Drivers of future water demand in Sydney, Australia: examining the contribution from population and climate change

Adrian Barker [1], Andrew Pitman [1], Jason P. Evans [1], Frank Spaninks [2] and Luther Uthayakumaran[2]

[1] ARC Centre of Excellence for Climate Extremes and Climate Change Research Centre, UNSW, Sydney, Australia

[2] Sydney Water, Level 14, 1 Smith Street, Parramatta, New South Wales, 2150, Australia

E-mail: [redacted]

Abstract. We examine the relative impact of population increases and climate change in affecting future water demand for Sydney, Australia. We use the Weather and Research Forecasting model, a water demand model and a stochastic weather generator to downscale four different global climate models for the present (1990-2010), near (2020-2040) and far (2060-2080) future. Each climate model is downscaled three times with variations in the boundary layer and convection schemes. Projected climate change would increase median consumption, at 2019/20 population levels, from around 484 GL in the present to 484-494 GL in the near future, and 495-505 GL in the far future. Population changes from 2014/15 to 2024/25 have a far larger impact, increasing median consumption from 457GL to 508 GL under present climate, 463GL to 515GL under near future climate and from 471GL to 524GL under far future climate. The projected changes in consumption are sensitive to the climate model used, but differences caused by varying the boundary layer and convection schemes rarely exceeds 1-2%. Overall, while population growth is a far stronger driver of increasing demand than climate change for Sydney, both act in parallel to reduce the time it would take for all storage to be exhausted. Failing to account for climate change would lead to overconfidence in the reliability of Sydney's water supply.

1. Introduction

Major cities are confronted by how best to manage water consumption under the joint challenge of growing populations framed by changing climate and climate variability (Gain & Wada (2014); Hoekstra, Buurman & van Ginkel (2018)). Long term planning for future water demand needs a mixture of social science, providing an understanding of how population growth (Polebitski & Palmer 2010), economic development (Tortajada & Joshi 2013) and social factors (Schleich & Hillenbrand 2009) will change over time, combined with the physical science challenge of predicting future regional patterns of weather and climate. These lead to an increasing demand for better information to plan engineering and policy actions to reduce demand, or increase supply of water, and thereby help the management of water resources in a changing environment (Padula, Harou, Papageorgiou, Ji, Ahmad & Hepworth 2013). Given increasing supply commonly involves billion dollar infrastructure investments (dams for example) and complex engineering solutions (desalinisation for example), evidence of any trends in water supply or water demand can be very valuable.

Future changes in average temperature and precipitation (Griffin & Chang 1991), changes in seasonality, and changes in extremes such as heatwaves or drought severity and length would have a major impact on water consumption (Meehl & Tebaldi 2004). To obtain estimates of how climate and climate variability will change in the future requires modelling, but the spatial resolution of most global climate models remains coarser than 1° x 1° making their direct use for city-scale projections of future climate difficult. Solutions to help link global models with scales relevant to major cities include dynamical downscaling. This approach is now widespread (see reviews by Fowler, Blenkinsop & Tebaldi (2007) and Ekstrom, Grose & Whetton (2015)) and groups have now downscaled multiple climate models, using combinations of methods that reflect uncertainties in key processes including the planetary boundary layer and convective processes (Evans, Ekstrom & Ji (2012); Evans, Ji, Lee, Smith, Argueso & Fita (2014)).

In this paper we bring together a major downscaling effort, the New South Wales/Australian Capital Territory Regional Climate Modelling (NARCliM) project with an established water demand model developed for New South Wales, Australia. The NARCliM project uses the Weather and Research Forecasting (WRF, Skamarock & Klemp (2008)) model to downscale four different global climate models for the present (1990-2010), near (2020-2040) and far (2060-2080) future. Unusually, each climate model is downscaled three times with variations in the boundary layer and convection parameterisation to capture the uncertainty in these processes. The water demand model, a method common in forecasting water demand (Arbues, Garcia-Valinas & Martinez-Espineira (2003); House-Peters & Chang (2011); Donkor, Mazzuchi, Soyer & Roberson (2014)), consists of multiple observations of the same population cross section at different points in time (Wooldridge 2010) and can include past values of the response variable as explanatory variables. We link the physical modelling of NARCliM with the water demand modelling via a stochastic weather generator (see Wilks & Wilby (1999); Ailliot, Allard, Monbet & Naveau (2015)) to enable probabilistic forecasting of Sydney's future water consumption.

Our goal therefore is to estimate the future of water consumption in Sydney and examine the extent to which future trends reflect population change, or climate change. We seek to determine the value of using multiple climate models relative to downscaling a single climate model with different physical options in the higher resolution model. Finally, where changes are identified, we seek to identify the climate variables that explain the changes in consumption. Ultimately, we seek to determine the scale of the threat climate change represents to managing water demand in the near and far future for Australia's largest city.

2. Methodology

2.1. Sydney Water Consumption Model

The Sydney Water Consumption Model (SWCM) is a dynamic panel data model (Wooldridge (2010); Bun & Sarafidis (2015)) used for the prediction of water consumption by Sydney Water customers based on the work of Abrams, Kumaradevan, Spaninks & Sarafidis (2012). The component of SWCM considered here models metered consumption only, which is about 90% of the total. The remaining 10%, approximately 57 GL per year, including leakage and meter under-read, is generally insensitive to weather and population. Water consumption is divided into residential and non-residential consumption. Residential properties are categorised into five dwelling types: single dwellings, townhouse units, strata units, flats and dual occupancies. Estimates for dwelling type numbers are made for the financial years 2014/15 to 2024/25 and are largely based on New South Wales Department of Planning and the Environment projections, adjusted to Sydney Water's area of operations. Three dwelling types are projected to increase between 2014/15 and 2024/25 (number of single dwellings, 1.05 million to 1.15 million; townhouse units, 103,000 to 131,000 and strata units 431,000 to 561,000) and two dwelling types are expected to remain constant (flats, 114,000 and dual occupancies, 26,000). The increase in some dwelling types relative to others leads to a small change in the mix of dwelling types in the population estimates over the period 2014/15 to 2024/25. We note that these estimates are regularly updated and while current when we undertook this analysis will inevitably be updated in the future.

The SWCM model predicts the water consumption at a residential property based on the dwelling type, compliance with the Building Sustainability Index (BASIX) regulation, participation in water efficiency programs and lot size. External drivers of water consumption include the weather, water price and season. Forecast water consumption for the individual properties are averaged to obtain the average demand for each segment, and then multiplied by the forecast number of dwellings for each segment to obtain total residential consumption.

The non-residential sector includes all property types not included in the residential models. These properties were hierarchically segmented on the basis of consumption levels, participation in water conservation programs and property types.

