Case study for Climate Resilience Analysis Framework and Tools (CRAFT): Managed aquifer recharge at Parafield Airport

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Introduction

Rainfall in Southern Australia, particularly in the cooler months, is projected to decrease with climate change (CSIRO and Bureau of Meteorology, 2015). Southern Australia has a distinct rainfall seasonality with most rainfall occurring in cooler months. The security of water supply for both urban as well as rural systems is a concern, and State Governments in Southern Australia are exploring options and costs of different system augmentation and modification into the future (South Australian Government, 2009).

However, successful adaptation to a hotter, drier climate requires an understanding of water resource and key water metrics. The question of how best to utilise climate projections, and incorporate them into a decision-centric context, has been an area of significant recent attention. Traditional methods such as the top-down (or scenario-led) approach to impact assessment (e.g. Chiew et al., 2009) start with climate scenarios and climate model outputs, which are then downscaled to smaller spatial scales for hydrological modelling. Arguably, these methods consider the system only as the last step in the modelling train, and it can be difficult to reconcile the results from top-down studies with the information needed to make system decisions under the considerable uncertainty of GCM projections (Wilby and Desai, 2010; Brown et al., 2012). An alternative is bottom-up (scenario-neutral or decision scaling) approaches. Here, the system under consideration is defined at the outset and thoroughly analysed and stress-tested before the consideration of climate model information. The Climate Resilience Analysis Framework and Tools (CRAFT) methodology (Bennett et al., 2018a; Zhang et al., 2017) is a scenario-neutral climate resilience analysis framework based on the decision-scaling framework developed by Brown et al. (2012) and other researchers.

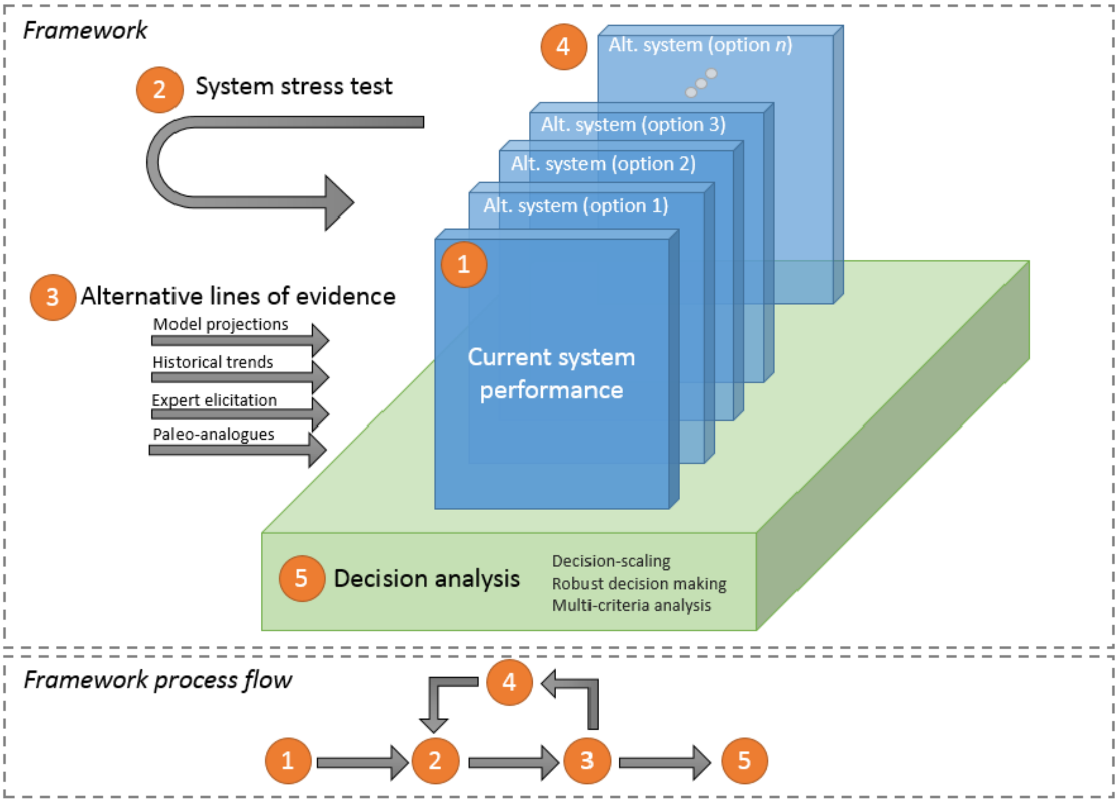

Figure 1. Conceptual diagram of the five steps in the CRAFT framework (Bennett et al., 2018a).

The framework is illustrated in Figure 1 and contains the following elements (Bennett et al., 2018a):

1. The system under consideration is analysed and modelled appropriately;
2. The current system design, as well as a set of alternative system designs, is ‘stress tested’ using perturbed climate inputs, to assess the rate of system performance degradation and/or identify situations under which systems can fail;

3. Multiple lines of evidence (e.g. climate model information, historical variability, expert judgement and analogues from paleo records) are projected onto the performance maps or “exposure space”;
4. System management options (alternative ways of managing or balancing competing demands) are explored in light of the system performance under different climate perturbations; and
5. Decision analysis combines the analysis in steps 2–4 by identifying a preferred option (or suite of options) through an in-depth analysis of the costs, benefits and feasibility of different options. Decision analysis can proceed in multiple ways, depending on user preference and interpretation of climate uncertainty.

In order to demonstrate how CRAFT can be used to assess climate change impacts on water resources systems, a managed aquifer recharge (MAR) scheme at Parafield in Salisbury, South Australia was selected as a case study site. This report illustrates CRAFT by describing the way the methodology might be applied to the Parafield MAR scheme. The report is organised according to the five steps outlined above.

The city of Adelaide shows strong support for the capturing of stormwater, in preference to other technologies such as desalinisation, in order to secure future water supply in the face of climate change (Mankad et al., 2013). A research project – the Managed Aquifer Recharge and Stormwater Use Options (MARSUO) project – was conducted from 2010–2014 (Dillon et al., 2014).The Parafield MAR scheme has been in operation since 2003 and a schematic diagram of the site is shown in Figure 2. The mean annual rainfall over the period of 1972 to 2009 is 438 mm with potential evaporation of 1442 mm. The Parafield catchment has an area of 15.9 km^2, of which 73% is urban land use (Dillon et al., 2014). Stormwater runoff generated from this catchment is diverted into two holding storages at the MAR site, and filtered through wetlands before being injected into a confined limestone aquifer for subsequent recovery.

Currently, water recovered from the Parafield MAR scheme is used for irrigating public open spaces and other industrial uses. Supplementing the potable water supply is also being considered, although the stricter water treatment process required for this remains an issue. A cost-benefit analysis showed that adequate treatment to potable water standards would be cheaper than construction of a new distribution for non-potable water, although there may be issues with the community acceptance of the inclusion of treated stormwater into main water systems (Dillon et al., 2014).

