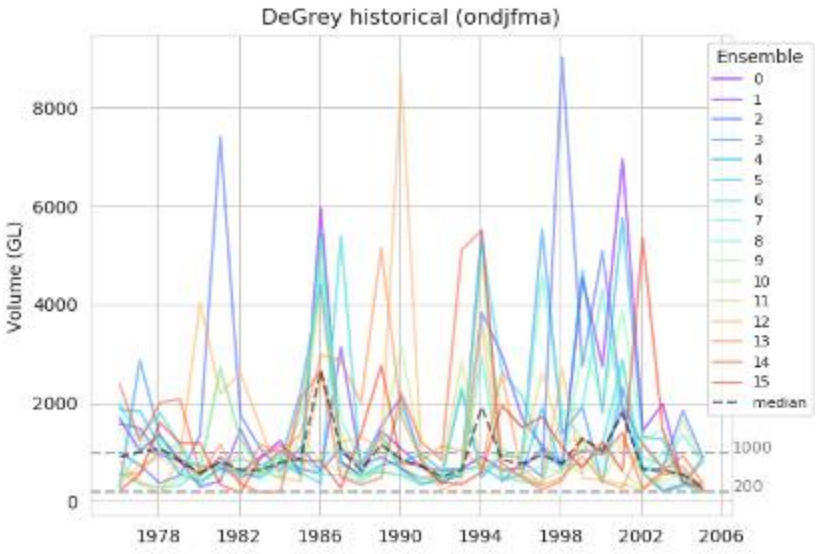

Figure A3.1a: Runoff calculated from the 16 NHP members (RCP8.5) and the DeGrey catchment during October to April (historical period).

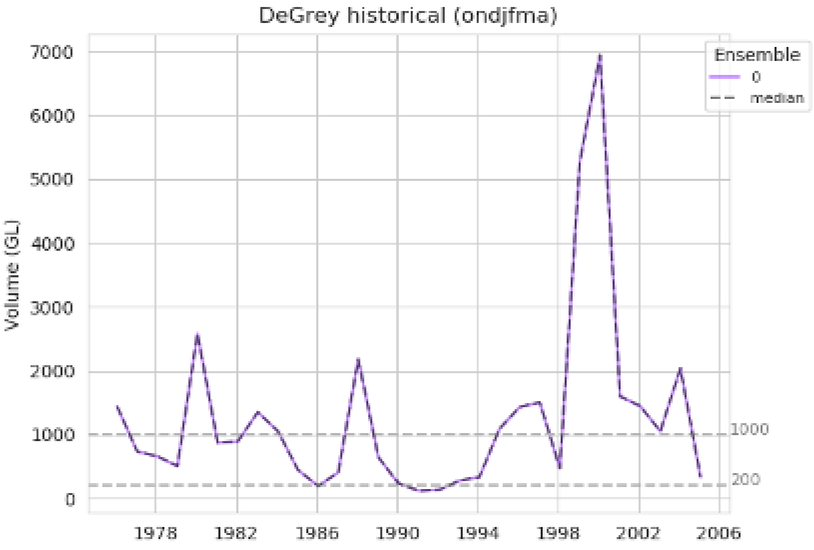

Figure A3.1b: Runoff calculated using AWAP gridded climate data as inputs to AWRA and theDeGrey catchment during October to April (historical period) shown.

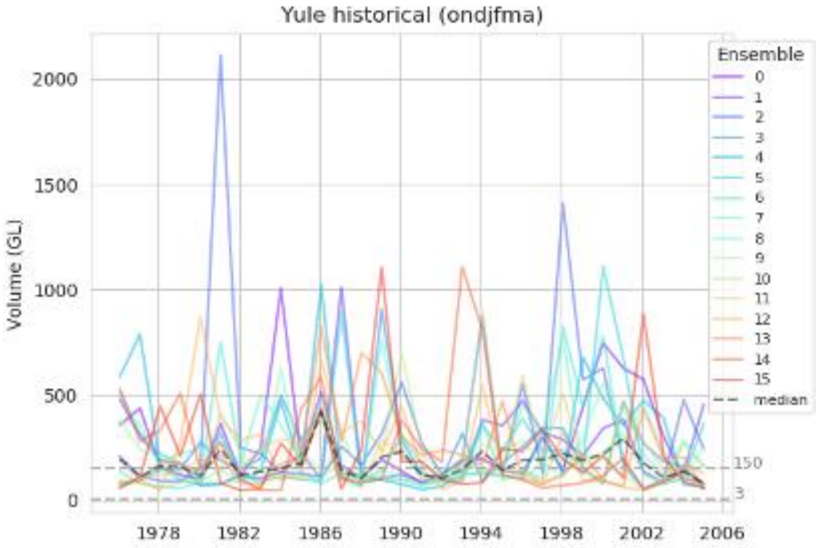

Figure A3.2a: Runoff calculated from the 16 NHP members (RCP8.5) and the Yule catchment during October to April (historical period).

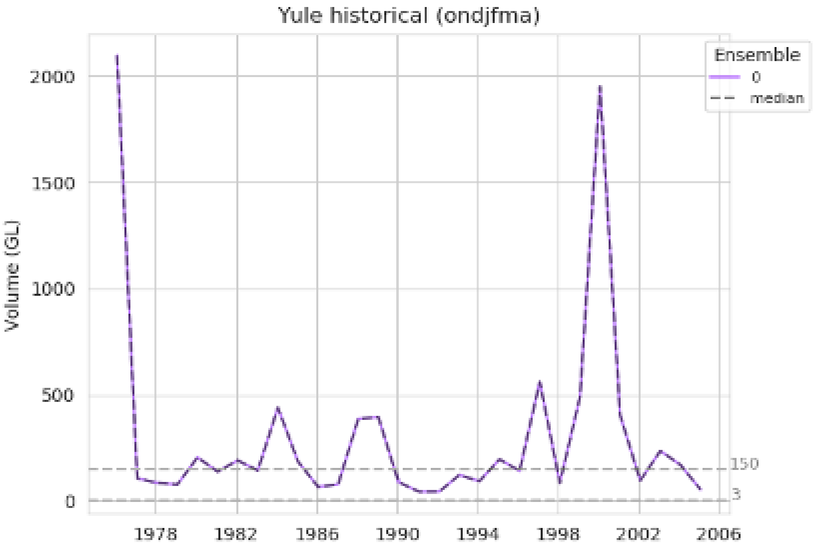

Figure A3.2b Runoff calculated using AWAP gridded climate data as inputs to AWRA over Yule during October to April.

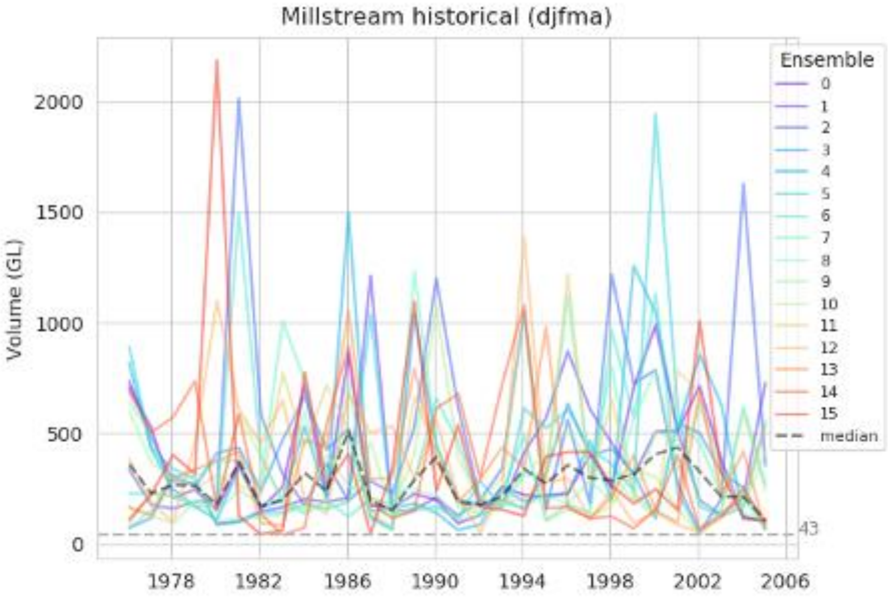

Figure A3.3a: Runoff calculated from the 16 NHP members (RCP8.5) and the Millstream region during October to April.

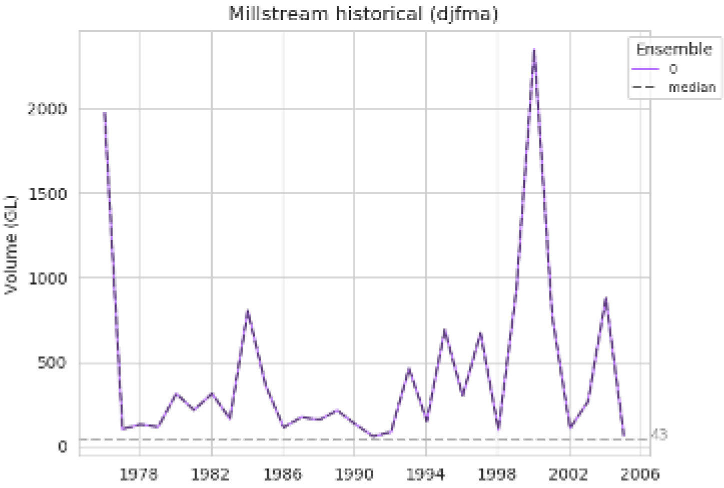

Figure A3.3b: Streamflow calculated using AWAP gridded climate data as inputs to AWRA over Millstream during October to April.

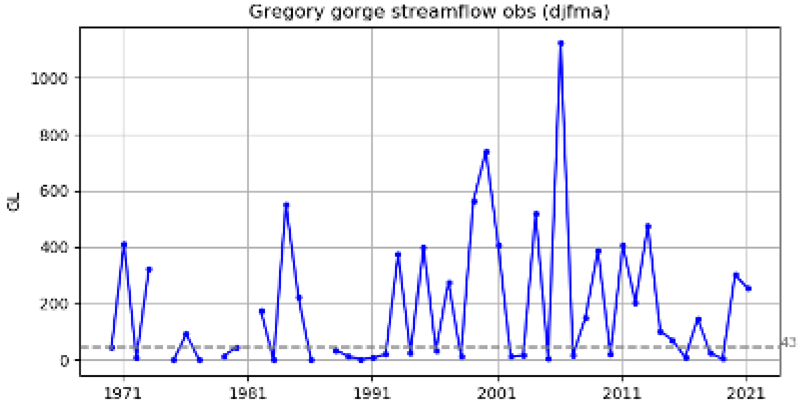

Figure A3.4a: Time series of the observed streamflow from Gregory Gorge (Millstream region) during December to April.

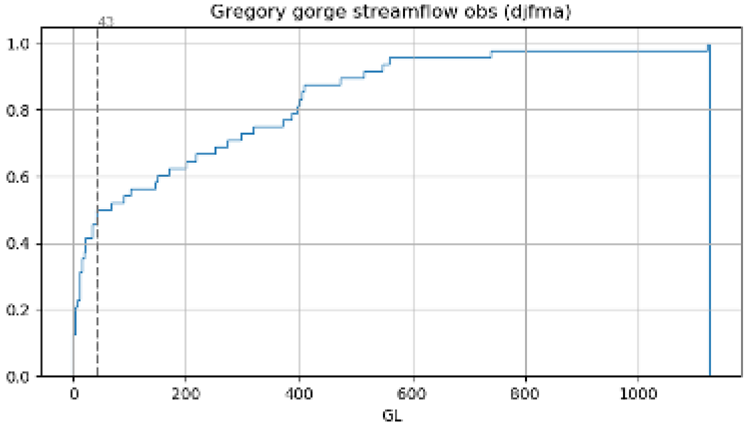

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Figure A3.4b: Cumulative probability distribution of the observed streamflow from Gregory Gorge (Millstream region) during December to April.