The SWCM uses five weather variables: average daily precipitation (PRE, mm); number of days when precipitation exceeds 2mm (GT2MM); average daily maximum temperature (TMAX, °C); number of days when maximum temperature exceeds 30°C (GT30C) and average daily pan evaporation (EVAP, mm). The weather stations used to provide weather variable data are listed in Table 1 and Figure 1. Weather variables are aggregated to quarterly variables when calculating residential consumption and to monthly variables when calculating non-residential consumption.

2.2. New South Wales / Australian Capital Territory Regional Climate Modelling Project

The New South Wales/Australian Capital Territory Regional Climate Modelling (NARCliM) project provides precipitation and temperature data from four different global climate models for the present (1990-2010), near (2020-2040) and far (2060-2080) futures. All future simulations used the SRES A2 emission scenario (Nakicenovic & Swart (2000)). The climate models were CCCMA3.1, CSIRO-MK3.0, ECHAM5 and MIROC3.0. Three simulations were conducted for each period/climate model combination. Data is available on a 10km x 10km grid, which covers south eastern Australia, including the greater Sydney metropolitan area.

The choice of which climate models were downscaled, and the physical parameterisations used with WRF is provided in Evans et al. (2014). Briefly, the climate models were chosen based on performance over eastern Australia (Evans et al. 2012) combined with a test of model independence proposed by Bishop & Abramowitz (2013). The climate models spanned the range of future change simulated using the A2 emission scenario in terms of precipitation and mean temperature. A large ensemble of WRF simulations were conducted and three configurations were selected that involved varying the convection, boundary layer, radiation and cloud microphysics schemes. Full details are provided by Evans et al. (2012) and are not repeated here; it will be shown later that the impact of these variations were very small. The NARCliM product has been used extensively to evaluate future climate change over south eastern Australia (e.g. Olson, Fan & Evans (2016); Evans, Argueso, Olson & Di Luca (2017)), to assess changes in future wind energy (Evans, Kay, Prasad & Pitman 2018) and the impact of urban expansion on temperatures (Argueso, Evans, Pitman & Di Luca 2015). Further details on NARCliM can be found at the AdaptNSW website (climatechange.environment.nsw.gov.au).

A bias correction is imposed on the NARCliM data so that the temperature and precipitation of each present day simulation has the same yearly averages as the Australian Water Availability Project (AWAP) data (Jones, Wang & Fawcett 2009) over the same period. A modification to the original NARCliM bias-corrected data was necessary in order to obtain realistic values for the GT2MM weather variable.

2.3. Stochastic Weather Generator

A stochastic weather generator developed by Barker, Pitman, Evans, Spaninks & Uthayakumaran (2018) was used for the generation of weather scenarios as inputs for the SWCM. A weather generator was used to overcome the problem that each NARCliM member only produces a single realisation of a stochastic process (i.e. weather). The weather generator enables multiple (in this case 100) realisations to be generated, each consistent with a NARCliM ensemble member, to examine the statistical distribution of weather and water consumption forecasts.

For each period/climate model/run combination, the stochastic weather generator

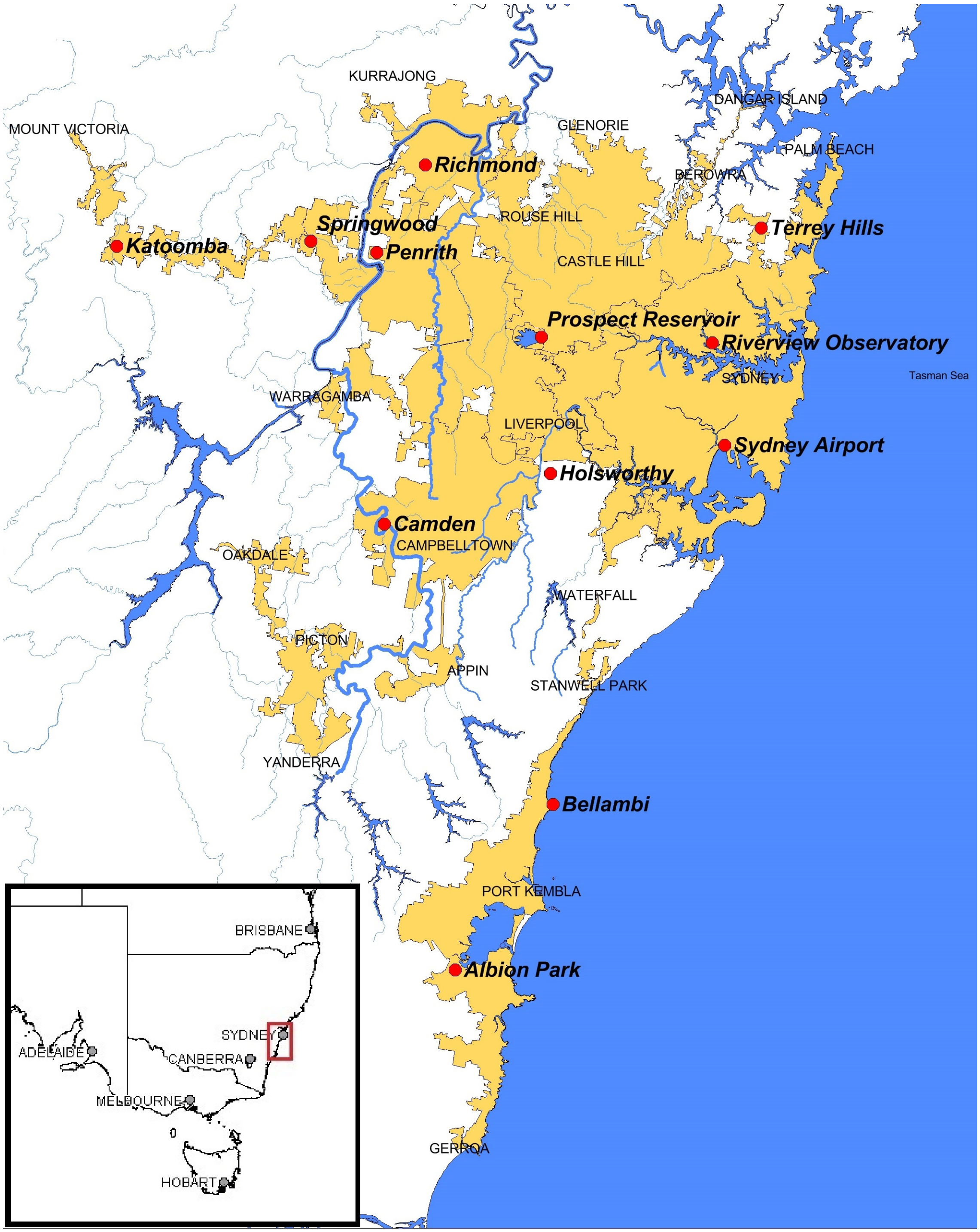


Figure 1. Area serviced with water by Sydney Water (orange) and location of the weather stations (red) used by the SWCM (see also Table 1). Inset of south eastern Australia.