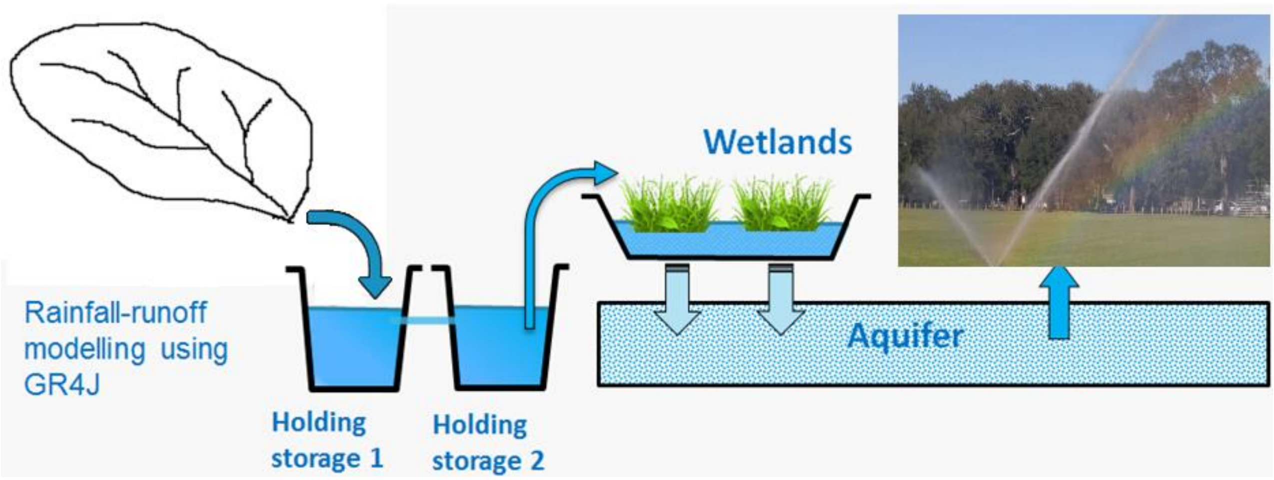

Figure 2. Schematic of the Parafield Managed Aquifer Recharge system.

1. Define the problem and system performance measures

1.1 System performance

The initial step in the CRAFT framework is identifying the problem definition. There are many ways to define the performance of water supply systems (McMahon et al., 2006). The Parafield MAR scheme supplements a traditional urban water supply scheme for the City of Salisbury. The provision of drinking water security (i.e. 100% reliability) is common in urban water-supply schemes, and the City of Salisbury has a 0% failure criteria for potable-water supply. Since the MAR scheme is only one part of the water supply system, we are not concerned with the success or failure of the scheme in terms of a given reliability threshold, but instead this case study examines how reliability of the system may change from the modelled 'historical' reliability in the future. In reality, water quality plays a key role in the MAR scheme with high-volume stormwater runoff events being unfit for capture. Nevertheless, in order to demonstrate the CRAFT methodology we neglect water quality issues and choose volumetric reliability (the ratio of total water supplied to the total water demanded in ML) as the performance measure.

1.2 Rainfall-runoff modelling

Runoff from the source catchment for the Parafield MAR scheme is modelled using a modified version of the GR4J rainfall-runoff model (Perrin et al., 2003). Climate data (rainfall and Morton's wet environment PET) was taken from the SILO data drill at the Parafield catchment centroid. Comparison with the Climate Ready hindcast dataset (Goyder Institute for Water Research, 2015) showed that the SILO historical data was very similar (within 1.7% of hindcast data). The land use of the Parafield catchment is predominantly residential and industrial, and observed runoff closely follows individual rain events, with little to no baseflow (Figure 3). Initial calibration experiments showed that GR4J was unable to adequately model the Parafield flow data due to the high-proportion of quick runoff response and low baseflow index of the hydrograph. As such, an impervious layer was added to the model, which represents the hard land surfaces of the residential and industrial part of the catchment.

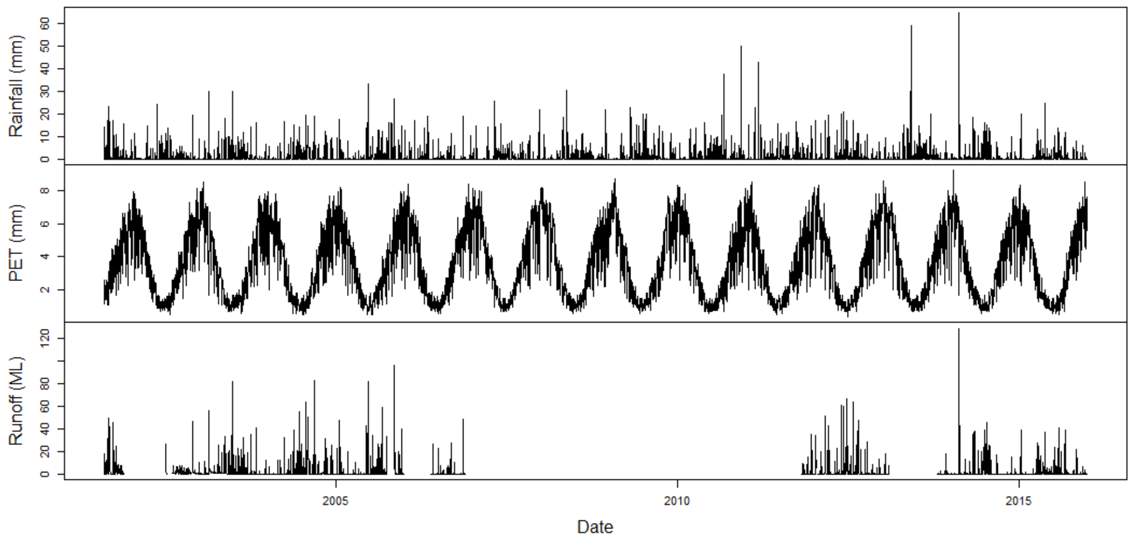

Figure 3. Rainfall, potential evapotranspiration (PET) and observed runoff at Parafield. Flow data was not recorded or judged poor quality during 2007–2012 and parts of 2002, 2005/2006 and 2013.

Following Clark et al. (2015), the impervious area was set at 38% of the total catchment area, with a 50% runoff coefficient over the impervious layer. The daily rainfall amounts falling over the pervious layer (i.e. 62% of daily amounts) is routed through GR4J, with the total daily runoff calculated as the sum of impervious and pervious runoff. The GR4J parameters are then calibrated using Shuffled-Complex Evolution method (Duan et al., 1992), a widely used hydrological parameter calibration routine, with the bias-penalised Nash-Sutcliffe Efficiency objective function following Viney et al. (2009).