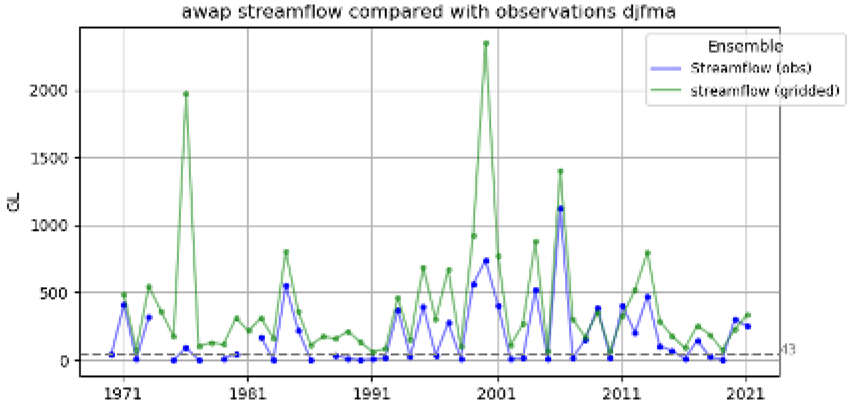

Figure A3.5a: Time series of both the observed streamflow (Gregory Gorge, blue), and simulated runoff using AWAP data as climate inputs to run AWRA (green).

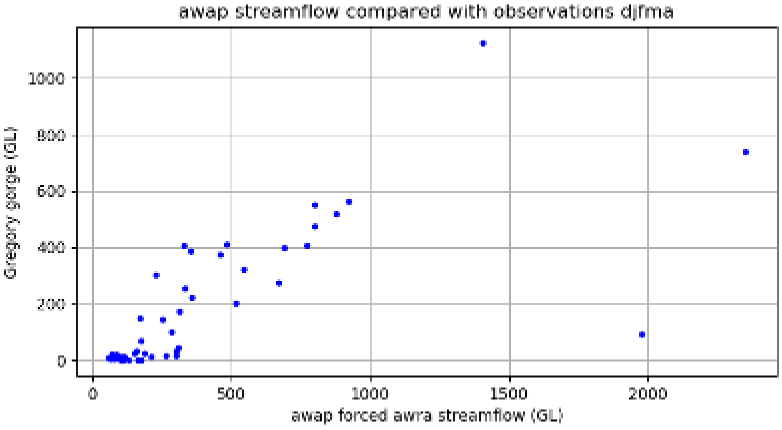

Figure A3.5b: Scatter plot of the observed streamflow (Gregory Gorge), and simulated runoff using AWAP data as climate inputs to run AWRA.

Figure A3.6 Map showing locations of BOM rainfall stations (blue squares), rivers (blue), and catchments (green) from http://www.bom.gov.au/waterdata/

Appendix 4: NHP runoff outputs and drought categorisation

De Grey (Coolenar)

The De Grey (Coolenar) catchment area is 50 575 km2. The total seasonal runoff (ML) can be calculated as the seasonal runoff rate per unit area (mm) multiplied by the catchment area (km2). Outputs from each of the NHP members can be assessed in terms of qualitative change against the historical baseline of 1976-2005.

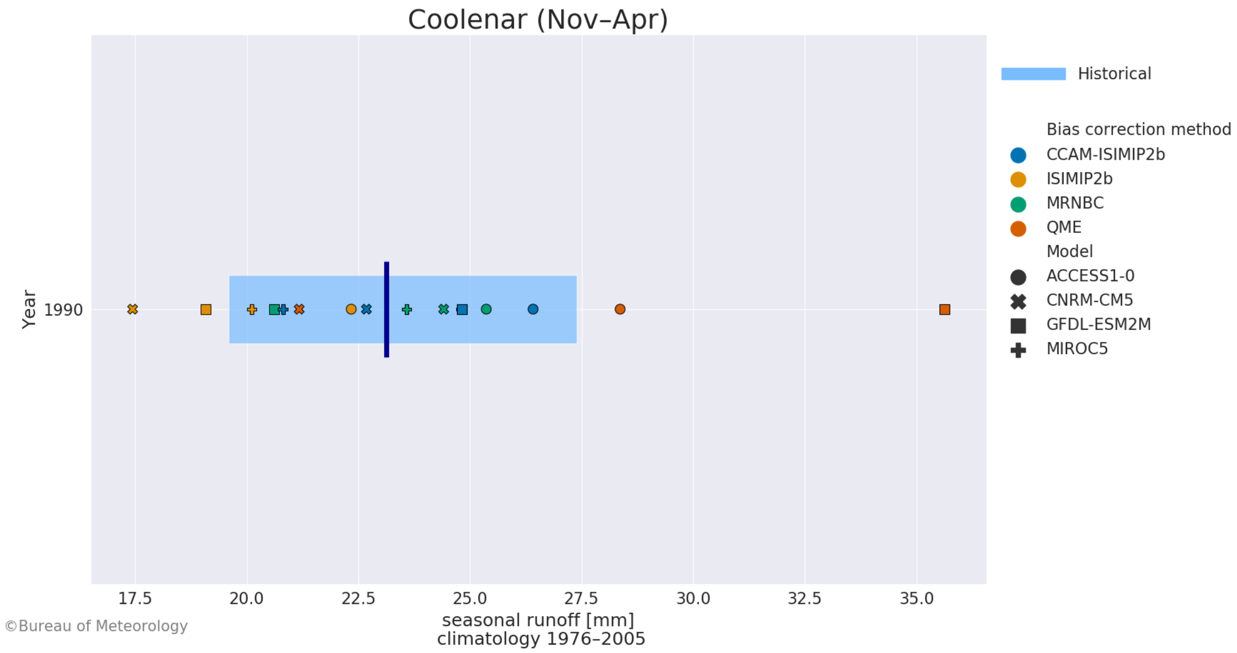

Figure A4.1: Historical baseline of the de Grey (Coolenar) catchment seasonal runoff rate per unit area for the November-April wet season (1976-2005) for each model (symbols) bias corrected in different ways (colours). The blue box plot represents the 10th, 50th and 90th percentiles of the NHP dataset.

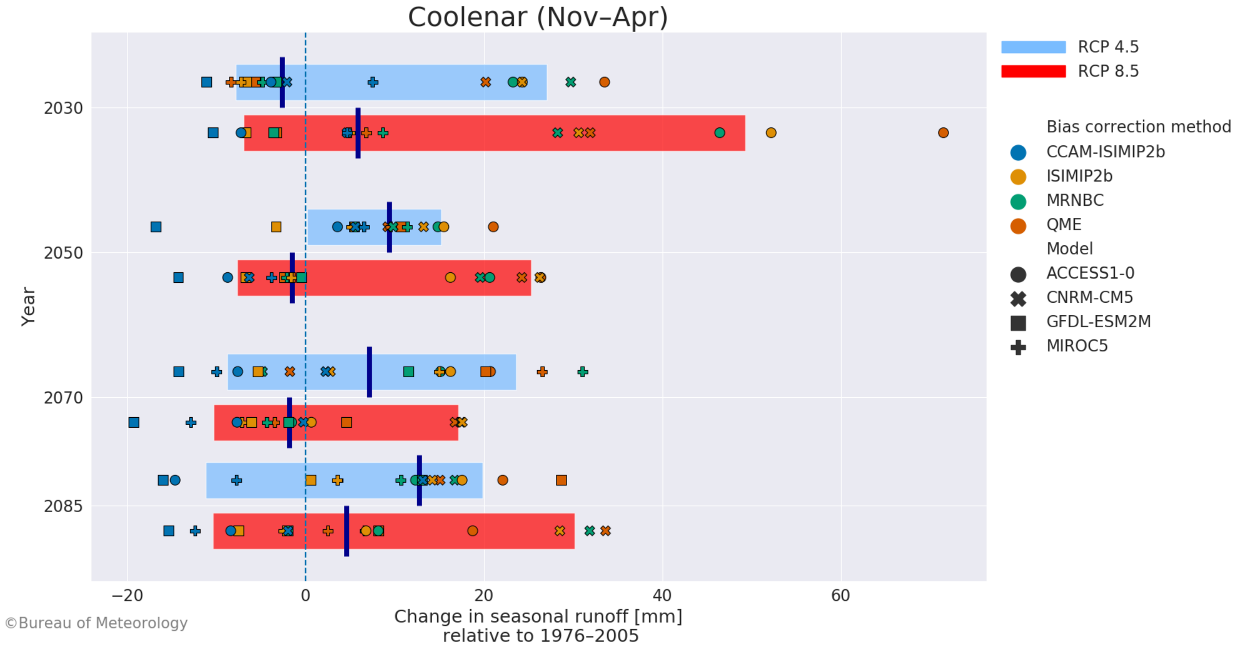

Figure A4.2: Future change in the de Grey (Coolenar) catchment seasonal runoff rate per unit area for the November-April wet season for 30-year centred periods when compared against a historical period (1976-2005) for each model (symbols) bias corrected in different ways (colours). The box plot represents the 10th, 50th and 90th percentiles of the NHP dataset, with a medium emissions scenario in blue and a high emission scenario in red.

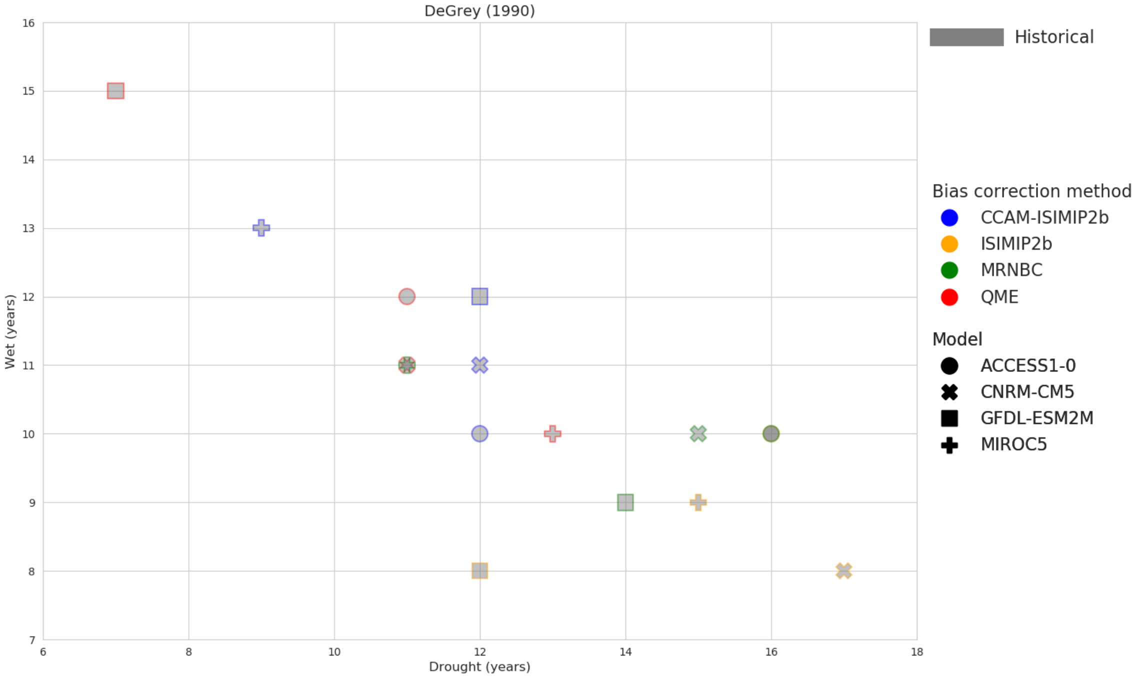

Figure A4.3: Frequency of drought years vs frequency of wet years for the de Grey (Coolenar) catchment for the November-April wet season (1976-2005) for each model (symbols) bias corrected in different ways (colours). Categorisation of seasonal runoff is conducted using absolute thresholds described in Appendix 1.