Table 1. Weather data provided by weather stations for the SWCM. Figure 1 shows the geographical location of these stations. The variables are: daily precipitation (PRE, mm); number of days when precipitation exceeds 2mm (GT2MM); average daily maximum temperature (TMAX, °C); number of days when maximum temperature exceeds 30°C (GT30C) and average daily pan evaporation (EVAP, mm).

Station Name	PRE	GT2MM	TMAX	GT30C	EVAP
Albion Park	Y	Y	Y	Y	N
Bellambi	Y	Y	Y	Y	N
Camden	Y	Y	Y	Y	N
Holsworthy	Y	Y	Y	Y	N
Katoomba	Y	Y	Y	Y	N
Penrith	Y	Y	Y	Y	N
Prospect	Y	Y	Y	Y	Y
Richmond	Y	Y	Y	Y	Y
Riverview	Y	N	Y	N	Y
Springwood	Y	Y	Y	Y	N
Sydney Airport	Y	Y	Y	Y	Y
Terrey Hills	Y	Y	Y	Y	N

was calibrated to produce weather scenarios with statistical properties similar to those of the NARCliM data. NARCliM weather data from the closest grid point to each of the weather stations in Table 1 was used to calibrate the stochastic weather generator. Each weather scenario contains data for the 11 financial years from 2014/15 to 2024/25 and 100 weather scenarios were generated for each period/climate model/run combination. In total 13,200 years of data are generated for each time period (present, near future, far future) allowing quantification of the variance due to changing weather.

All weather variables were assumed not to have a yearly trend within the 20 year NARCliM period. Estimates of water demand by SWCM requires pan evaporation, a variable not generated by most weather and climate models including the NARCliM project. Instead, the evaporation model described by Barker et al. (2018) was used to generate evaporation data as a function of precipitation and maximum temperature.

2.4. Experiments Performed

In summary, our consumption forecasts reflect changes in population and weather with weather responding to climate change in the future. The population data associated with a given forecast is estimated for each of the financial years between 2014/15 and 2024/25, allowing population to vary over this ten year period. The weather data associated with a forecast is taken from a stochastic weather generator simulation based on data from a NARCliM ensemble member in one of the present, near or far future periods. We can vary the NARCliM ensemble member and time period represented, such that the weather reflects the present, near or far future. We can therefore examine the consumption forecasts for combinations of populations between 2014/15 and 2024/25 with weather for the present, near future or far future. We therefore undertake three analyses, each for the present, near and far future:

(a) isolate the effect of climate change on water consumption. Here, population is held at 2019/2020 levels and the dwelling type mix uses the population estimates;

(b) isolate the effect of population change on water consumption. Here, population varies from 2014/15-2024/25 and the dwelling type mix uses population estimates;

(c) isolate the effect of dwelling type mix. Here, population varies from 2014/15-2024/25 and the dwelling type mix varies between the dwelling type mix estimate, simulations with no single dwellings, and simulations assuming all single dwellings. The average number of people in each dwelling type was 3.11 per single dwelling; 2.17 per unit and 2.39 per townhouse. The ratio of units to townhouses was 4.2:1 and the number of flats and dual occupancies remained constant.

3. Results

Figure 2 shows the annual consumption for the present, near future and far future climates across all dwelling types projected using four global climate models each downscaled three times using different configurations of WRF. These simulations reflect population and dwelling configuration representative of 2019/20 and therefore isolates the effect of climate change. The range for an individual projection stems from the use of 100 stochastic weather time series. Figure 2 shows a trend upward with median consumption increasing from around 484 GL in the present to 484-494 GL in the near future, and 495-505 GL in the far future due to climate change. There are differences between the projected consumption with MIROC3.2 tending toward lower estimates than the other models. Given the small differences between the WRF configurations, we average them to calculate the change in demand. Median annual demand increases from the present to the near future by between 1.1 GL (0.2%, MIROC3.2) and 9.2 GL (1.9%, ECHAM5) and increases further by between 11.1 GL (2.3%, MIROC3.2) to 19.4 GL (4%, ECHAM5) between the present and the far future. CCCMA3.1 displays higher variability in the near future (the range from the minimum to the maximum estimate is 10% in comparison to 6% for CSIRO and ECHAM5 and 8% for MIROC3.2). However, CCCMA3.1 predicts lower variability in the far future (range 6-7% compared with 8-10% for the other models). However, if an individual model, for an individual time period is examined, the differences caused by varying the boundary layer and convection parameterisations rarely exceeds 1-2%.

We next examine how future changes in water consumption due to population growth compare to changes due to climate change. Figure 3 shows the total annual consumption forecasts for each level of population between 2014/15 and 2024/25 for the present day, near and far future weather. Figure 3 shows the total annual consumption

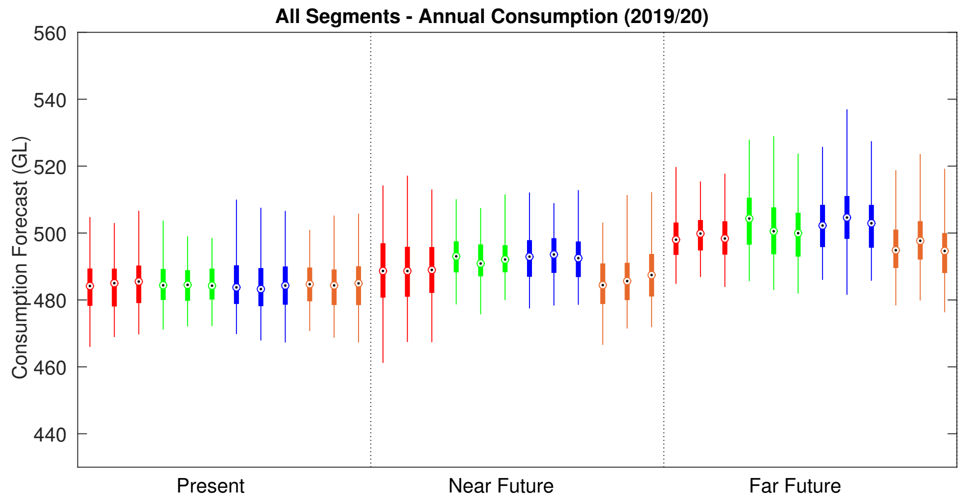


Figure 2. Consumption forecasts by model (CCCMA3.1 - red, CSIRO-MK3.0 - green, ECHAM5 blue and MIROC3.2 - orange) showing three ensemble members for each model. Total consumption for all dwellings types (includes single dwellings, units, town houses and non-residential). Each bar shows the median (open circle), the range derived using the stochastic weather generator. Three time periods are shown: the present, near future and far future and assuming 2019/2020 populations.

increases with population (the overall trend from 2014/15 to 2024/25) and that changes due to weather between the present (red bars), near future (green bars) and far future (blue bars) have a relatively small impact relative to the changes due to population. The increase in median consumption from 2014/15 to 2024/25 due to population increase over the same period is from 457.1 GL to 507.6 GL (50.5 GL) in the present, 462.6 GL to 514.5 GL (51.9 GL) in the near future and from 471.2 GL to 524.2 GL (53 GL) in the far future. The increase in median consumption from the present to the far future due to climate is between 14.1 GL (2014/15) to 16.6 GL (2024/25). In comparison to the small increases in consumption shown in Figure 2, the increases due to population growth are very large. To compare, the climate driven increase between the present and far future is matched by about 3 years of population growth.