Table 1. Optimised GR4J parameters, daily Nash-Sutcliffe efficiency (NSE), mean absolute error (MAE) and bias (simulation minus observed). Validation metrics are calculated using observed flow in the period of data not used for calibration.

	GR4J parameters				Calibration			Validation		
Calibration period	x1	x2	x3	x4	NSE	MAE (mm)	Bias (mm)	NSE	MAE (mm)	bias (mm)
2001–2015	785.5	−25.0	43.0	1.39	0.81	0.09	0.04			
2001–2006	365.8	−9.8	2.3	2.00	0.82	0.10	0.04	0.79	0.08	0.05
2012–2015	567.9	−25.0	26.8	1.75	0.79	0.08	0.05	0.82	0.10	0.04

Table 1 shows the optimised parameters for GR4J. The flow data has a long period of missing data between 2007 and 2011. We used this break for split sampling, i.e. calibrating over the first and second periods of data in order to compare parameters as well as calibration and validation goodness-of-fit metrics. Although there are differences between the parameters when calibrated over different periods, the resulting runoff is very similar over calibration and validation periods. This is because most of the runoff is in fact generated from the impervious layer, as discussed above, and that the modelled flow is fairly insensitive to the GR4J parameters. Validation and calibration statistics are very similar when calibrated under different time periods.

1.3 System model

The MAR system model is set up largely following the description by Clark et al. (2015) and City of Salisbury (2017). Although the wetlands component is critical for water quality concerns, we disregard the wetlands as in this case study, the most important part of the system affecting reliability is the holding times of the basins and transfer capacities. Harvested stormwater is held in two basins to reduce the levels of suspended sediment. The first basin is an in-stream basin, which reduces the larger sediments and pollutants, and has a capacity of 49ML. Water is held in the first basin for 3 consecutive days of inflow less than 2ML/day. The threshold was chosen as inflows from the rainfall-runoff model decrease exponentially, so there is often very small volumes of inflow into the holding basin long after any rainfall, which would otherwise result in basin transfer occurring only when the first basin is completely full.

The second basin, or holding store, further improves water quality by settling of sands and fines and has a capacity of 48ML. As described by Clark et al. (2015), the pump capacity is able to transfer the entire contents of basin 1 to basin 2 in one day. Since the model is run on a daily time step, this transfer occurs in one time step. The second holding basin has another 3-day holding period, at which point it can be injected into the aquifer via four aquifer storage recovery (ASR) wells with a combined daily transfer capacity of 7.8ML/day. These wells are used for both injection and recovery. We assume that the pumps are used to supply any unmet demand before being used for injection and that the pump capacity can be used for either injection or recovery continuously (i.e. pumps can switch from injection to recovery at any time to provide recovery/supply at any rate between 0–7.8 ML/day). Mixing of the fresh water with the more brackish water already present in the aquifer means that not all the injected water can be recovered. This is modelled with a “depreciation” term, such that 0.043% of the fresh water volume in the aquifer is lost. These assumptions are summarised in Figure 4.

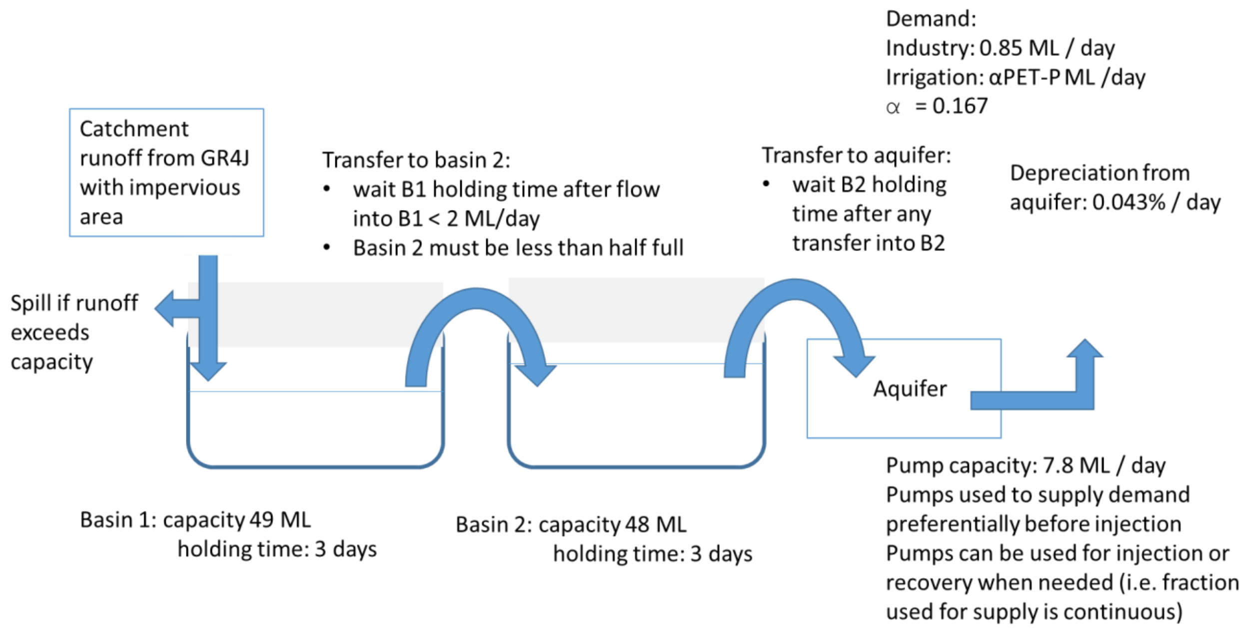

Figure 4. MAR system model assumptions

1.4 Demand model parameterisation

Following Clark et al. (2015), demand is set at 30% industrial (constant) usage and 70% (seasonal) irrigation. The irrigation demand model was parameterised by optimising parameters *a* and *b* of $a.\cos(j \cdot 2\pi / 365) + b$ to both daily average rainfall and PET, where j is the Julian day. Irrigation demand is given by $\sum \max(0, \alpha PET(j) - P(j))$ with α equal to 0.167 in order to get annual irrigation demand of 650 ML to match total demand of 960 ML as reported in Clark et al. (2015). Volumetric reliability is calculated as the proportion of total demand (ML) over a given time period that is supplied by the system model. The demand model is adaptive so that, when perturbed climate time series are used during stress testing of the system, the total and seasonal demand can increase or decrease as necessary.

1.5 Identify variables and processes that may change in the future

An important aspect of defining the system model is identifying variables and processes that may change into the future. Whereas we stress-test the system by perturbing the climate inputs (see below), it is essential that exogenous influences are at the very least identified. Since the Parafield catchment is largely urbanised, and features a large impervious area, it is unlikely that catchment processes (e.g. hydrological non-stationarity) will change in the future. However, an increase or decrease in the impervious area is very possible, and this may affect the rainfall-runoff relationship into the future. Changes in population may also affect demand for water, and this could potentially change the demand parameterisation and hence the system reliability.