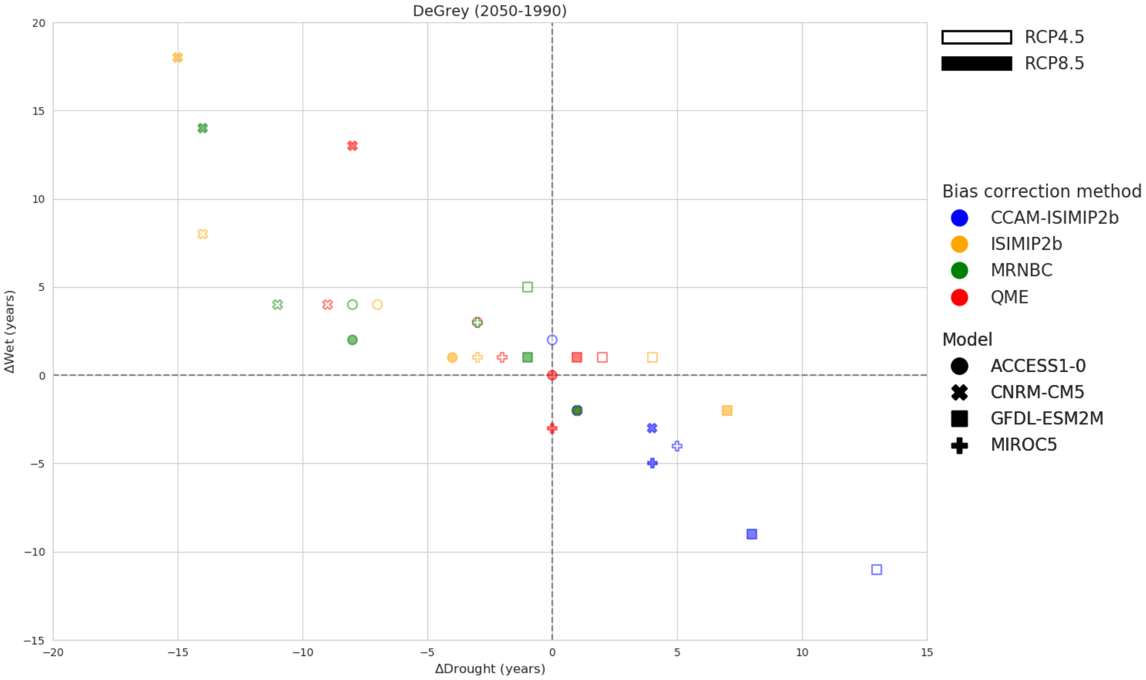

Figure A4.4: Change in the frequency of drought years vs frequency of wet years for the de Grey (Coolenar) catchment for the November-April wet season (2036-2065 minus 1976-2005) for each model (symbols) bias corrected in different ways (colours). Filled markers indicate a high emissions scenario (RCP8.5) while open markers indicate a medium emissions scenario (RCP4.5). Categorisation of seasonal runoff is conducted using absolute thresholds described in Appendix 1.

Yule (Jelliabidina)

The Yule (Jelliabidina) catchment area is 8 861 km2. The total seasonal runoff (ML) can be calculated as the seasonal runoff rate per unit area (mm) multiplied by the catchment area (km2).

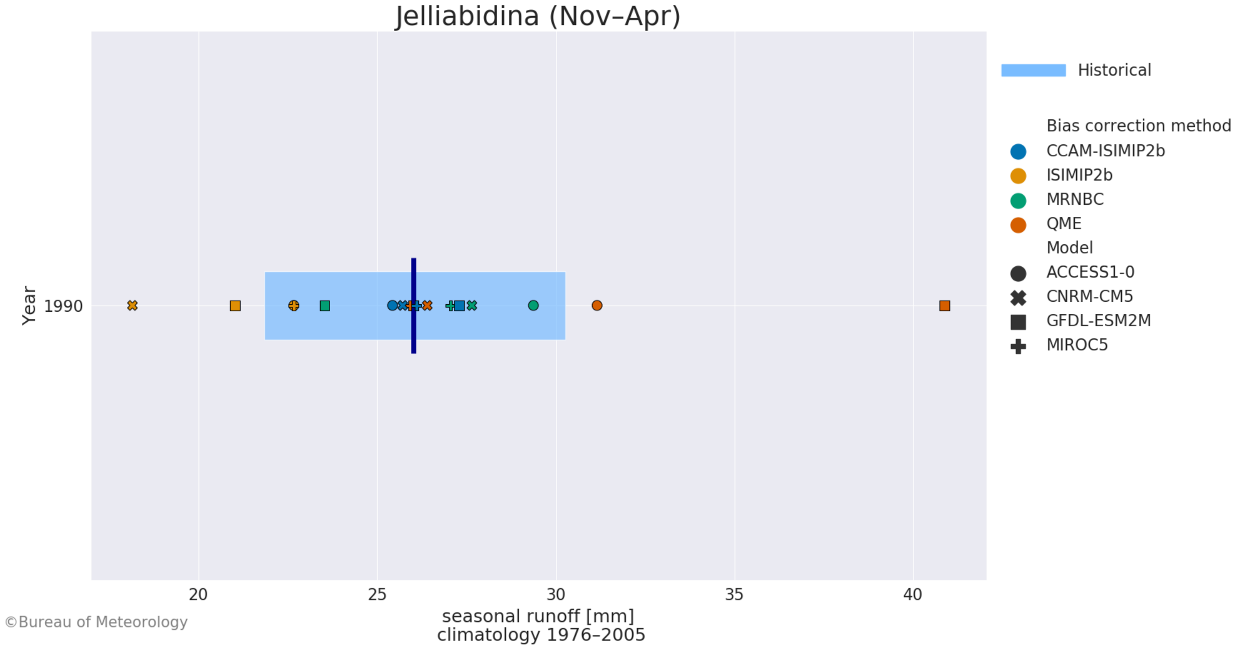

Figure A4.5: Historical baseline of the Yule (Jelliabidina) catchment seasonal runoff rate per unit area for the November-April wet season (1976-2005) for each model (symbols) bias corrected in different ways (colours). The blue box plot represents the 10th, 50th and 90th percentiles of the NHP dataset.

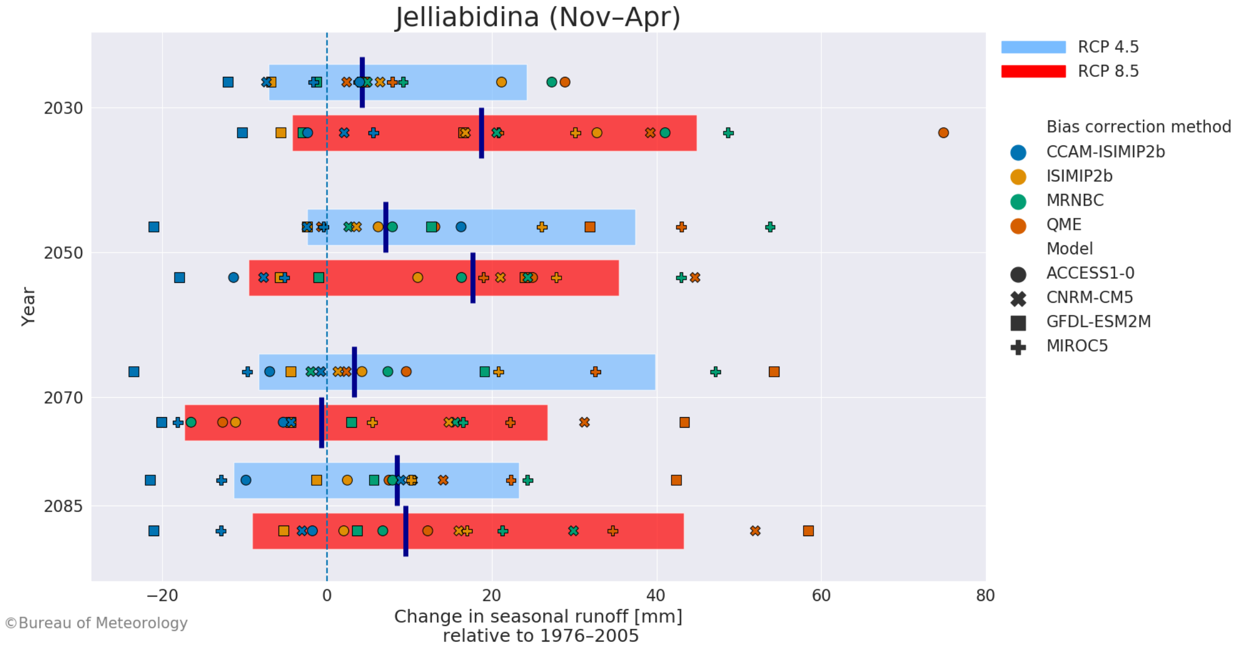

Figure A4.6: Future change in the Yule (Jelliabidina) catchment seasonal runoff rate per unit area for the November-April wet season for 30-year centred periods when compared against a historical period(1976-2005) for each model (symbols) bias corrected in different ways (colours). The box plot represents the 10th, 50th and 90th percentiles of the NHP dataset, with a medium emissions scenario in blue and a high emission scenario in red.

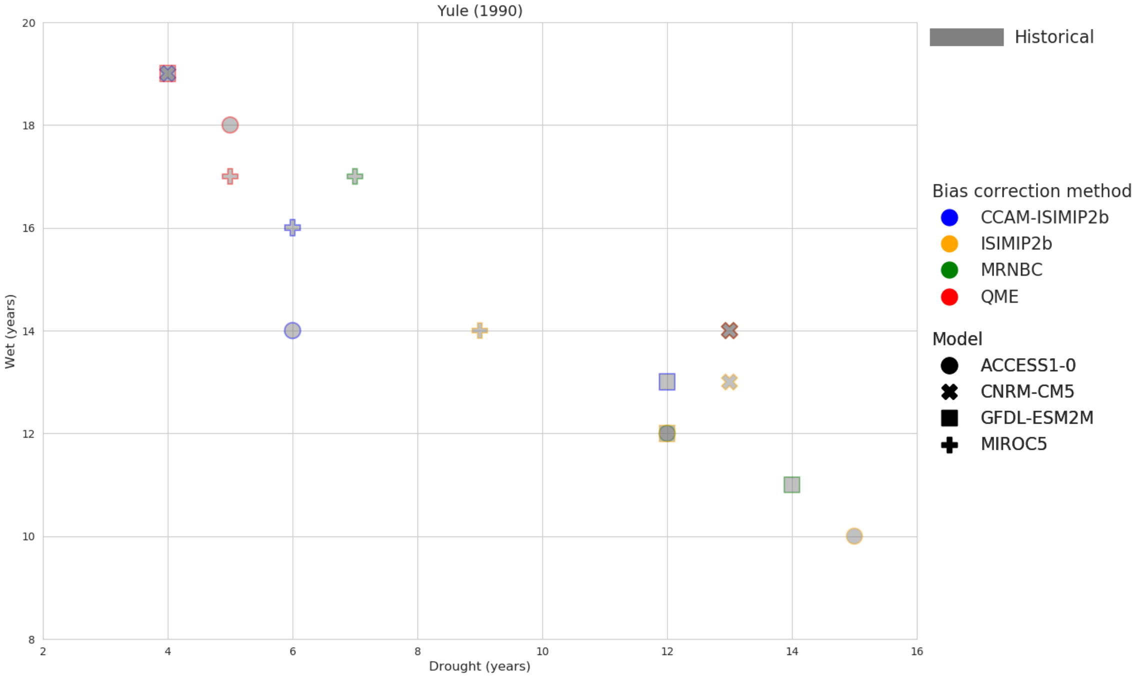

Figure A4.7: Frequency of drought years vs frequency of wet years for the Yule (Jelliabidina) catchment for the November-April wet season (1976-2005) for each model (symbols) bias corrected in different ways (colours). Categorisation of seasonal runoff is conducted using absolute thresholds described in Appendix 1.