Population growth clearly increases water demand, and dominates the climate contribution, but how much water demand increases depends on the nature of the dwellings people occupy. We therefore explored how water demand would vary into the future if all population growth was accommodated via single dwellings, or via a mixture of dwellings, or without any single dwellings. In the present, all three planning options lead to similar median water consumption (Figure 4a) for a given year with the overall trend upwards between 2014/15 and 2024/25 caused by the population growth. However, in the present, the variability in the consumption forecast (the length of the bars for each period) increases as the fraction of single dwellings increases. In the near future (Figure 4b) there are hints that the median increases as a function of the fraction

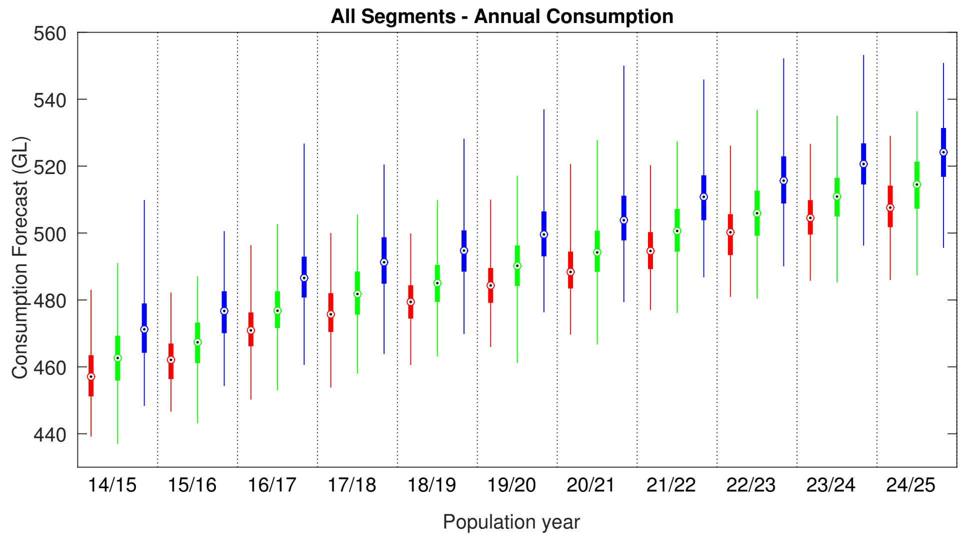
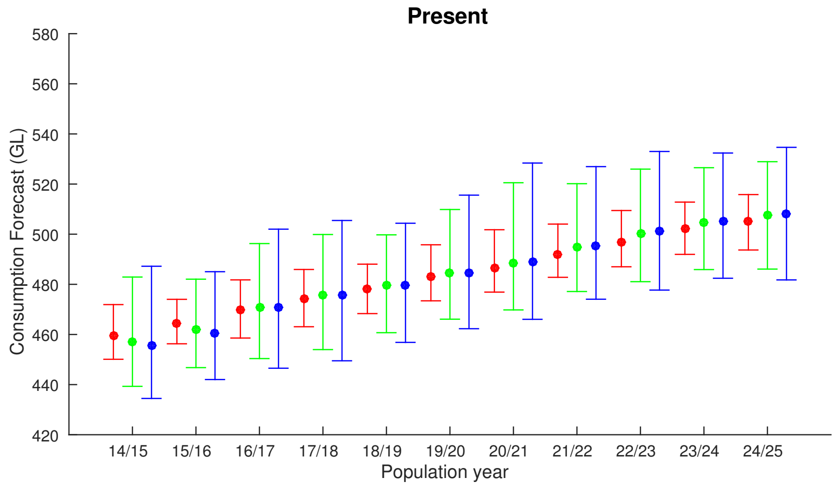


Figure 3. Consumption forecasts across all dwelling types by year for each NARCliM period (Present - red, Near Future - green, Far Future - blue) for population increases from 2014/15 to 2024/25. Each bar shows the range across the 12 NARCliM ensemble members (4 climate models, 3 perturbations).

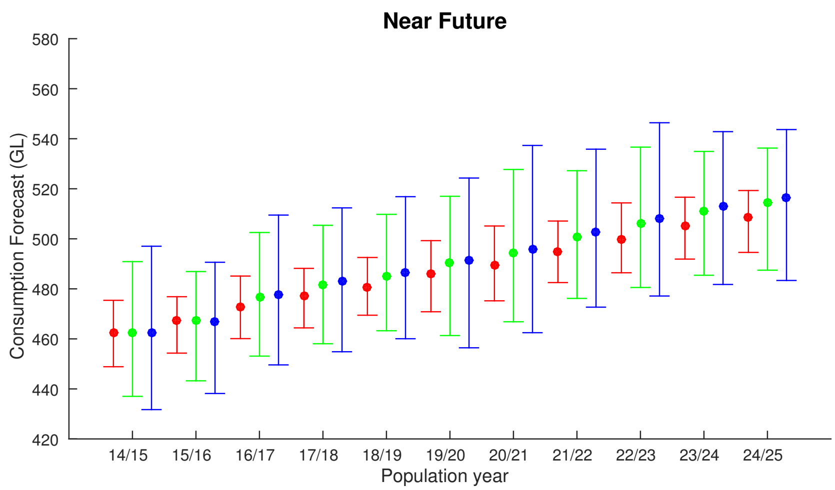
of single dwellings, and this becomes clearer in the far future (Figure 4c). In addition, the variability increases markedly as the fraction of single dwellings increase.