2. 'Stress-test' the system

Stress testing refers to running perturbed climate time series through the system model to generate an 'exposure space' and identify vulnerabilities of the system to changes in climate attributes. Stress testing the system should be carried out independently from any climate model information that may be known a priori, i.e. it is important at this stage to examine the system's sensitivity to a wide range of different climate attributes. The goal here is a thorough understanding of the system itself and its vulnerabilities.

A variety of options with different degrees of sophistication exist for generating climate scenarios. An open-source R package, *fore*SIGHT ('Systems Insight from Generation of Hydrolclimatic Timeseries'), has been developed to generate perturbed climate scenarios (Bennett et al., 2018b). Supporting material is provided with the software including examples, help documentation and step-by-step tutorials.

2.1 Simple scaling

The easiest way to generate climate scenarios is through "simple scaling", which is equivalent to the "change factor" method of downscaling climate outputs (e.g. Chen et al., 2011). Here, the observed historical (daily) time series is multiplied by a range of different factors. In the example in Figure 5, both rainfall and potential evaporation time series are multiplied by factors ranging from −25% to +25% at 5% increments. Passing these into the system model ultimately results in supply and demand time series, from which volumetric reliability can be calculated.

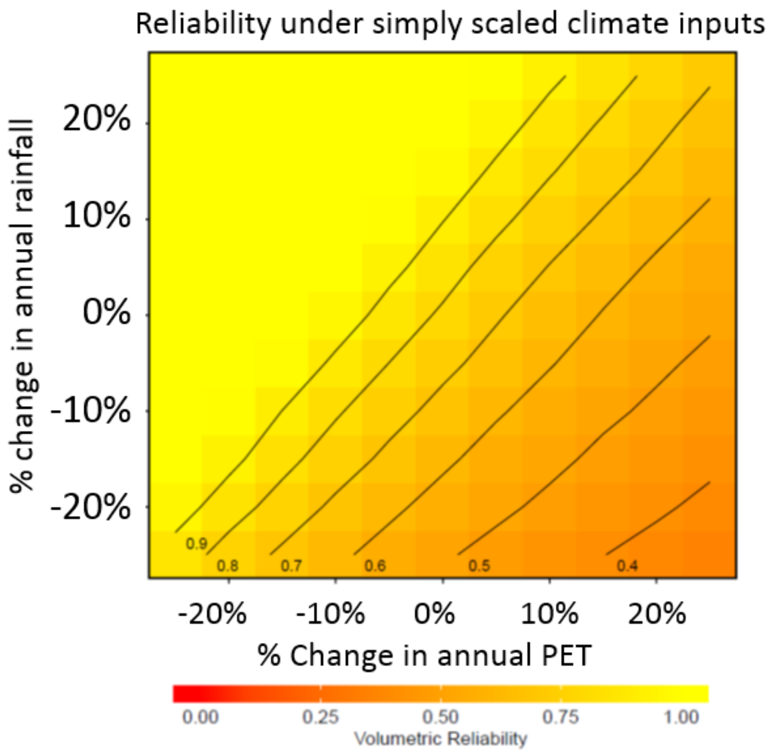

Figure 5. Reliability under simply scaled climate inputs

The contours and colours in Figure 5 show the volumetric reliability. From the baseline scenario (historical rainfall and PET), we see that volumetric reliability for the MAR scheme under the parameter assumptions described in section 1 is approximately 0.8. The magnitude of the volumetric reliabilities for the baseline scenario is much less than that reported by Clark et al. (2015), which was close to 1.0. One key simplifying assumption in Clark et al. (2015) was the lumping of the two holding basins into one basin. Since we assume any water is held for at least three days in each basin, the holding time of any parcel of captured stormwater is at least 6 days, i.e. double that as assumed by Clark et al.

A 10% change in rainfall and/or PET results in an increase or decrease of about 0.1 at this point in the exposure space. As rainfall decreases and PET increases, the sensitivity to both variables generally becomes less. It is perhaps surprising that PET sensitivity is similar in magnitude to rainfall sensitivity for the MAR scheme, particularly in light of our understanding of climate sensitivities to runoff (e.g. Chiew, 2006; Potter et al., 2011). However, the performance measure of the MAR scheme (reliability) is very closely connected to demand and hence PET, since demand has been parameterised to change with changing PET.

The benefits of simple scaling are that it is very easy to adjust the time series, and thus easy to construct an initial exposure space. The relative sensitivities to rainfall and PET can be quickly and easily identified, and this may help to guide the choice of which variables to perturb in subsequent stress testing. However, changes to secondary climate characteristics (such as variability, seasonality and so on) cannot be tested using simple scaling and more sophisticated methods are needed to do this.

2.2 One-at-a-time testing

Having seen that the system is sensitive to changes in both rainfall and PET, we can explore other climate attributes that are of interest. For example, given that water demand is seasonally varying, changes in rainfall seasonality may prove to be important in altering future reliability. So called "one-at-a-time" testing perturbs selected attributes of the climate time series while holding other aspects of the time series constant using an inverse approach (Guo et al., 2016). Briefly, the inverse approach calibrates the parameters of a stochastic climate model to match the selected climate attributes. These parameters are then used to generate perturbed climate time series. For example, we can increase or decrease the seasonality index (ratio of rainfall occurring in wet and dry seasons) while holding mean annual (and other attributes of) rainfall constant. The climate attributes that can currently be perturbed by the CRAFT toolkit (*fore*SIGHT) and stochastic generator options are listed in the Appendix.

The inverse approach produces a set of parameters to be used for the stochastic climate generator, and hence numerous stochastic replicates of the climate time series, as opposed to the simple scaling approach which only produces one climate time series for each scaling factor. Figure 6 shows the range of reliabilities for 10 replicates for each target change in different climate characteristics as black dots, with the means connected by the red lines.

The following climate attributes were modified to stress-test the system: a) mean annual rainfall; b) mean annual PET; c) seasonality index (annual ratio of winter to summer rainfall totals); d) average of annual wet spell durations; e) 99th percentile of rainfall (including dry days); f) number of wet days; and g) annual range (amplitude) of PET. We found from the simple scaling above that the system reliability was sensitive to changes in both mean annual rainfall and PET (Figure 5). The magnitude of rainfall and PET sensitivities averaged from stochastic replicates generated the inverse approach are similar (Figure 6a and b), although the reliability from the baselines (no change to annual mean) is somewhat higher than those simple scaling, due to differences between historical climate and the baseline climate generated by the stochastic climate generator.

System reliability is also sensitive to changes in rainfall seasonality (Figure 6c) and the number of wet days (Figure 6f). Increasing the degree of seasonality, i.e. increasing winter rainfall and decreasing summer rainfall averages, results in less reliability and this is because if more rainfall occurs when the system is at full holding capacity then there is less chance of capturing each rainfall event. Similarly, when the number of wet days decreases, with total rainfall held constant, daily rainfall intensity increases, which reduces the amount able to be captured. Changes to wet-spell duration, 99th percentile rainfall and PET range have small effects on system reliability, with the clearest signal from PET range, although this is still negligible in comparison with the effect from the other climate attributes.