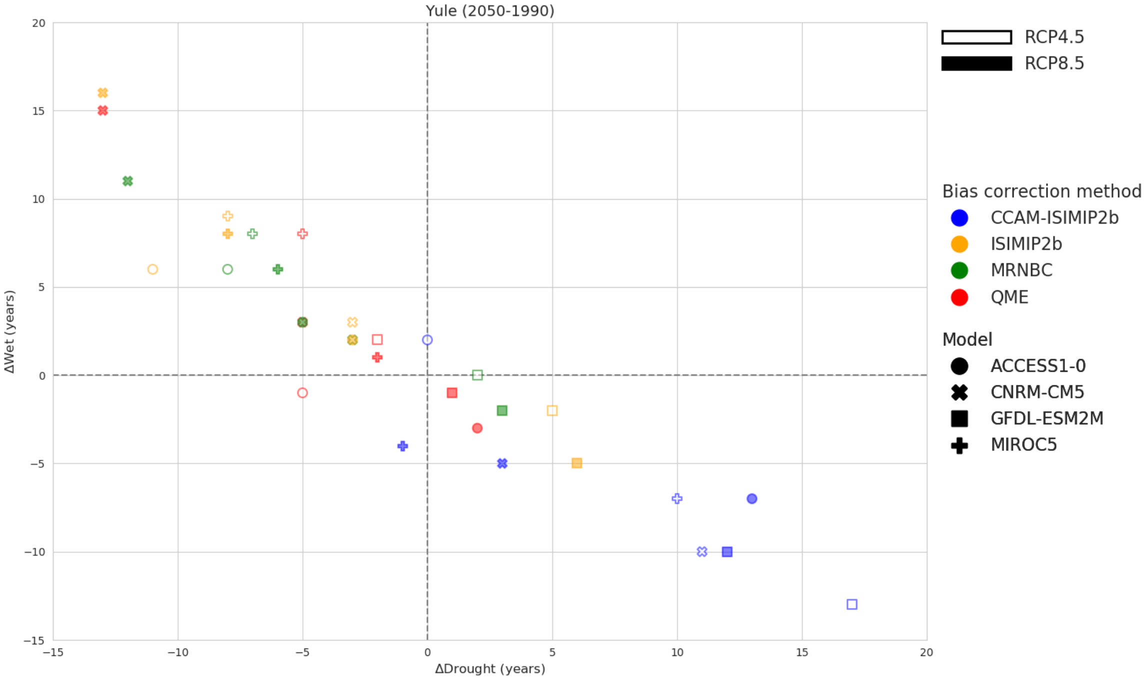

Figure A4.8: Change in the frequency of drought years vs frequency of wet years for the Yule (Jelliabidina)catchment for the November-April wet season (2036-2065 minus 1976-2005) for each model (symbols) bias corrected in different ways (colours). Filled markers indicate a high emissions scenario (RCP8.5) while open markers indicate a medium emissions scenario (RCP4.5). Categorisation of seasonal runoff is conducted using absolute thresholds described in Appendix 1.

Millstream (Gregory Gorge)

The Millstream (Gregory Gorge) catchment area is 18 608 km2. The total seasonal runoff (ML) can be calculated as the seasonal runoff rate per unit area (mm) multiplied by the catchment area (km2).

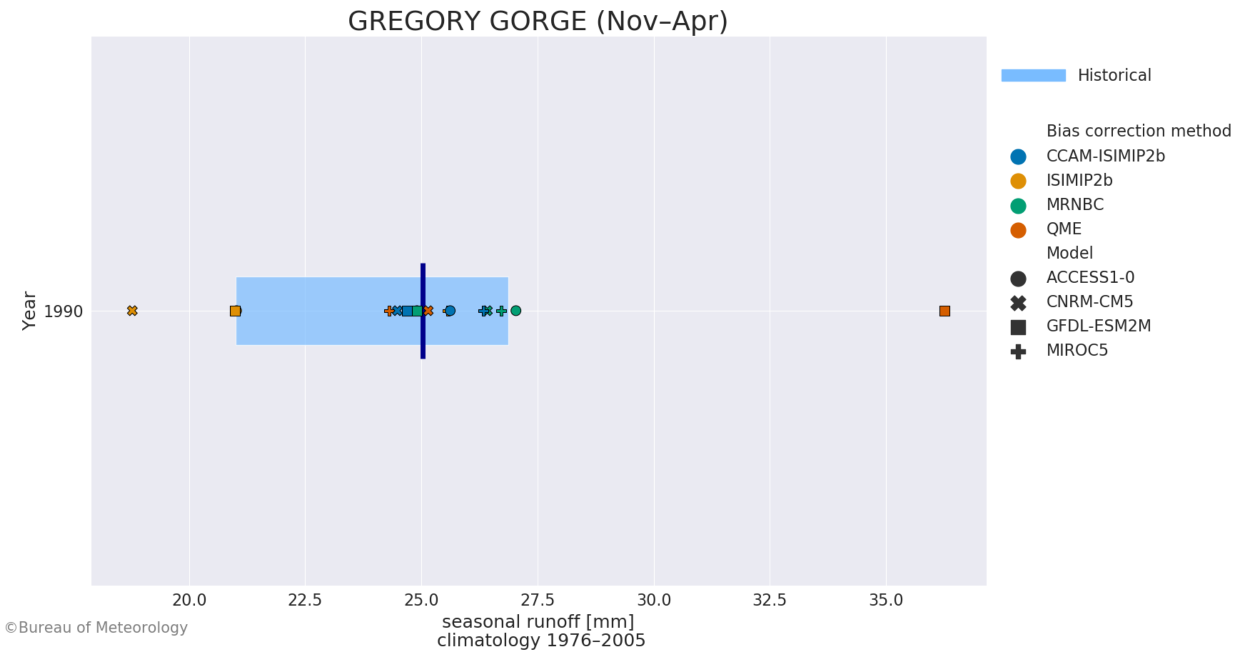

Figure A4.9: Historical baseline of the Millstream (Gregory Gorge) catchment seasonal runoff rate per unit area for the November-April wet season (1976-2005) for each model (symbols) bias corrected in different ways (colours). The blue box plot represents the 10th, 50th and 90th percentiles of the NHP dataset.

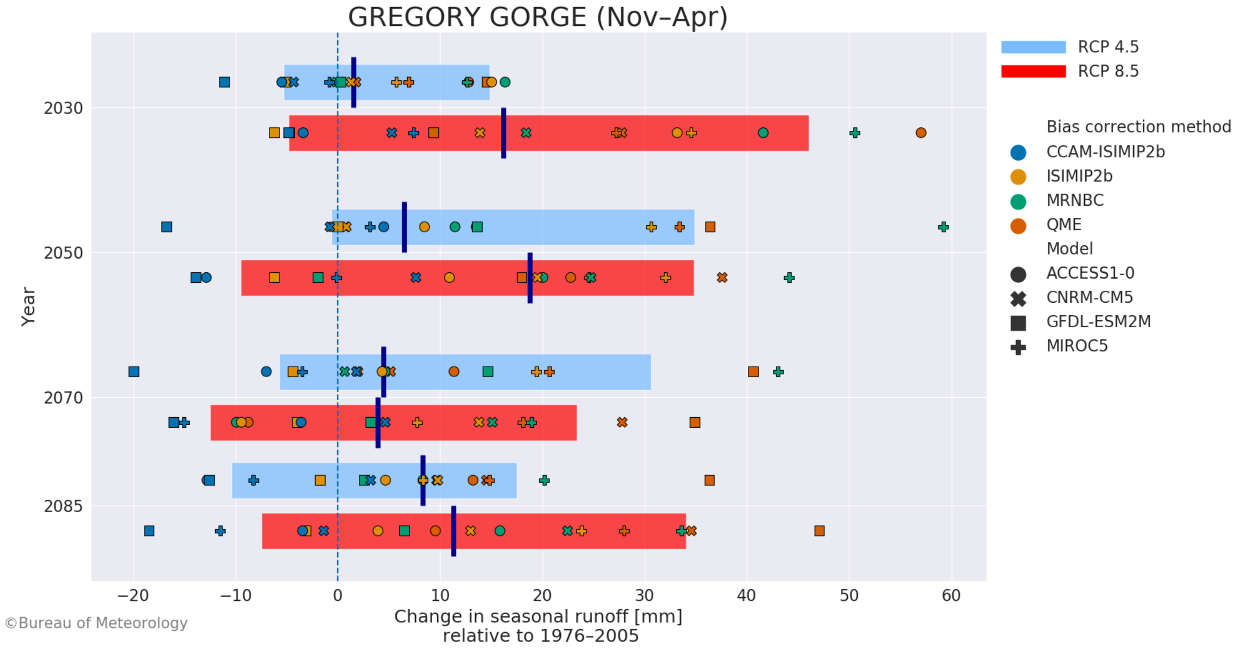

Figure A4.10: Future change in the Millstream (Gregory Gorge) catchment seasonal runoff rate per unit area for the November-April wet season for 30-year centred periods when compared against a historical period(1976-2005) for each model (symbols) bias corrected in different ways (colours). The box plot represents the 10th, 50th and 90th percentiles of the NHP dataset, with a medium emissions scenario in blue and a high emission scenario in red.

Runoff categorisation for the Millstream catchment was not possible due to a large mismatch between NHP catchment averages and the observed streamflow at Gregory Gorge.

Appendix 5: GCM evaluation for the western Pilbara region

The results described in this section are used as context for informing climate change storylines of the western Pilbara region.

In figure A5.1 we show the 1976 to 2005 November to April rainfall climatology in an observation-based dataset (GPCP, Adler et al. 2003) and in the four NHP models. Each model has its own particular regional biases. The ACCESS1-0 model has a wet bias over the Maritime Continent, but is too dry over the western Pilbara. The CNRM-CM5 model has a close representation of wet season climatology compared to observed, with small biases along the east coast of Australia and the Arafura Sea, but similar climatology over the western Pilbara. The GFDL-ESM2M model rains too much over northern Australia and the Maritime Continent, as does the MIROC5 model.