We next explain these results in terms of changes in weather variables. Figure 5 shows precipitation, number of days with more than 2mm of precipitation, maximum temperature and number of days where the temperature exceeds 30°C. Bias correction of NARCliM results constrains total precipitation and mean temperature for the present to be similar to observations (red symbols in Figure 5), but the standard deviations of each variable are less constrained. The CSIRO-MK3.0 model simulates a reduction in rainfall in the near and far future, ECHAM5 shows little change for the near future but increases in the far future, CCCMA3.1 and MIROC3.2 increase in both the near and far future. The resulting range in NARCliM results shown in Figure 5a is considerable, with some models predicting decreases of 100 mm y^{-1} and others predicting increases of 200 mm y^{-1}. This reflects the well-known challenge in climate modeling of constraining the regional projections of future rainfall and is an uncertainty that is very difficult to reduce. To add to this uncertainty, Figure 5b shows projections of rainfall events exceeding 2 mm d^{-1} range from 70 to 85 days a year with almost no clustering amongst the models, or by time period. There are projections for both the near and far future in the range of 70-75 days, and in the range exceeding 80 days.

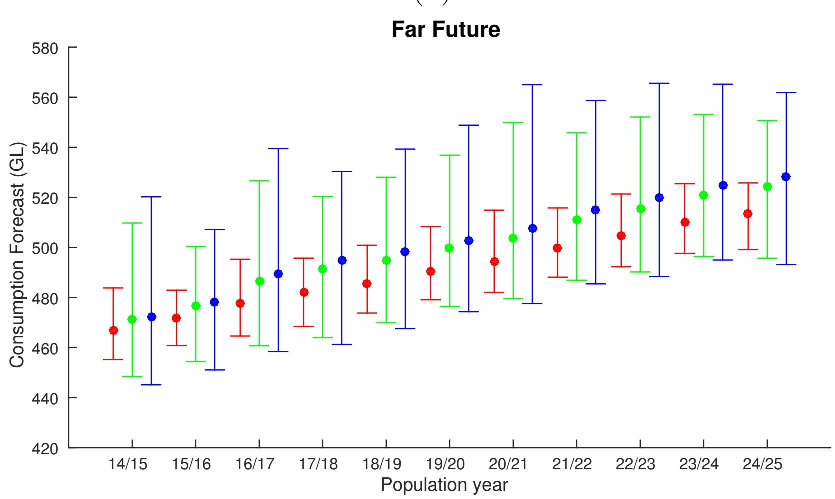
The projections of maximum temperature (Figure 5c) and days over 30°C (Figure 5d) clearly depend on the time period associated with the emission scenario. The climate models provide distinct projections for both temperature metrics, increasing by 0.5°C in the near future, through to 1.5-2.0°C in the far future with reasonable agreement amongst the models in terms of the maximum temperature change (Figure 5c). The



(a)



(b)



(c)

Figure 4. Consumption forecasts for the present, near and far future climate as a function of population growth and the nature of the dwelling type. Red bars indicate no single dwellings, green indicates the dwelling mixture and blue indicates where all properties are single dwellings.

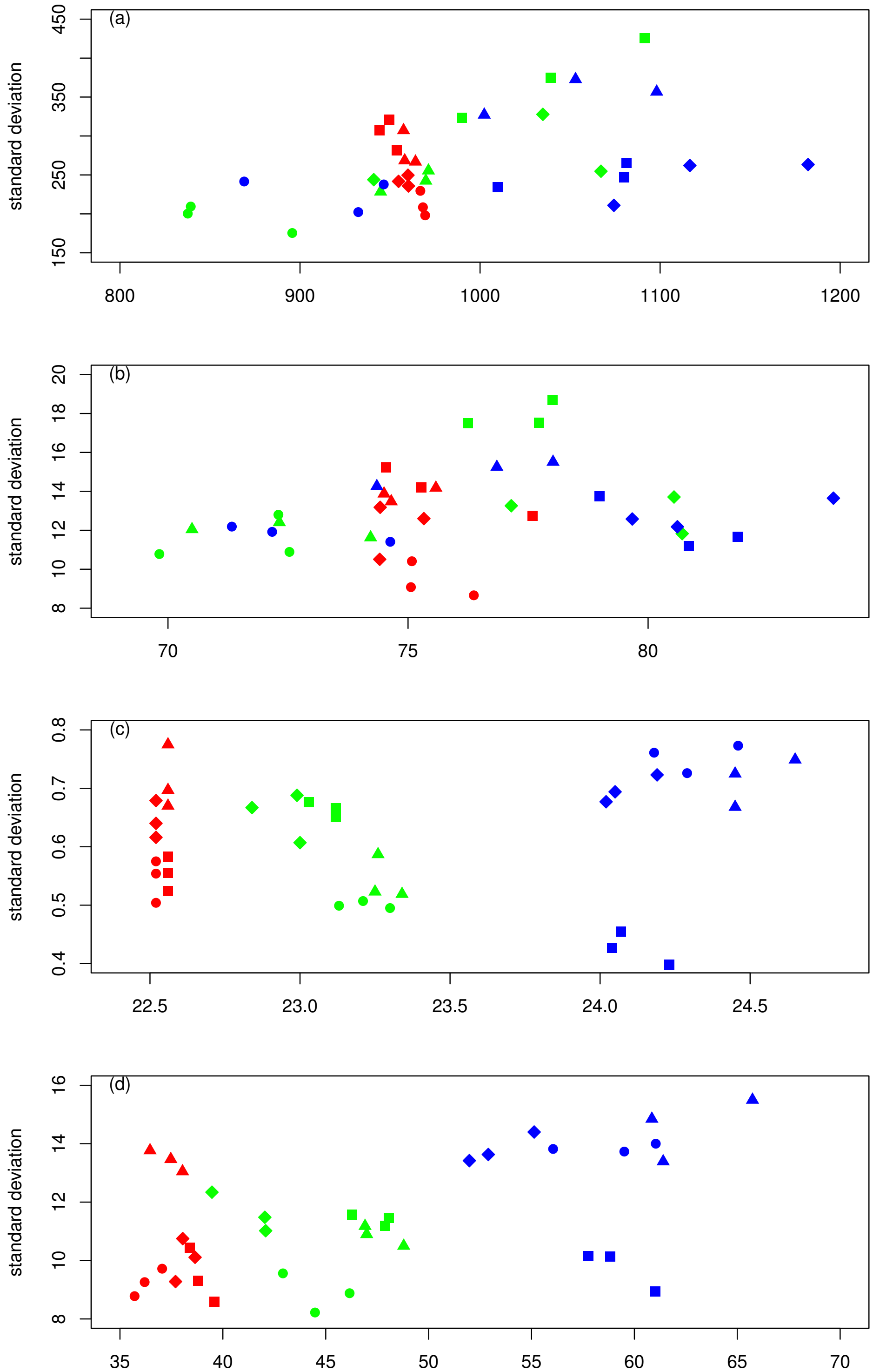


Figure 5. Plots of annual standard deviation versus annual mean of weather variables for each of the NARCliM ensemble members. (CCCMA3.1 - square, CSIRO-MK3.0 - circle, ECHAM5 - triangle and MIROC3.2 - diamond), (Present - red, Near Future - green, Far Future - blue). (a) precipitation (mm), (b) number of days > 2mm, (c) maximum temperature ($^\circ C$) and (d) number of days > $30^\circ C$.

number of days over 30°C increase from 35-40 in the present, to 40-50 days in the near future to 52-65 days in the far future, highlighting increasing uncertainty based on climate model choice further into the future.