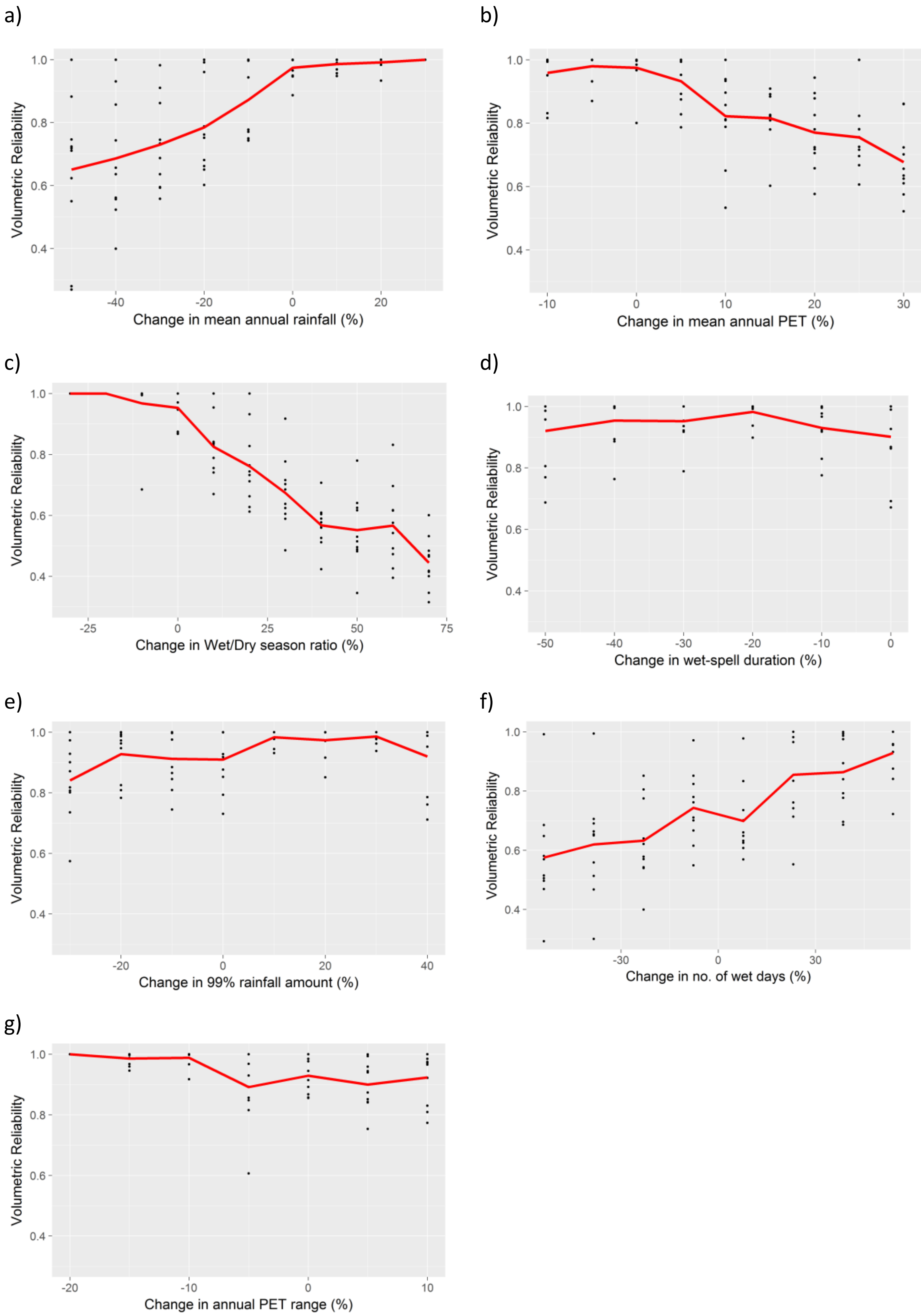

Figure 6. Average reliability from one-at-a-time changes to climate attributes using the inverse approach.

2.3 Generating full exposure spaces

From above, the four significant climate attributes are: mean annual rainfall; mean annual PET; seasonality index; and average number of wet days per year. The inverse method was used to perturb all combinations of these attributes for the following range of targets: −50% to +30% of historical annual rainfall; −10% to +30% of historical annual PET; −55%, 0% and +55% of the historical number of wet days; and seasonality index (ratio of winter to summer rainfall) equal to –30% to +60% of historical seasonality.

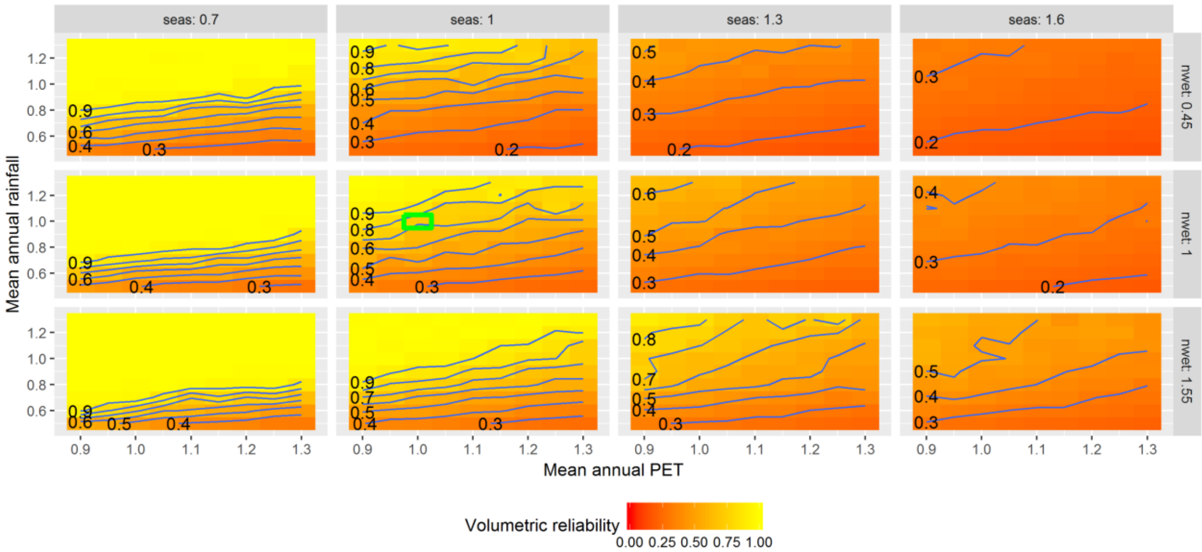

Figure 7. Exposure space generated by perturbing four climate attributes: mean annual rainfall, mean annual PET, mean number of wet days per year, and rainfall seasonality. The green box outlines that part of the exposure space closest to historical conditions.