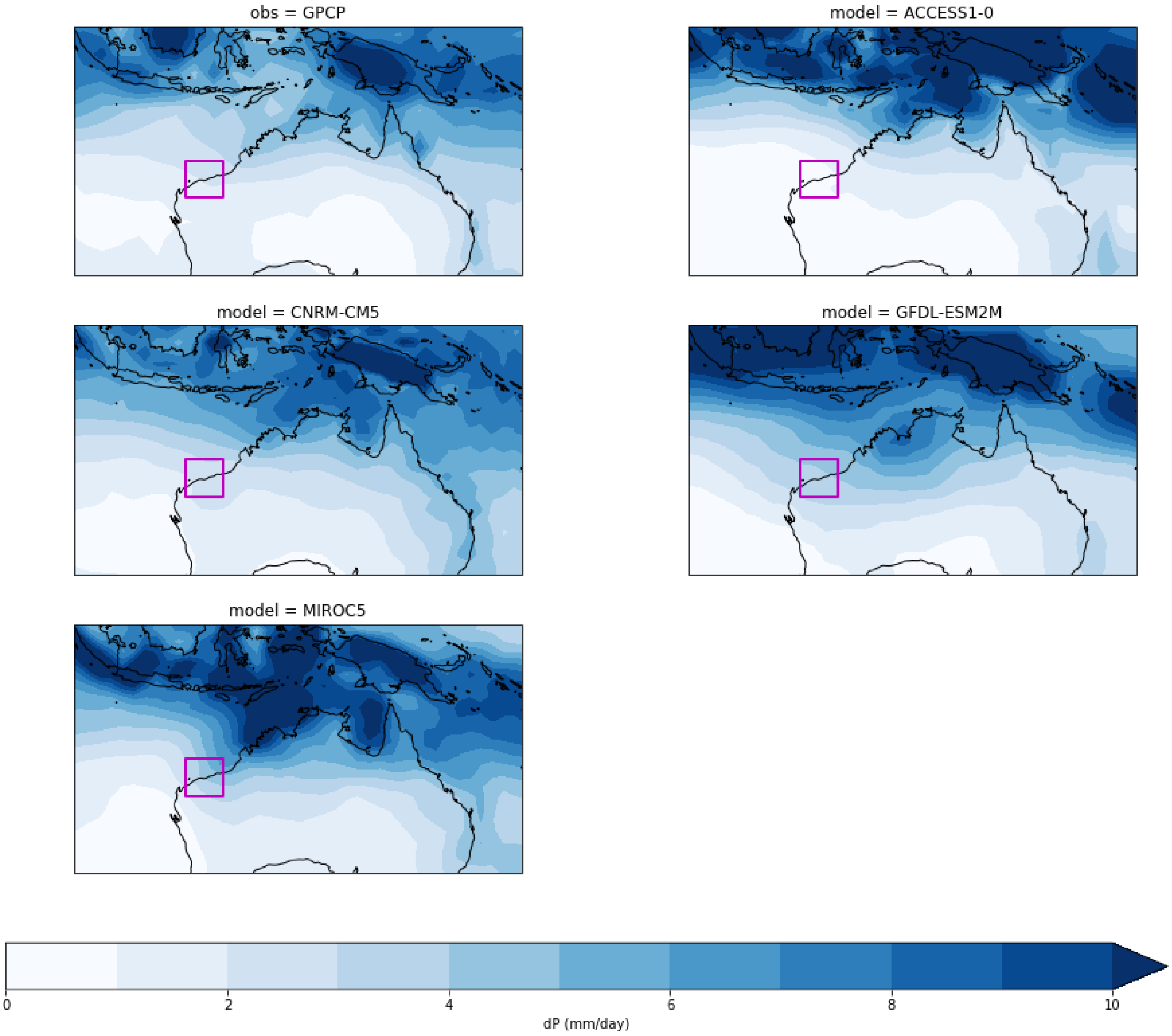

Figure A5.1: 1976 to 2005 November to April rainfall climatology for the GPCP observation-based dataset, and the 4 NHP GCMs.

In Figure A5.2 we consider monthly climatological rainfall zonally averaged between 115E and 120E, the approximate longitudes of the western Pilbara. The purpose of this analysis is to investigate both the seasonal progression and extent of the northern Australian monsoon relevant to the Pilbara region. The dotted magenta lines indicate the approximate latitudes of the western Pilbara region. In the real world the monsoon progresses southward in the Austral summer, reaching latitudes just north of the Pilbara between December and February. This seasonal progression of the monsoon is clearly visible in all of the CMIP5 models, however significant variations are clearly seen. The ACCESS1-0 model has an appropriate seasonal progression of the monsoon, as does the CNRM-CM5 model, terminating just north of the western Pilbara region. The GFDL-ESM2M appears to have a later and sharper onset to the monsoon, that extends further south into the western Pilbara latitudes in the late Austral summer months. The MIROC5 model has the least realistic monsoon progression, with sharp jumps in the monsoon precipitation in the Austral summer and an extension of the monsoon well into the western Pilbara latitudes.

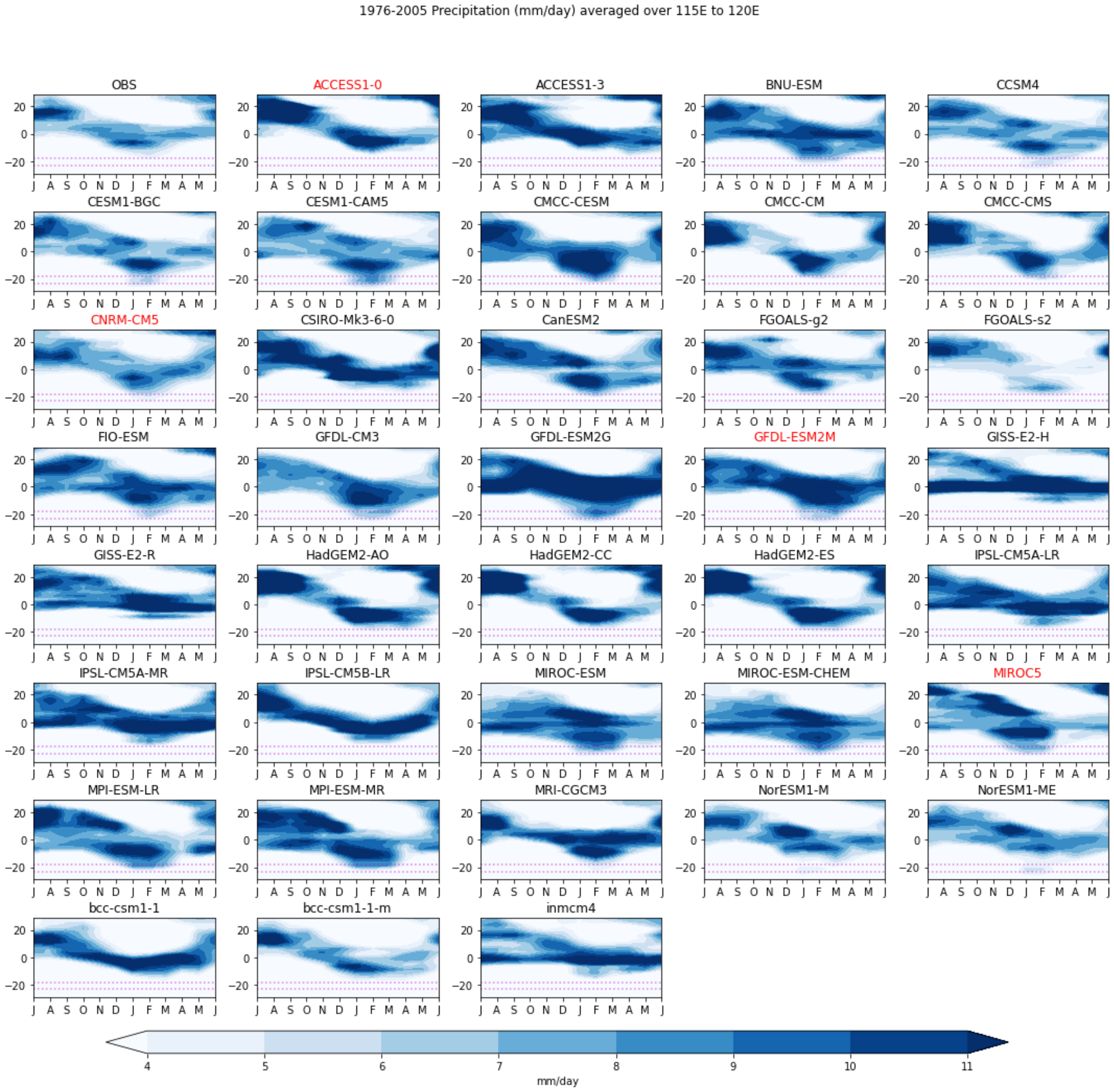

Figure A5.2: 1976 to 2005 monthly climatological rainfall zonally averaged between 115E and 120E for the GPCP observation based dataset (top left) and all available CMIP5 GCMs. NHP selected models are indicated with red labels.

We next turn our attention to the annual cycle of rainfall in the western Pilbara (Figure A5.3). The CMIP5 models span a wide range in magnitude of precipitation and annual cycle, however the NHP models approximately capture this range. The CNRM-CM5, GFDL-ESM2M and MIROC5 models all have a rainfall peak that is larger than observed, while the ACCESS1-0 model rains too little during the Austral summer and autumn months. The MIROC5 model peaks too early (January) while the CNRM-CM5 rainfall peaks too late (March).

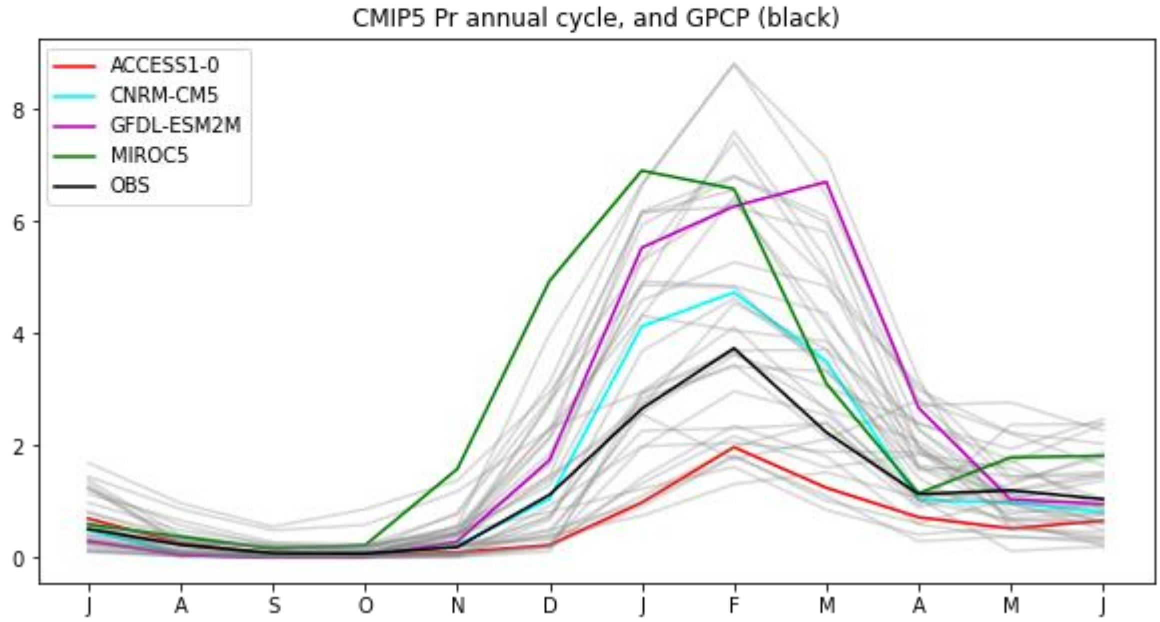

Figure A5.3: Seasonal cycle of rainfall (1976 to 2005) averaged over the region 115E to 120E, 18S to 23S. NHP models shown in colour, GPCP observations in black, and all other CMIP5 GCMs in light grey.

The annual cycle of temperature in the GCMs more accurately follows that in observations, although the majority of models (including the NHP models) are warmer than observed.