4. Discussion and Conclusions

In this paper we estimate Sydney's future water consumption by combining the physical modelling of NARCliM with water demand modelling using the Sydney Water Consumption Model (SWCM) via a stochastic weather generator. We can separate the impact of changes in climate from changes in population through to 2025. We find that population changes are the dominant driver of increases in future water demand, increasing demand by 51.9 GL per decade. This contrasts with a far smaller impact from climate change from the present to the near future of between 1.1 GL and 9.2 GL based on 2019/20 population. However, there are two caveats to this outcome: first both drivers act in parallel and thus are additive and second there is no reason why planning for climate change should pick any single estimate of the increase in consumption and any one climate scenario can produce a wide range of future consumption forecasts.

The increase in median consumption due to population, approximately 5 GL per year, is much greater than the increase due to climate change, which ranges between 14.1 GL and 16.6 GL in 70 years. However, for any single year and any one NARCliM climate period, changes in the weather can produce a large range of consumption forecasts (Figure 3). Density functions of the difference in consumption forecasts from 2019/20 to 2020/21 (Figure 6) shows that while the median of these differences is a measure of the increase in consumption due to the increase in population from 2019/20 to 2020/21, there are examples where the difference between the consumption forecasts is as low as -31 GL and as high as 43 GL. Indeed, with this pair of financial years for 30-34% of the time the increase in consumption forecast due to the weather is greater than the increase due to population. In terms of water demand, Figure 6 shows that using the median estimates is a very poor basis for managing risk.

The NARCliM product provides estimates of near future and far future climate from four climate models, each downscaled three times. A bias correction procedure ensures that the average annual maximum temperatures and total annual number of wet days are almost identical for all climate models in the present, but due to divergent future projections there is no such constraint in the near and far future for averages or variability. We have shown that the three regional simulations driven by the same climate model provide future climate information with very similar statistical properties. However, when considering projections driven by the same climate model, the difference between the near future and present is a poor predictor of the difference between far future and near future for all weather variables except mean temperature (Figure 5). For example, in the CSIRO MK3.0 model, precipitation decreases from the present to the near future by 50-100 mm but increases between the near future and the far future. In contrast, ECHAM5.0 precipitation changes little from the present to the near

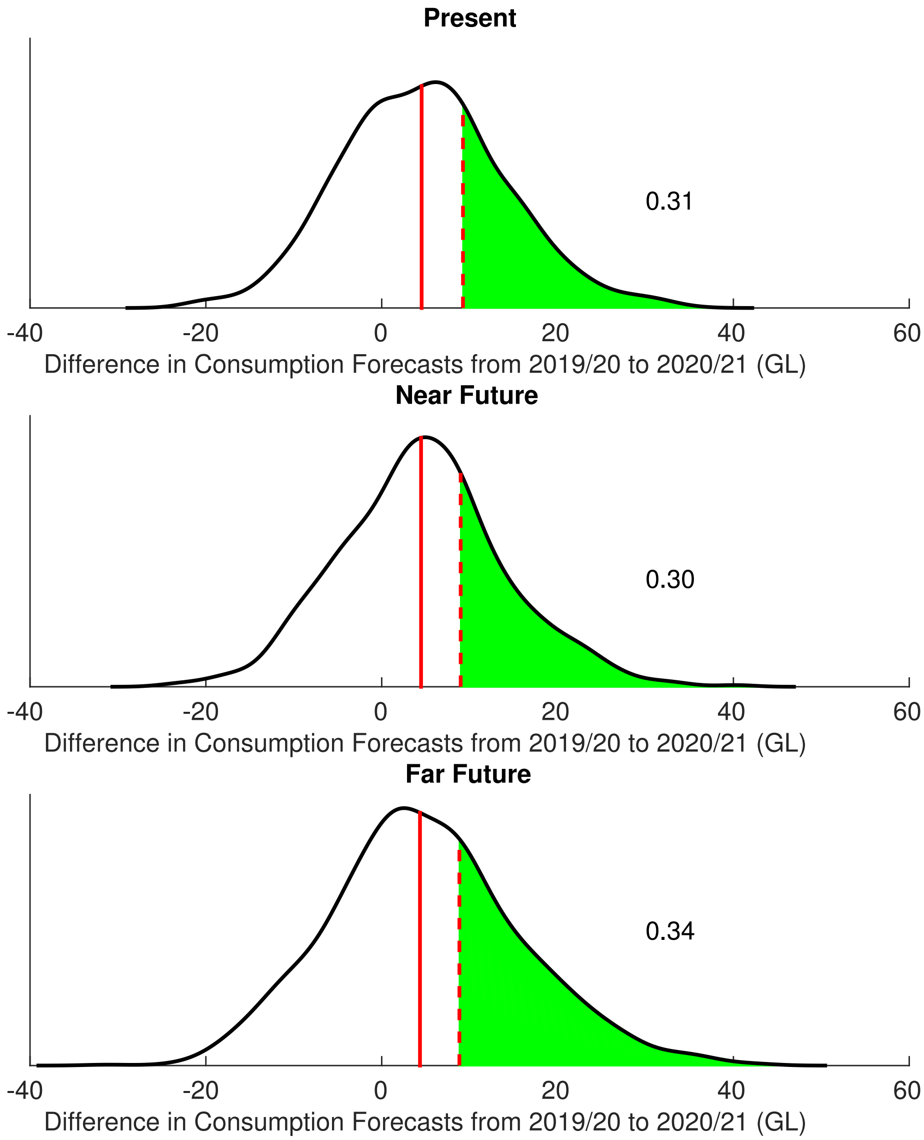
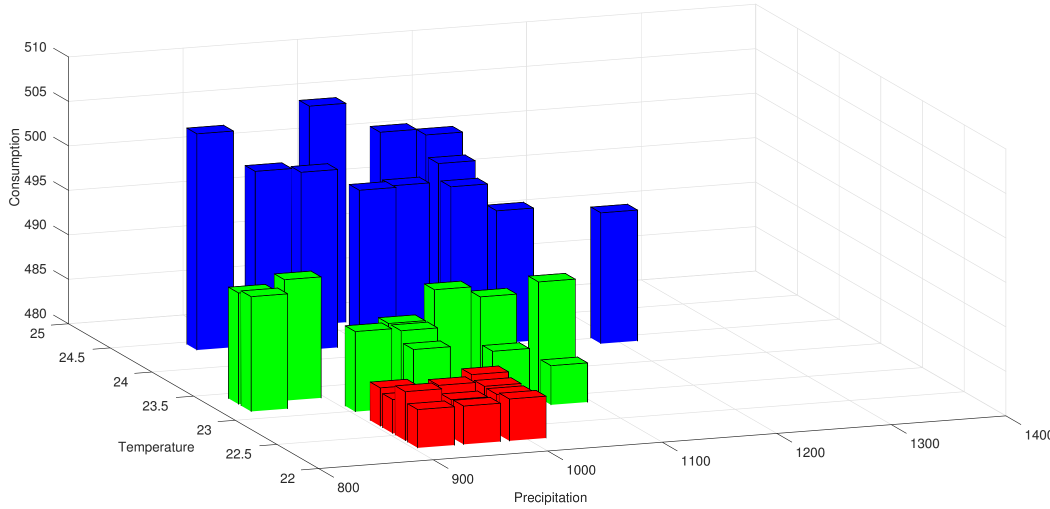