The resulting four-dimensional exposure space is shown in Figure 7. Whereas two-dimensional exposure spaces (e.g. Figure 5) are easy to visualise, three and four-dimensional spaces are harder. In Figure 7 each of the twelve panels shows reliability for PET-rainfall combinations similarly to Figure 5, but for a given target value of seasonality and wet days. Panels to the top of the grid have fewer wet days, and panels to the right of the grid have increased rainfall seasonality. Historical conditions are outlined with the green box.

The system sensitivities to rainfall and PET are similar to Figure 5, although the sensitivities change with changes in the other climate attributes. We see decreased reliability with increased rainfall seasonality (moving from left-to-right through the grid of panels), and decreased reliability with fewer rain days per year. This is consistent with the one-at-a-time testing, and the conceptual reasons for these sensitivities are discussed in connection with Figure 6.

3. Climate projections and other lines of evidence

The third step of CRAFT involves uniting the system understanding developed in step 2 ('Stress-test' the system) with the climate information that is available. The system understanding consists of exposure spaces and system sensitivities developed earlier, and was developed independently from the future climate projections (although it is important that the exposure spaces cover fully the range of projected climate attributes). For this case study, we use the output from the 15 GCMs downscaled using the Non-homogeneous Hidden Markov Model (Charles, 2014). The method is described in detail by Charles and Fu (2015). However, other lines of evidence that may be available (such as observed historical climate variability, expert knowledge, and/or paleo-climate information) may also be usefully overlaid on the exposure spaces generated in step 2.

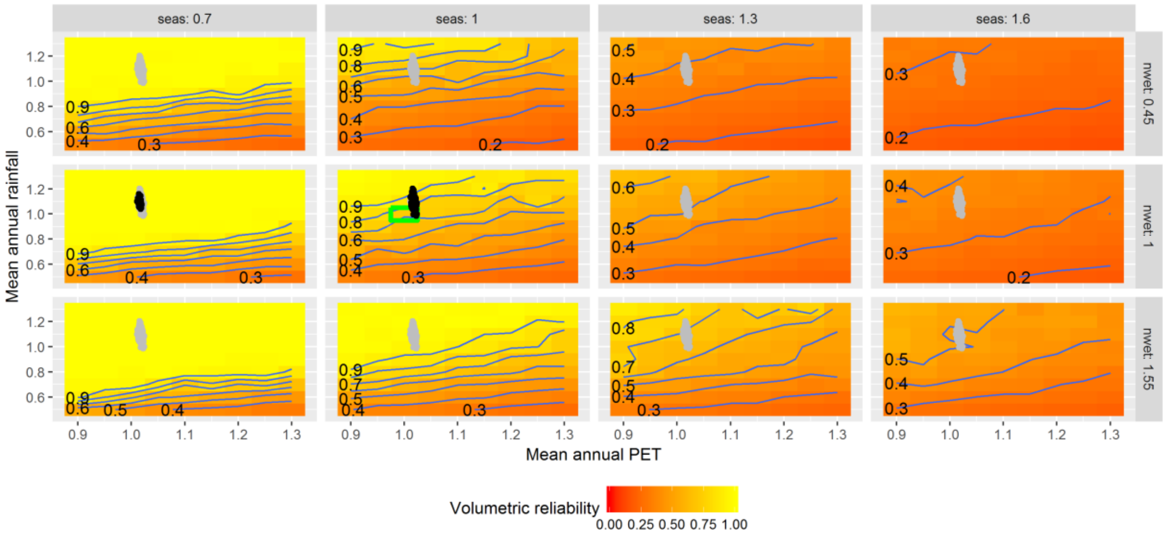

Figure 8. Full exposure space with hindcast climate model statistics. Black points are plotted in the panel with seasonality and wet day targets closest to the hindcast statistics. Grey points are 'shadows' of the cluster of all points.

Figure 8 shows the full exposure space generated by the inverse method with the hindcast (historical simulation) GCM climate statistics superimposed. Each panel has the full cloud of data points plotted in grey, with points plotted in black when the statistics for seasonality and number of wet days are closest to the corresponding attribute targets. As such, all of the GCM statistics for average historical number of wet days are closest to 1 (as the black cloud of points are all in the middle row of panels). Most climate model statistics have historical rainfall seasonality similar to historical observations, but a few models have rainfall seasonality underestimated somewhat (i.e. the seasonal variation is more uniform than observations). Hindcast mean annual PET is close to historical values, and we have a tendency for some models to overestimate historical rainfall by up to 20% (as evidenced by the vertical elongation of the cloud of data points). Looking at the GCM hindcast statistics shows how well the GCMs estimate the climate attributes identified earlier. If large bias or variability of climate statistics exists for a particular attribute, we may disregard the climate model projections for this attribute. Figure 8 shows that in general, the climate attributes we identified are mostly well estimated by the GCMs, noting the slight bias in seasonality, which was also noted by Hope et al. (2016) for Victorian rainfall seasonality.

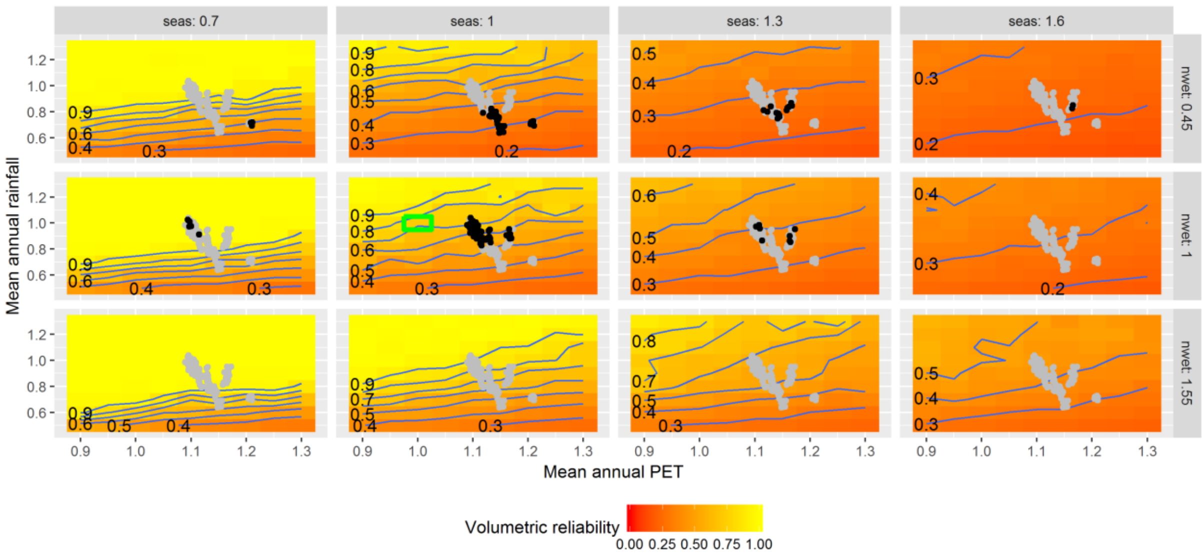

Figure 9. Exposure space with climate model projections of selected attributes.