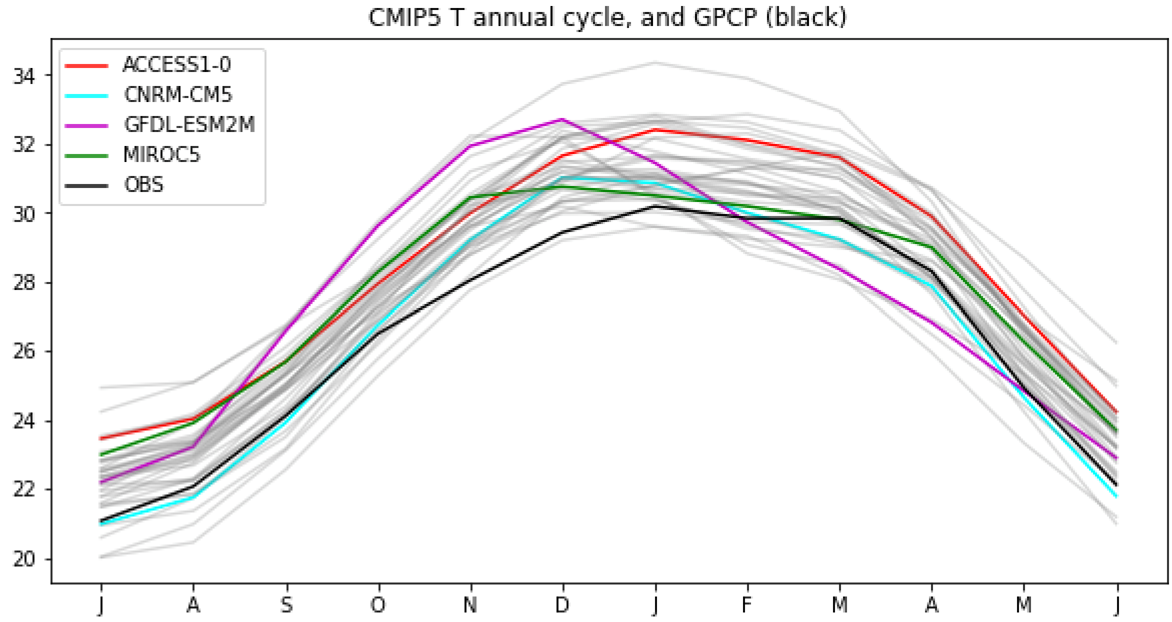

Figure A5.3: Seasonal cycle of surface air temperature (1976 to 2005) averaged over the region 115E to 120E, 18S to 23S. NHP models shown in colour, ERA Interim reanalysis (Dee et al 2011) in black, and all other CMIP5 GCMs in light grey.

We now investigate projected changes in rainfall in the western Pilbara region by 2050. For brevity we focus here on the high emissions scenario, comparing the future period (2036-2065) with a historical period (1976-2005). CMIP5 models show a wide range in rainfall and surface temperature changes, see (reference) for all individual model projected changes. In Figure A5.4 below we correlate the projected rainfall changes over the western Pilbara with projected rainfall changes everywhere (left) and projected surface temperature changes everywhere (right). The projected rainfall change over the western Pilbara correlates strongly with rainfall changes over Western Australia and the eastern Indian Ocean, and negatively correlates with rainfall changes over the western tropical Pacific Ocean. This is consistent with previous studies showing a relationship between western Pacific SST changes and changes to the Australian monsoon (Brown et al. 2016). The rainfall changes over the western Pilbara are found to be positively correlated with surface temperature changes over much of the Southern Hemisphere, and negatively correlated with surface temperature changes over the Northern Hemisphere. This is consistent with previous studies showing a relationship between changes in the Australian monsoon and hemispheric scale patterns of change (Narsey et al 2020).

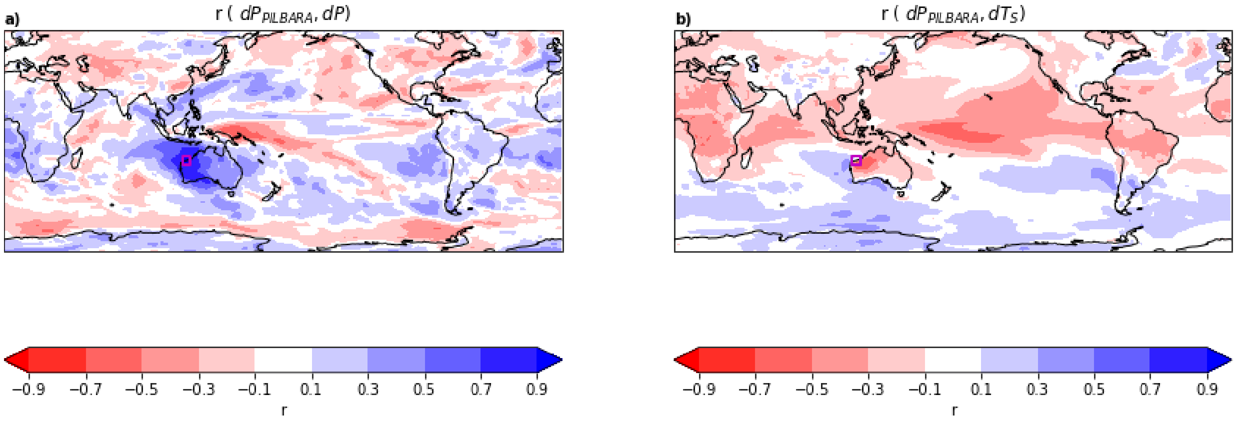

Figure A5.4: Correlation between model-to-model differences in west Pilbara precipitation change under a high emissions scenario RCP8.5 (magenta box) with precipitation change (left) and surface air temperature change (right) at every location (November to April 2036-2065 minus 1976-2005).

A closer inspection of the relationship between projected changes in western Pilbara rainfall and precipitation and surface temperature changes is shown in Figure A5.5. The projected changes in western Pilbara rainfall are negatively correlated with surface temperature over much of north-western Australia, and positively correlated with surface temperature off the western coast of Australia. This suggests a possible role for changes to the “Ningaloo Nino” phenomena in future projections (Tozuka et al. 2015). The western Pilbara is known to be influenced by this phenomena, as well as the El Nino Southern Oscillation which has a remote effect on this region resulting from changes in Pacific Ocean sea surface temperature variations (Risbey ref).

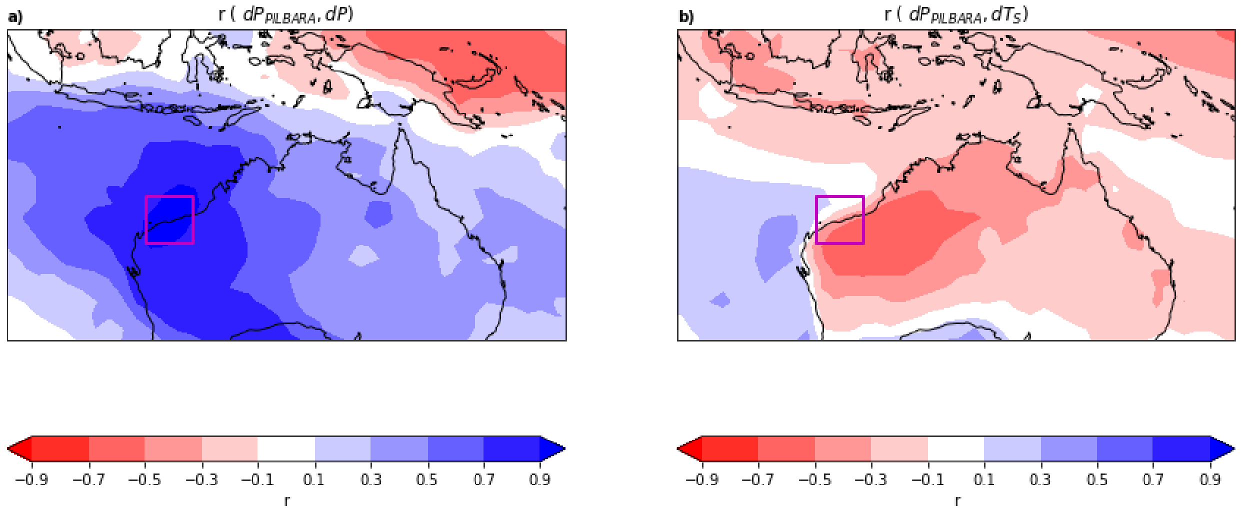

Figure A5.5: As in Figure 5.4, but for the domain around northern Australia only.

In figure A5.6 we show the change in November to April rainfall by 2050 under the high emissions scenario for the four NHP models. We also show the historical and projected monsoon shear line. The monsoon shearline here is defined as the zero wind contour in zonal (east-west) winds. The wet season monsoon shearline does not change substantially between historical and future periods. The actual changes to the monsoon shearline may be diluted here by averaging over the entire wet season, rather than focusing on the peak monsoon (December to February), however these negligible changes to the shearline are not representative of rainfall changes, which are substantial in individual models. In particular, strong wetting is seen over the western Pilbara in the CNRM-CM5 model, while extensive drying is projected by the GFDL-ESM2M model. The MIROC5 model has a coherent region of wetting over the northwest coast of Australia, which extends into the western Pilbara coastline.

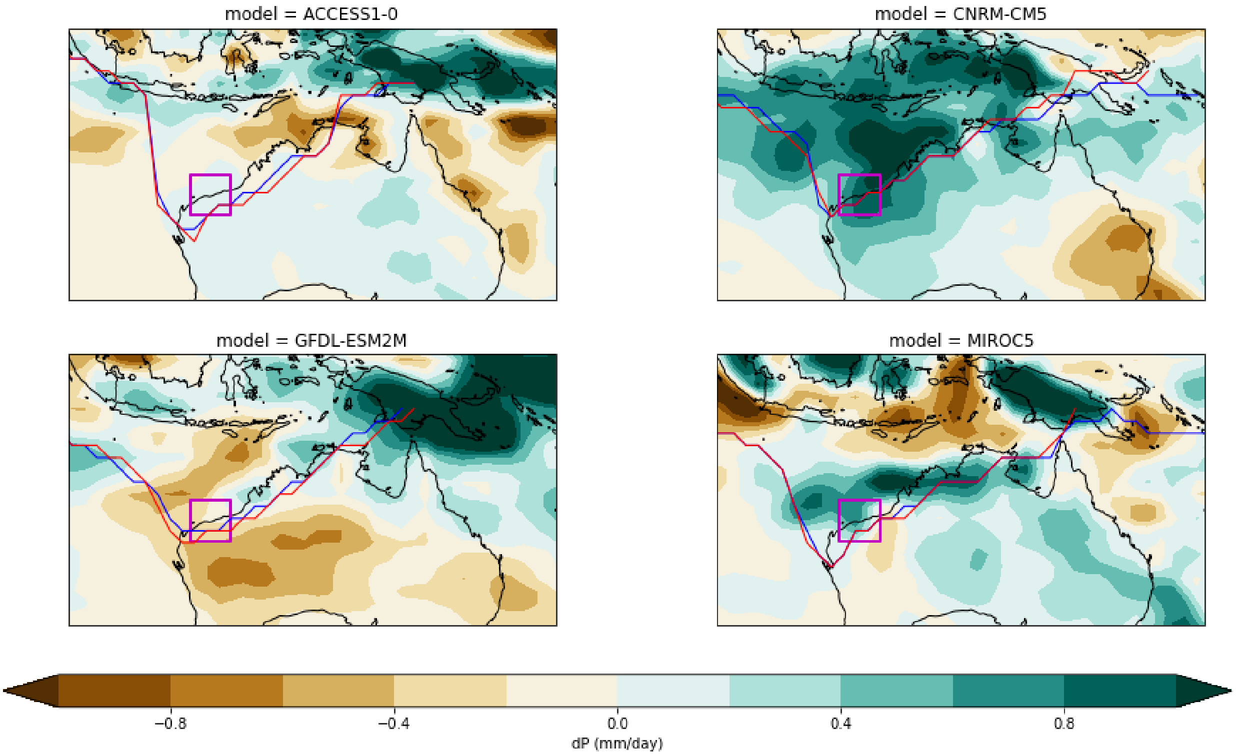

Figure A5.6: Precipitation change (November to April 2036-2065 minus 1976-2005) for the high emissions scenario (RCP8.5). Study region shown in magenta box. The monsoon shear line for the November to April season is shown for the historical (blue) and future (red) periods, following Colman et al (2011).