Figure 6. Density function of difference in consumption forecasts from 2019/20 to 2020/21 for the present, near and far futures. Solid red line is at the median of the consumption forecast differences and the dashed red line is at twice that median. The filled green region represents the consumption forecasts where the increase in consumption due to the weather is greater than the increase in consumption due to population. The area of the filled green region is written as a probability in the figure. Each probability density function was estimated from 1200 consumption forecasts, 100 from each of the 12 NARCliM ensemble members.

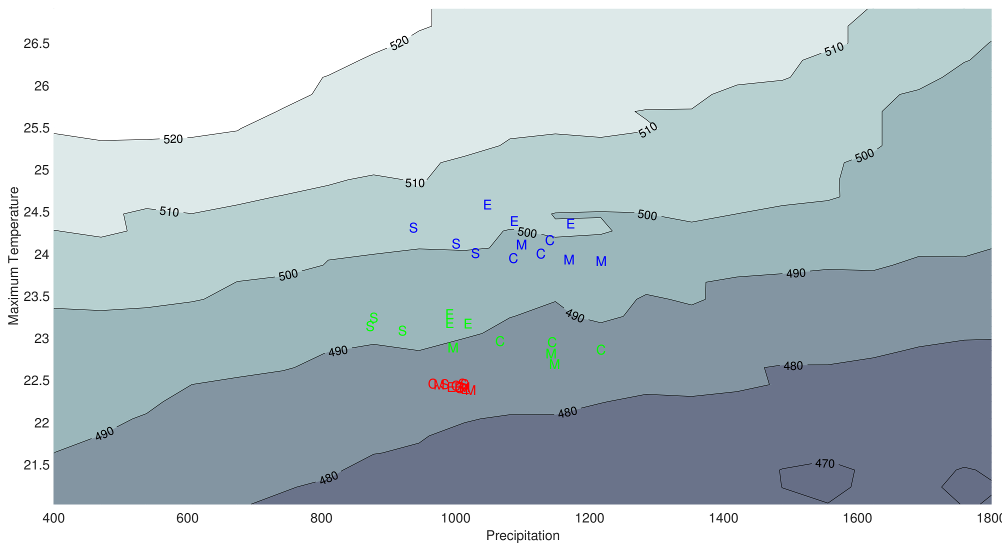
future, increases by about 100mm between the near and far future. This is also true for the standard deviation of weather variables. The standard deviation of maximum temperature for CCCMA3.1 increases from the present to the near future by about 0.1 and decreases from the near to the far future by about 0.2. In contrast, the standard deviation of maximum temperature from the CSIRO Mk3.0 model is almost unchanged from the present to the near future, but increases by 0.2 from the near to the far future. These results suggest that future climate change will occur non-linearly with time. Better characterisation of uncertainty in projecting climate-related water demand requires more global climate models to be downscaled as a priority over downscaling individual climate models multiple times.

We now combine the changes in climate variables (Figure 5) with the changes in water demand (Figures 2 and 3). Figure 7 shows the changes in maximum temperature, precipitation and demand for the present, near future and far future. Consumption tends to increase with temperature and decrease weakly as precipitation increases and there is a major increase in demand from the relatively cool present, to the relatively warm far future. In the present, the median forecasts of water consumption are all around 484 GL due to the bias correction process used. While the change in rainfall between the present and the near future (Figure 5a) affects water consumption, forecasts remain between 484-494 GL that is the forecasts are relatively insensitive to the precipitation change (Figure 7). In the far future, forecasts remain similar (495-505 GL) but some models are always on the dry-end of the range (CSIRO-MK3.0), some commonly in the centre (ECHAM5) and some at the upper end (MIROC3.0) but demand does not respond to changes in precipitation strongly. This is reassuring given Figure 5a showed changes in rainfall to be uncertain. In contrast, the increasing maximum temperature drives demand such that consumption is clearly higher in the far future than in the near future or the present.

A key implication of our results is that if we take median climate projections from the NARCliM product and use them to project water consumption, the impact of climate change in the near future and far future are small compared to population growth. We can quantify this in terms of the ratio of dam capacity to metered consumption at 2019/20 population levels. Sydney's water supply is considerable and at maximum capacity is of order 2,582 GL (https://www.waternsw.com.au/supply/dam-levels/greater-sydneys-dam-levels). Using the median estimate of demand for the present day (484.4 GL), this represents about 5.3 years of storage. This decreases under the single climate model, maximum consumption scenario (509.8 GL) to 5.1 years of storage. Taking changes in climate into account and considering the near future, the median estimate of demand (489.9 GL) represents 5.3 years of storage and under the most extreme weather scenario consumption reaches 517.0 GL but there is still 5.0 years of storage. Note that the years of storage ratios calculated here are not intended as precise estimates of the length of available water supply because they do not take into account the ∼57GL per year of un-metered consumption, or any water loss due to evaporation. They are also not adjusted to account for the desalination plant, opened



(a)



(b)

Figure 7. (a) 3D bar chart map of consumption forecasts from all NARCliM ensemble members for the financial year 2019/20 as a function of precipitation and maximum temperature. The NARCliM periods are indicated by red for the present, green the near future and blue for the far future; (b) Contour map of consumption forecasts from all NARCliM ensemble members for the financial year 2019/20 as a function of precipitation and maximum temperature. Letters represent the average precipitation and maximum temperature for each ensemble member over 100 weather scenarios. The NARCliM models are indicated by the letters C for CCCMA3.1, S for CSIRO-MK3.0, E for ECHAM5 and M for MIROC3.0. The NARCliM periods are indicated by the colours red for the present, green for the near future and blue for the far future.

in 2010, which has a current capacity of about 90 GL per year and the ability to be extended to 180 GL per year. Despite these caveats, in a climate influenced by the El Nino-Southern Oscillation which is associated with above and below normal rainfall over south eastern Australia, the reduction in the effective storage implied by the combination of population growth and climate change increases the vulnerability of Sydney's water supply.

