Check for updates

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

Adrian Barker, Andrew Pitman, Jason P. Evans, Frank Spaninks and Luther Uthayakumaran

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. Projected climate change would increase median metered consumption, at 2019/2020 population levels, from around 484 GL under present climate to 484–494 GL under near future climate and 495–505 GL under far future climate. Population changes from 2014/2015 to 2024/2025 have a far larger impact, increasing median metered consumption from 457 to 508 GL under the present climate, 463 to 515 GL under near future climate and from 471 to 524 GL under far future climate. The projected changes in consumption are sensitive to the climate model used. Overall, while population growth is a far stronger driver of increasing water 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 therefore lead to overconfidence in the reliability of Sydney's water supply.

Key words | climate change, population growth, stochastic weather generation, urban water consumption

Adrian Barker (corresponding author)
Andrew Pitman
Jason P. Evans
ARC Centre of Excellence for Climate Extremes and Climate Change Research Centre,
UNSW,
Sydney,
Australia
E-mail: *adrian.barker@unsw.edu.au*; *adrian.barker@students.mq.edu.au*

Frank Spaninks
Luther Uthayakumaran
Sydney Water,
Level 14, 1 Smith Street, Parramatta, New South Wales, 2150,
Australia

HIGHLIGHTS

- This paper combines an urban water consumption model, regional climate models and a stochastic weather generator to generate probabilistic consumption forecasts.
- This paper analyses the effect of climate change on urban water consumption.
- This paper compares the relative effect of climate change and population on urban water consumption.
- This paper analyses the effect of dwelling type on urban water consumption.
- This paper compares the statistical properties of weather variables from different regional climate models.

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 *et al.* 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

This is an Open Access article distributed under the terms of the Creative Commons Attribution Licence (CC BY 4.0), which permits copying, adaptation and redistribution, provided the original work is properly cited (http://creativecommons.org/licenses/by/4.0/).

doi: 10.2166/wcc.2020.230

Downloaded from http://iwa.silverchair.com/jwcc/article-pdf/12/4/1168/896194/jwc0121168.pdf
by guest

(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 the supply of water and thereby help the management of water resources in a changing environment (Padula *et al.* 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. In this paper, we examine future water demand in the area serviced by Sydney Water, (Figure 1). A model for the water supply to Sydney, WATHNET, has been developed by Water NSW, the operator of water supply systems throughout NSW including the Sydney basin (WaterNSW 2016).

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 (GCMs) remains coarser than $1^\circ \times 1^\circ$ making their direct use for city-scale projections of future climate difficult. This is a significant problem for Sydney, which has a varying topography and a strong temperature and rainfall gradient from the coast, across the Sydney Basin, through to the location of the main water storages west of Warragamba (Figure 1).

Solutions to help link coarse global models with scales relevant to major cities include dynamical downscaling. This approach is now widespread (see reviews by Fowler *et al.* (2007) and Ekström *et al.* (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 *et al.* 2012, 2014).

In this paper, we bring together a major dynamical 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 GCMs 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 is a panel data model, a method common in forecasting water demand (Arbués *et al.* 2003; House-Peters & Chang 2011; Donkor *et al.* 2014), where multiple observations are made of the same population cross-section at different points in time (Wooldridge 2010). The response variable is the quarterly consumption at each property. Explanatory variables include various characteristics of the property, the weather and past values of the response variable. We link the physical modelling of NARCliM with the water demand modelling via a stochastic weather generator (see Wilks & Wilby 1999; Ailliot *et al.* 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.

METHODOLOGY

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 *et al.* (2012). Use of the SWCM has been reported in Barker *et al.* (2019). The component of SWCM considered here models metered consumption only, which is about 90% of the total. The remaining 10%, approximately

Downloaded from http://iwa.silverchair.com/jwcc/article-pdf/12/4/1168/896194/jwc0121168.pdf
by guest