In Figure A5.7 we explore how these wet season changes occur throughout the year over the western Pilbara region. For most models the largest changes occur during the wet season (November to April), however the changes are not always consistent throughout the year in any given model. For example, the GFDL-ESM2M model projects decreases in rainfall in most wet season months, except for a large increase in the peak of the wet season (February).

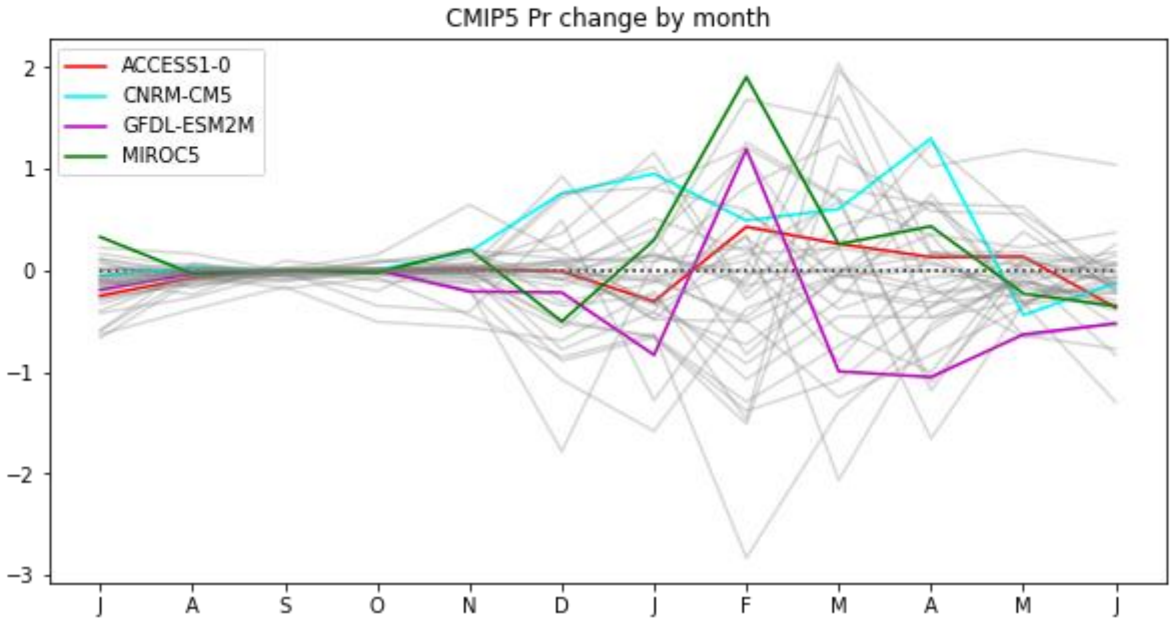

Figure A5.7: Change in the seasonal cycle of rainfall (RCP8.5 2036-2065 minus historical 1976-2005) averaged over the region 115E to 120E, 18S to 23S. NHP models shown in colour, and all other CMIP5 GCMs in light grey.

In Figure A5.8 we show the change in wet season rainfall projected over the western Pilbara smoothed with a 30-year running mean. The four NHP models are shown to sample the middle and upper ends of the rainfall change distribution, but do not sample the lower end of the changes in rainfall by 2050. For some models there is a clear change signal, for example the CNRM-CM5 model projects a nearly monotonic increase in rainfall over time. However, for other models the role of internal variability, or perhaps competing climate change related processes are visible in the projected precipitation changes. For example, the MIROC5 model initially projects a decrease in rainfall which reverses in signal to become an increase before 2050.

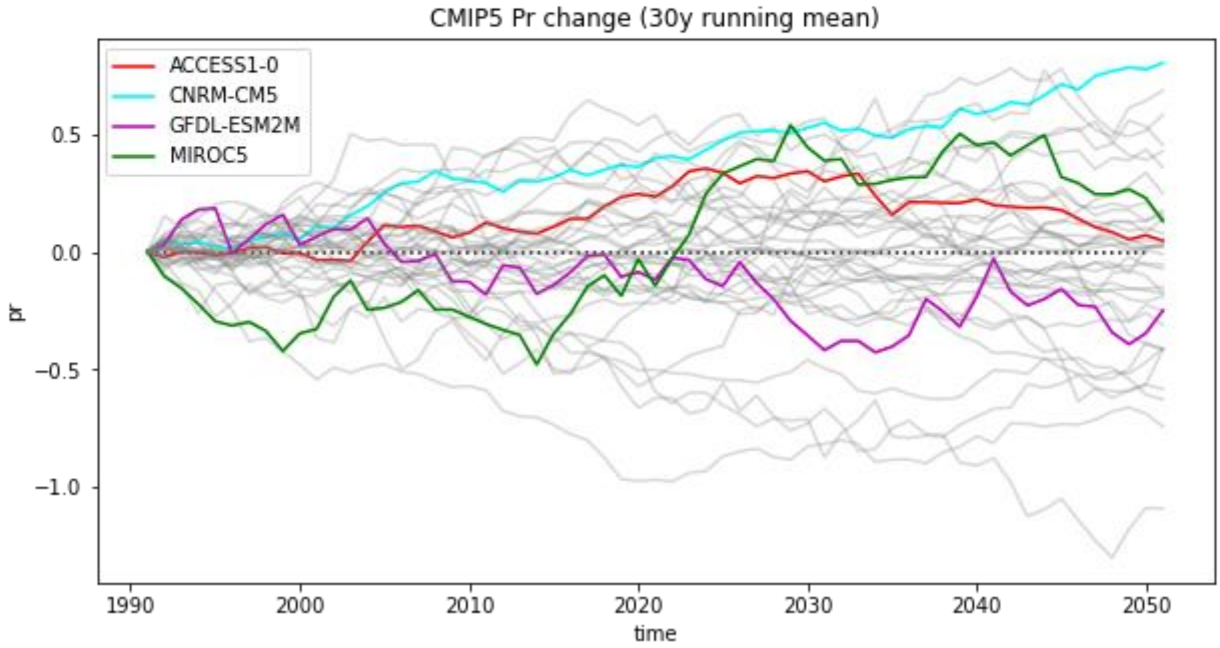

Figure A5.8: Change in the rainfall under a high emissions scenario (RCP8.5) averaged over the region 115E to 120E, 18S to 23S. NHP models shown in colour, and all other CMIP5 GCMs in light grey. Timeseries are smoothed with a 30-year centred running mean.

CMIP5 models simulate a wide range in year-to-year variability of western Pilbara wet season rainfall. In Figure A5.9 we show the time series of standard deviation calculated for centred 30-year periods for each model. The four NHP models capture both the upper and lower ends for year-to-year variability, with the ACCESS1-0 and CNRM-CM5 models displaying low variability, and the MIROC5 and GFDL-ESM2M models displaying high variability between years. None of the NHP models project a strong increase or decrease in the standard deviation of wet season rainfall (for 30-year periods).

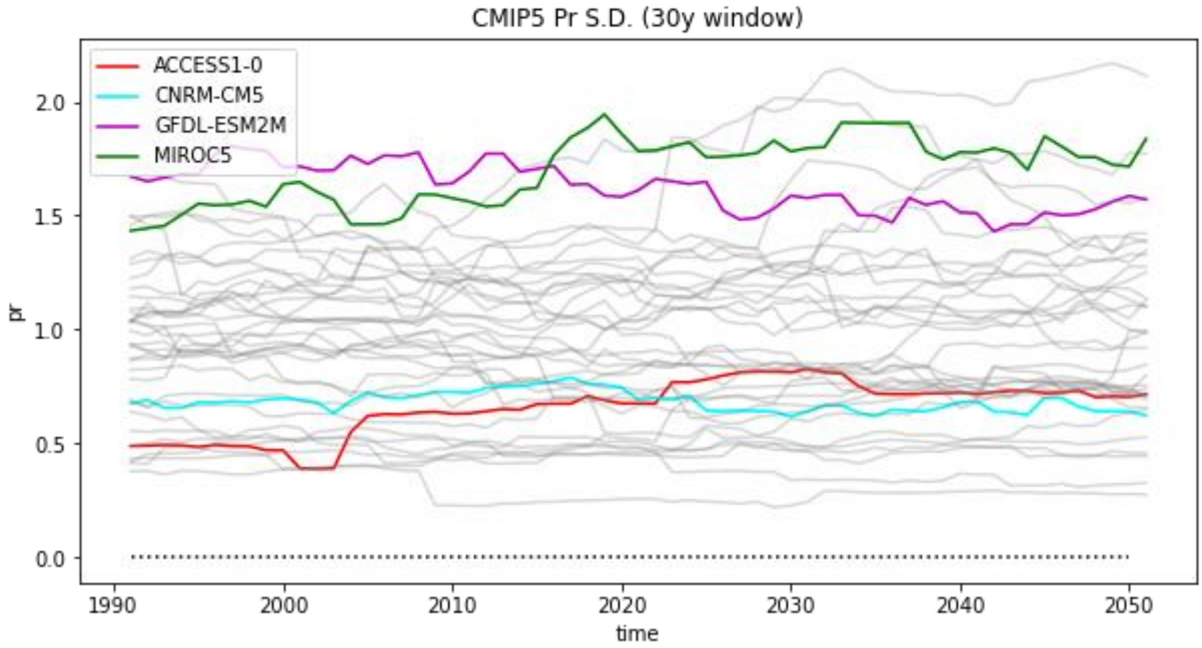

Figure A5.9: The standard deviation of rainfall under a high emissions scenario (RCP8.5) averaged over the region 115E to 120E, 18S to 23S. NHP models shown in colour, and all other CMIP5 GCMs in light grey. Standard deviation is calculated using a 30-year centred running window.

In figure A5.10 we show the change in the coefficient of variation (CV), which is the change in mean rainfall divided by the standard deviation, for a moving 30-year window. As with the change in wet season rainfall, the NHP models capture the high and middle range of the projected changes in CV in CMIP5 models, but do not capture the largest decreases in CV from CMIP5 models.

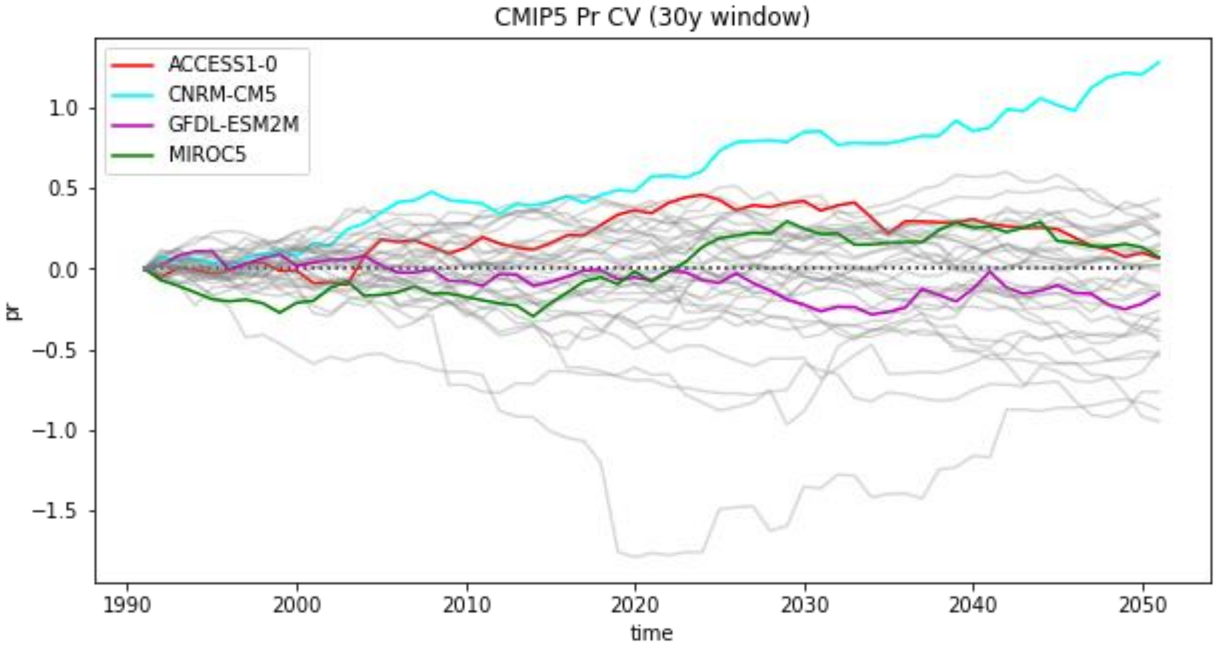

Figure A5.10: The coefficient of rainfall under a high emissions scenario (RCP8.5) averaged over the region 115E to 120E, 18S to 23S. NHP models shown in colour, and all other CMIP5 GCMs in light grey. Coefficient of variation is calculated as the mean rainfall divided by the standard deviation calculated using a 30-year centred running window.