Figure 9 shows the exposure space of Figure 7, but this time with projected climate statistics for emissions pathway RCP8.5 centred around 2085 (i.e. a time slice of 2071–2100). The highest emissions scenario and the most distant time slice was chosen in order to demonstrate the largest differences in climate attributes. Regressing the reliabilities calculated from the climate model data directly forcing the system model and the reliability of each climate model run as inferred from its position in the exposure space of Figure 9 indicates that the two reliability estimates are largely unbiased, although the very low reliabilities indicated in Figure 9 are a little underestimated and the high reliabilities are a little overestimated. This means that the exposure space has included the important climate attributes, except that the extreme edges of the space are less accurate.

Comparing Figure 9 and Figure 8, we can describe the changes projected by the climate model ensemble in both the climate attributes and system reliability. First, for mean annual rainfall and PET, the cloud of data points has shifted down (less rainfall) and to the right (more PET). Mean annual rainfall is projected to decrease by up to 40%, and practically all climate models have projected decreases. Mean annual PET is projected to increase by 10–20% as well. These projected changes by themselves would tend to decrease volumetric reliability from 0.8 to at least 0.7, and possibly down to 0.4.

Most models have the number of wet days projected to remain similar to historical levels, but a sizable proportion of models have fewer wet days (shown by the shift of the black points into higher panels). Interestingly, the models with fewer wet days tend to be those with the largest decrease in mean annual rainfall. A few climate models suggest that rainfall seasonality may increase, yet there are some models that have less rainfall seasonality projected into the future. However, note that there were some models with a bias in hindcast rainfall seasonality (Figure 8).

In contrast to a top-down (scenario-led) approach to modelling the Parafield MAR scheme, Figure 9 provides useful information on climate-model projection uncertainty. A top-down approach to estimating future reliability of the MAR scheme would use the downscaled GCM time-series directly as inputs into the MAR system model. The end result of this is an ensemble of future reliability values for the MAR system, rather than the in-depth understanding of the system sensitivities and climate-model uncertainty that has been developed. In this example, Figure 9 shows not only the range of future reliability values, but the spread and uncertainty of climate model projections.

There appear to be four distinct groupings of climate model statistics. Firstly, there is an outlying group (the cluster apart from the main “V” pattern in Figure 9). These all have many fewer wet days and the largest changes to mean annual rainfall and PET. The reason for this unusual behaviour could be investigated with closer examination of which models are producing this, and if the projections may be suspect. A second grouping occurs at the bottom of the “V” pattern in Figure 9. These too have fewer wet days and large declines in mean annual rainfall, but the projected changes to PET are more consistent with the rest of the model projections. The third and fourth groups (being on the top halves of the “V” pattern) have milder reductions in rainfall and similar (that is to say little) change to the number of wet days, but different PET projections. The changes to rainfall seasonality appear to hold the most uncertainty, with no discernible relationship with changes to other climate attributes. A more in-depth scrutiny of climate-model uncertainty could look at which models appear in which grouping, and whether the observed bias in rainfall seasonality or mean annual rainfall identified in Figure 8 have similar changes to climate attributes.

The projected changes to the number of wet days (generally fewer) and rainfall seasonality (generally increasing) all point to further reductions in system reliability, as discussed in connection with Figure 6. Although there is a range of uncertainty in model results, the direction of projected change in all four climate attributes leads to a reduction in reliability from around 0.8 historically to about 0.5 by 2085 under RCP8.5. The range of reliability as measured by the inter-quartile range is about 0.4 to 0.6.

4. System management options

The results from climate model projections show future reductions in system reliability through changes in all four climate attributes that were found to have the greatest influence on the MAR scheme. Step 4 of the CRAFT methodology involves considering different management options for the system that could increase resilience. System management options can include: modification of operating rules; system re-optimisation (e.g. changing the balance of cost of supply and water quality considerations); infrastructure augmentation (e.g. changing storage capacity); economic signalling (e.g. modification of prices). To illustrate system management options for the MAR case study, we consider modifying the parameters of the system model as described in Figure 4.

The scenarios considered are feasible changes to the system including:

- Increasing impervious area of the source catchment to generate more stormwater runoff available for harvesting
- Increasing basin holding times
- Increasing injection/recovery pump capacity
- Increasing holding-basin capacity.

Depending on the level of detail required, system management options can be explored using one of the stress-testing methodologies outlined in Step 2 ('Stress-test' the system), that is, simple scaling, one-at-a-time testing, or generating full exposure spaces. For this case study, we demonstrate the effect of different options in Figure 10 using one-at-a-time testing for mean annual rainfall (i.e. the equivalent of Figure 6a).

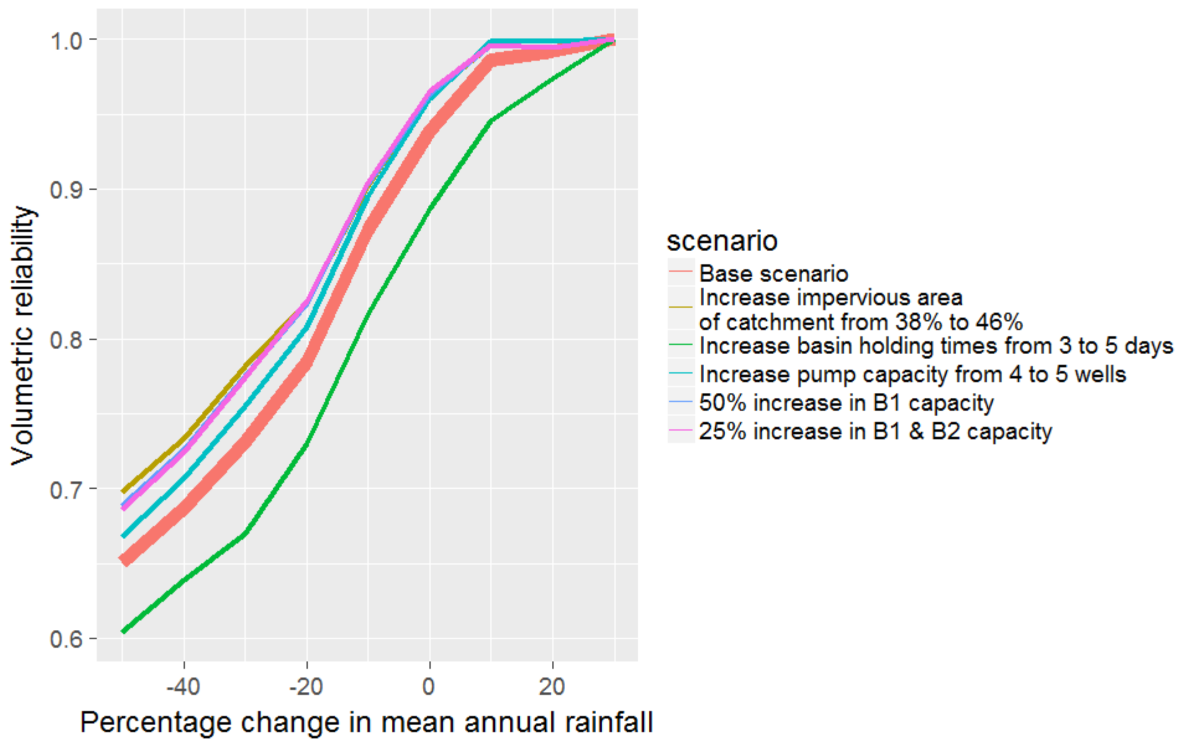

Figure 10. Some example system management options and their effect on system reliability.