We conclude by noting that the dominant driver of Sydney's water demand is population not climate change. However, we have not examined the impact of climate change on supply; water storage for Sydney is very sensitive to the frequency of east coast lows that provide the key synoptic scale mechanism to fill water storages (Pepler & Rakich 2010). If these systems changed in frequency or magnitude they would have a profound impact on water storage and could significantly change the vulnerability of Sydney to climate change. In the absence of changes in water supply, our results point to two drivers of changes in water demand for Sydney, population and climate change, acting in parallel to reduce the storage in the near future significantly. We do not attempt to estimate the impact of population change in the far future and interpolating the population changes relevant to the near future into the far future is infeasible given the likely impact of technological innovation on water demand and supply management.

Acknowledgments

We acknowledge the NSW Office of Environment and Heritage backed NSW/ACT Regional Climate Modelling Project (NARCliM) project for providing the climate projection data.

References

Abrams, B., Kumaradevan, S., Spaninks, F. & Sarafidis, V. (2012). An econometric assessment of pricing Sydney's residential water use, *The Economic Record* **88**: 89–105.

Ailliot, P., Allard, D., Monbet, V. & Naveau, P. (2015). Stochastic weather generators: an overview of weather type models, *Journal of the French Statistical Society* **156**: 101–113.

Arbues, F., Garcia-Valinas, M. A. & Martinez-Espineira, R. (2003). Estimation of residential water demand: a state-of-the-art review, *Journal of Socio-Economics* **32**: 81–102.

Argueso, D., Evans, J. P., Pitman, A. J. & Di Luca, A. (2015). Effects of city expansion on heat stress under climate change conditions, *PLoS ONE* **10(2)**.

Barker, A., Pitman, A. J., Evans, J. P., Spaninks, F. & Uthayakumaran, L. (2018). Probabilistic forecasts for water consumption in Sydney, Australia from stochastic weather scenarios and a panel data consumption model, *submitted to Water Resources Management* .

Bishop, C. H. & Abramowitz, G. (2013). Climate model dependence and the replicate Earth dependence, *Climate Dynamics* **41**: 885–900.

Bun, M. J. G. & Sarafidis, V. (2015). Dynamic panel data models, *in* B. H. Baltagi (ed.), *The Oxford Handbook of Panel Data*, Oxford University Press.

Donkor, E. A., Mazzuchi, T. A., Soyer, R. & Roberson, J. A. (2014). Urban water demand forecasting: Review of methods and models, *Journal of Water Resources Planning and Management* **140**: 146–159.

Ekstrom, M., Grose, M. R. & Whetton, P. H. (2015). An appraisal of downscaling methods used in climate change research, *WIREs Climate Change* **6**: 301–319.

Evans, J. P., Argueso, D., Olson, R. & Di Luca, A. (2017). Bias-corrected regional climate projections of extreme rainfall in south-east Australia, *Theoretical and Applied Climatology* **130**: 1085–1098.

Evans, J. P., Ekstrom, M. & Ji, F. (2012). Evaluating the performance of a WRF physics ensemble over South-East Australia, *Climate Dynamics* **39**: 1241–1258.

Evans, J. P., Ji, F., Lee, C., Smith, P., Argueso, D. & Fita, L. (2014). Design of a regional climate modelling projection ensemble experiment - NARCliM, *Geoscientific Model Development* **7**: 621–629.

Evans, J. P., Kay, M., Prasad, A. & Pitman, A. (2018). The resilience of Ausralian wind energy to climate change, *Environmental Research Letters* **13**.

Fowler, H. J., Blenkinsop, S. & Tebaldi, C. (2007). Linking climate change modelling to impacts studies: recent advances in downscaling techniques for hydrological modelling, *International Journal of Climatology* **27**: 1547–1578.

Gain, A. K. & Wada, Y. (2014). Assessment of future water scarcity at different spatial and temporal scales of the Brahmaputra river basin, *Water Resources Management* **28**: 999–1012.

Griffin, R. C. & Chang, C. (1991). Seasonality in community water demand, *Western Journal of Agricultural Economics* **16**: 207–217.

Hoekstra, A. Y., Buurman, J. & van Ginkel, K. C. H. (2018). Urban water security: A review, *Environmental Research Letters* **13**.

House-Peters, L. A. & Chang, H. (2011). Urban water demand modeliing: Review of consepts, methods and organizing principles, *Water Resources Research* **47**.

Jones, D. A., Wang, W. & Fawcett, R. (2009). High-quality spatial climate data-sets for Australia, *Australian Meteorological and Oceanographic Journal* **58**: 233–248.

Meehl, G. A. & Tebaldi, C. (2004). More intense, more frequent and longer lasting heat waves in the 21st century, *Science* **305**: 994–997.

Nakicenovic, N. & Swart, R. (eds) (2000). *IPCC Special Report on Emissions Scenarios*, Cambridge University Press.

Olson, R., Fan, Y. & Evans, J. P. (2016). A simple method for Bayesian model averaging of regional climate model projections: Application to South-East Australian temperatures, *Geophysical Research Letters* **43**: 7661–7669.

Padula, S., Harou, J. J., Papageorgiou, L. G., Ji, Y., Ahmad, M. & Hepworth, N. (2013). Least economic cost regional water supply planning - Optimising infrastructure investments and demand management for South East England's 17.6 million people, *Water Resources Management* **27**: 5017–5044.

Pepler, A. S. & Rakich, C. S. (2010). Extreme inflow events and synoptic forcing in Sydney catchments, *IOP Conference Series: Earth and Environmental Science* **11**.

Polebitski, A. S. & Palmer, R. N. (2010). Seasonal residential water demand forecasting for census tracts, *Journal of Water Resources Planning and Management* **136**: 27–36.

Schleich, J. & Hillenbrand, T. (2009). Determinants of residential water demand in Germany, *Ecological Economics* **68**: 1756–1769.

Skamarock, W. C. & Klemp, J. B. (2008). A time-split nonhydrostatic atmospheric model for weather research and forecasting applications, *Journal of Computational Physics* **227**: 3465–3485.

Tortajada, C. & Joshi, Y. K. (2013). Water demand management in Singapore: Involving the public, *Water Resources Management* **27**: 2729–2746.

Wilks, D. S. & Wilby, R. L. (1999). The weather generation game: a review of stochastic weather models, *Progress in Physical Geography* **23**: 329–357.

Wooldridge, J. M. (2010). *Econometric Analysis of Cross Section and Panel Data*, 2nd edn, MIT Press.