Surface temperature increases everywhere in the NHP models by 2050 under a high emissions scenario. Differences in the spatial patterns of temperature change can be seen in Figure A5.11. The CNRM-CM5 model has the largest increases in surface temperature over the southeast of Australia and weaker warming over the north west of Australia. The other three NHP models project stronger warming over the west and northwest of the Australian continent.

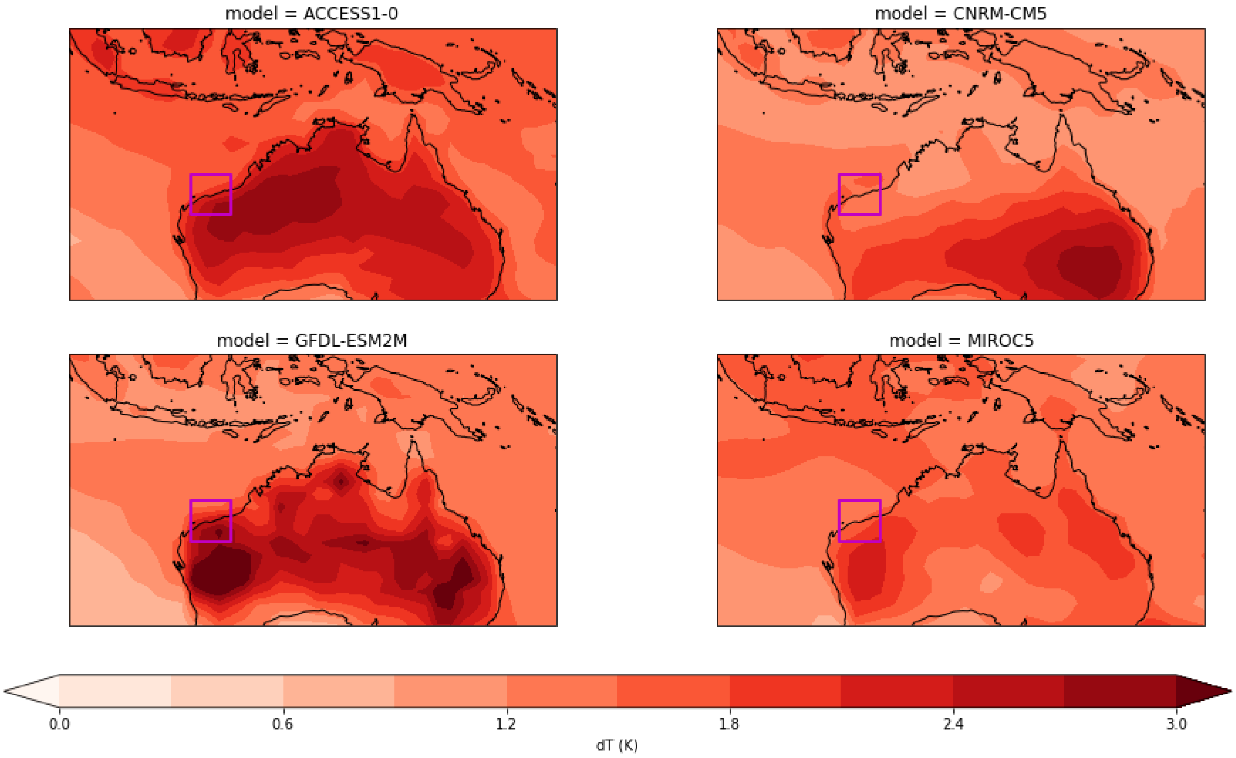

Figure A5.11: Surface temperature change (November to April 2036-2065 minus 1976-2005) for the high emissions scenario (RCP8.5). Study region shown in magenta box.

The projected temperature changes over the western Pilbara are shown in Figure A5.12. These are smoothed with a 30-year running mean. The NHP models are shown to broadly capture the range in projected surface temperature for the western Pilbara in CMIP5 models, although they do not sample the highest and lowest changes.

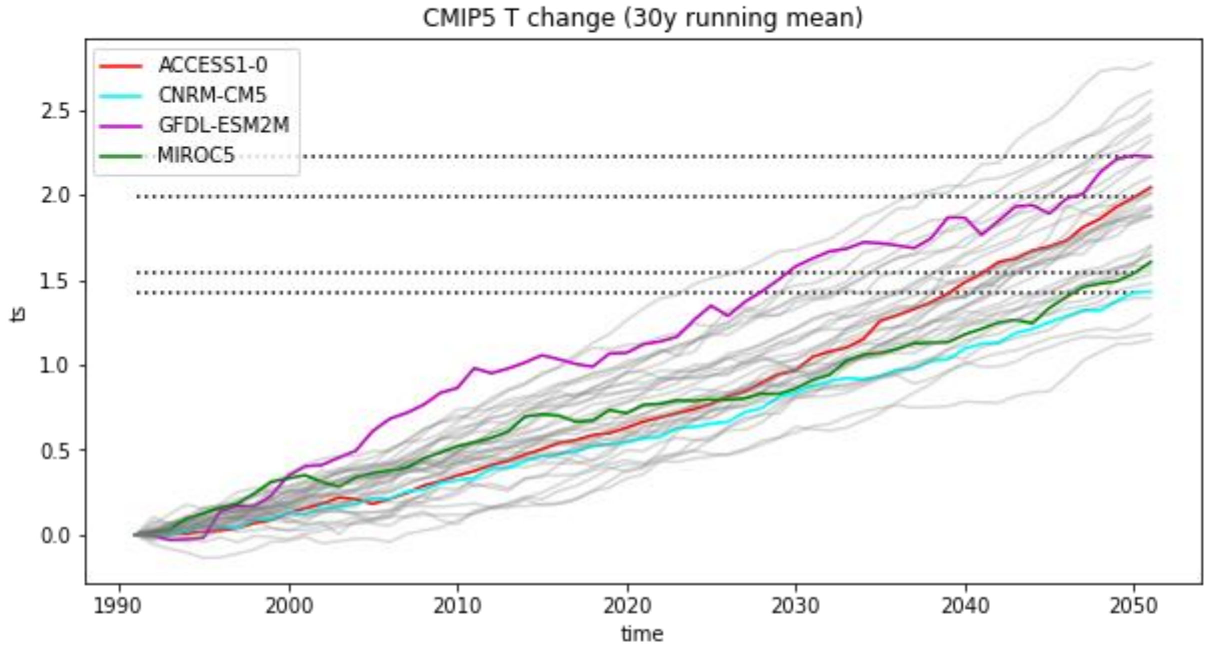

Figure A5.12: Change in surface temperature under a high emissions scenario (RCP8.5) averaged over the region 115E to 120E, 18S to 23S. NHP models shown in colour, and all other CMIP5 GCMs in light grey. Timeseries are smoothed with a thirty-year centred running mean.

Appendix 6: Storyline data

Based on the data shown in Appendix 4, the following quantities are used for storylines.

De Grey catchment:

De Grey catchment	**Extreme wet storyline**	**Little change storyline**	**Extreme dry storyline**
Model	CNRM-CM5	MIROC5	CCAM (GFDL-ESM2M)
Bias correction method	ISIMIP2b	ISIMIP2b	CCAM-ISIMIP2b
RCP	RCP8.5 and historical	RCP8.5 and historical	RCP8.5 and historical
Period	2036-2065 minus 1976-2005	2036-2065 minus 1976-2005	2036-2065 minus 1976-2005
Historical runoff (mm)	17.5 mm	20 mm	25 mm
∆ runoff (mm)	26 mm	-2 mm	-14.5 mm
∆ runoff (%)	150%	-8%	- 58%
Wet years (n/30-years)	8 years	9 years	12 years
∆ wet years (n/30-years)	18 years	-2 years	-9 years
∆ wet years (%)	225 %	-22 %	-75 %

Drought years (n/30-years)	17 years	15 years	12 years
∆ drought years (n/30-years)	-15 years	1 years	8 years
∆ drought years (%)	-88 %	7 %	67 %

Yule catchment:

Yule Catchment	**Extreme wet storyline**	**Little change storyline**	**Extreme dry storyline**
Model	CNRM-CM5	ACCESS1-0	CCAM (GFDL-ESM2M)
Bias correction method	ISIMIP2b	ISIMIP2b	CCAM-ISIMIP2b
RCP	RCP8.5 and historical	RCP8.5 and historical	RCP8.5 and historical
Period	2036-2065 minus 1976-2005	2036-2065 minus 1976-2005	2036-2065 minus 1976-2005
Historical runoff (mm)	19 mm	23 mm	28 mm
∆ runoff (mm)	21 mm	11 mm	-19 mm
∆ runoff (%)	113 %	49 %	-67 %
Wet years (n/30-years)	13 years	10 years	13 years
∆ wet years (n/30-years)	16 years	2 years	-10 years

∆ wet years (%)	123 %	20 %	-77 %
Drought years (n/30-years)	13 years	15 years	12 years
∆ drought years (n/30-years)	-13 years	-3 years	12 years
∆ drought years (%)	-100 %	-20 %	100 %

Other climate considerations for future exploration

The following factors haven't been assessed in detail. If plausible physical changes in the GCMs are identified that lead to plausible changes in the climate then it may be important for DWER to assess the impact more closely (a top-down approach). Note that this may link to the future national climate scenarios.

- Temperature and soil moisture may have an indirect influence on ongoing vegetation condition in that they can influence the incidence and severity of fire for instance. Vegetation will use soil moisture when available so reduced soil moisture will also result in a greater dependence on groundwater, increasing demand and affecting water availability thresholds for runoff.
- For groundwater dependent vegetation the groundwater level drawdown and drawdown rate, plus flood occurrence (and flood extent) matter in regard to ongoing ecosystem recruitment. Evapotranspiration therefore has an influence as it influences groundwater drawdown.
- For Pilbara wetlands and their surrounding vegetation such as Millstream, pool levels, and connectivity between pools is important. Evapotranspiration/evaporative loss may have an added influence over the dry season.
- If the climate gets more variable or experiences events outside the typical wet season period, this may have an impact on groundwater levels and pool connectivity.
- The historical climate influences the vegetation resilience. For example, Yule aquifer has already had to adapt to a greater rate of groundwater decline during drought periods. Whereas the same vegetation species at Millstream aquifer are not as resilient to extended droughts and sharp groundwater declines occur as they are used to a higher level of water availability.