The largest effect is from increasing the impervious area of the catchment, although this is similar in magnitude to increasing the holding basin capacities. Both of these management options could potentially increase the reliability by 0.05. Interestingly, increasing the first holding basin by 50% has a very similar effect to increasing both basins by 25%. Increasing the injection/recovery pump capacity by adding an extra ASR also results in increased reliability, but less so for a much drier future. One of the key considerations of the MAR scheme is water quality from large runoff events from the urbanised catchment. We have seen rainfall intensity may increase in the future, with many climate projections having fewer wet days (Figure 9). Increasing the basin holding times from three to five days each could act to improve water quality but the effect on reliability is for a reduction in reliability of 0.05 across the range of rainfall changes considered. Conversely, it is expected that decreasing the holding times could potentially improve reliability but at the cost of decreased water quality.

The system management options outlined above have different effects on system reliability and water quality. Indeed, several options had similar effects on reliability, but none were able to mitigate the large reductions in reliability possible by the end of the century. Future work could examine the effect of more extreme changes to system management options in order to ameliorate system performance under projected climate change. Generating full exposure spaces for different scenarios can highlight the interactions between changes in rainfall seasonality or number of wet days and the available management options. Results (not shown here) provide some evidence that particular options, such as increasing basin holding times, have increased sensitivity under increased rainfall seasonality, although the effect is small.

5. Decision analysis

At this stage of the CRAFT methodology, the different scenarios should be costed and rated in terms of feasibility, community and political acceptance and in terms of effects on water quality considerations.

For example, the largest effect on future reliability occurs from increasing the impervious area of the catchment. However, this is something that may not be able to be changed directly. On the other hand, it is possible that impervious area could increase naturally through increased urbanisation of the catchment. In this respect, the costs of this scenario would not be borne by the MAR scheme operators, but indirectly by land holders. Increasing basin holding capacity and pumping rate are both easily changed by the MAR scheme operators, but could have very different costs, both monetary as well as environmental, and this needs to be considered. Consultation with stake-holders might suggest other management options, and these could then be re-modelled using the system model and exposure spaces already generated.

Another aspect of decision analysis is consideration of the timing of system management options. Exposure spaces similar to Figure 9 can be generated for different time slices. The certainty or uncertainty of climate model projections as expressed through the shape and location of the cloud of data points in Figure 9 can be used to supplement a cost-benefit analysis. For example, how certain do we need to be of changes in future climate attributes before a certain management option becomes cost effective? This requires that the climate model ensemble be interpreted probabilistically, which is the subject of on-going climate research. Alternatively, if climate model groupings are interpreted as scenarios, robustness approaches may be required.

Conclusion

This report described a case-study application of the Climate Resilience Analysis Framework and Tools (CRAFT) methodology to the Managed Aquifer Recharge (MAR) scheme at Parafield in Salisbury, South Australia, with the goal of examining and quantifying projected reductions in reliability and system management options that could potentially mitigate these reductions. After parameterising the system model, the system was stress tested using the open-source R package *fore*SIGHT to generate perturbed climate series. The system was found to be most sensitive to changes in mean annual rainfall, potential evapotranspiration, rainfall seasonality and mean number of wet days per year. Climate model information was presented on 'full exposure spaces' generated through the stress-testing step of CRAFT. In contrast to more traditional top-down approaches, the presentation of climate model information in this way allows a more transparent way of visualising the uncertainty inherent in the climate model ensemble. System management options and decision scaling considerations were examined and discussed.

The Climate Resilience Analysis Framework and Tools (CRAFT) as described here is different from traditional scenario-led (top-down) approaches to climate adaptation. By focusing on a particular water resources system, rather than starting the analysis with the climate model outputs and scenarios, a comprehensive understanding of system resilience is developed. In contrast, the scenario-led approach considers the system only at the end of the process, and a detailed understanding of the system is lacking. Since decision makers and system operators are involved in the process from the outset, CRAFT facilitates communication between modellers and decision makers in a way that traditional approaches do not. This provides unique opportunities and benefits to climate adaptation modelling.

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Appendix

Table 2. Summary of stochastic weather generators and hydroclimate variable attributes available for perturbation in R-package foreSIGHT

Hydroclimate variable	Stochastic model	Variable Attributes
Rainfall	Annual Seasonal Single harmonic using 12 intervals Single harmonic using 26 intervals Two harmonics using 26 intervals	Annual total (mm) Annual number of wet days (days) Annual 99th percentile rainfall (mm) Annual 99th wet day percentile rainfall (mm) Annual maximum dry & wet spell durations (days) Annual average dry & wet spell durations (days) Annual average wet day amounts (mm) Annual average daily amounts (mm) Annual number of wet days above 10 mm rainfall (days) Annual volume above a threshold (mm) Annual ratio between winter and summer rainfall totals (-) Seasonal totals (DJF, MAM, JJA, SON) (mm) Seasonal average wet day amounts (DJF, MAM, JJA, SON) (mm) Seasonal average daily amounts (DJF, MAM, JJA, SON) Coefficient of variation of seasonal totals (-) Coefficient of variation of monthly totals (-) Seasonal average dry & wet spell durations (DJF, MAM, JJA, SON) (days)
Temperature	Single harmonic using 26 intervals (additional functionality: temperature conditional on rainfall wet/dry sequence) Two harmonics using 26 intervals (additional functionality: temperature conditional on rainfall wet/dry sequence)	Annual average temperature (°C) Annual 5th percentile temperature (°C) Annual 95th percentile temperature (°C) Annual range between the 5th and 95th percentile temperatures (°C) Annual number of frost days (days) Annual growing season length (days)
Potential Evapotranspiration	Single harmonic using 26 intervals (additional functionality: temperature conditional on rainfall wet/dry sequence) Single harmonic using 12 intervals	Annual average potential evapotranspiration (mm) Annual total potential evapotranspiration (mm) Annual range between the 5th and 95th percentile potential evapotranspiration days (mm) Annual percent of days above potential evapotranspiration threshold (-)

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