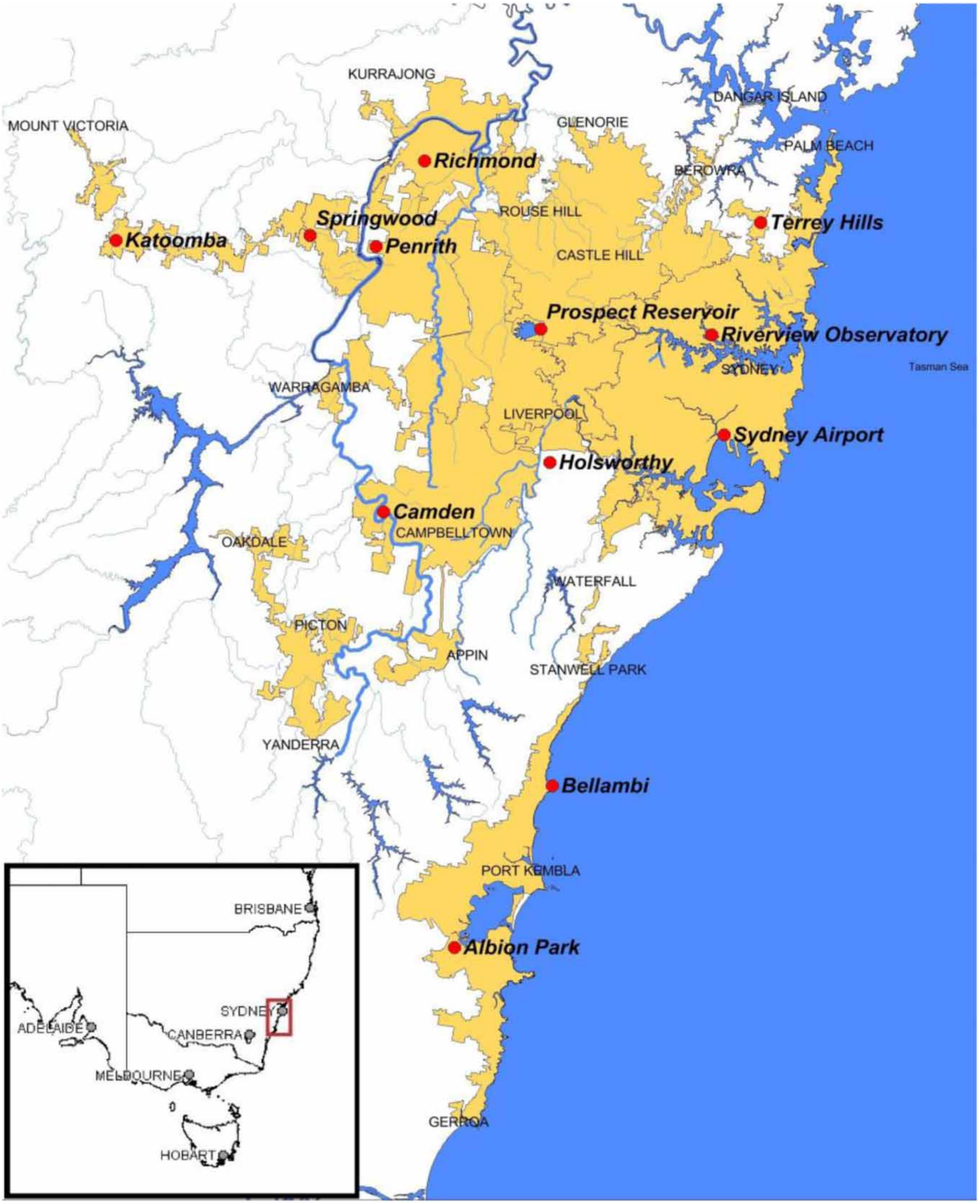

Figure 1 | Area serviced with water by Sydney Water (shaded) and location of the weather stations used by the SWCM (see also Table 1). Inset of south eastern Australia.

57 GL per year, including leakage and metre under-read, is generally less sensitive to weather and population and not included in the SWCM. 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

Downloaded from http://iwa.silverchair.com/jwcc/article-pdf/12/4/1168/896194/jwc0121168.pdf
by guest

occupancies. This categorisation is undertaken in order to properly model their different consumption characteristics. Demand by single dwellings is more seasonal and responsive to weather than demand by units and flats due to factors, such as the presence of garden areas and swimming pools. Estimates for dwelling type numbers are made for the financial years 2014/2015 to 2024/2025 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 2014/2015 and 2024/2025 (number of single dwellings, from 1.05 to 1.15 million; townhouse units, from 103,000 to 131,000 and strata units from 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 2014/2015 to 2024/2025. We note that these estimates, while current when we undertook this analysis, have since been updated.

The SWCM model predicts the water consumption at a residential property based on the dwelling type, compliance with the Building Sustainability Index 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 is 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 2 mm (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 shown in Figure 1. Barker *et al.* (2019) provide a summary of the weather statistics at each of these weather stations. We

Table 1 | Weather data provided by weather stations for the SWCM

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

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

note that the SWCM does not include some higher-order rainfall statistics such as dry spells; these are being added to the next generation of water demand models. Weather variables are aggregated to quarterly variables when calculating residential consumption and to monthly variables when calculating non-residential consumption. In general, hotter, dryer weather leads to increases in urban water consumption, due to increased outdoor water use, use of evaporative coolers (Roberts *et al.* 2011; Athuraliya *et al.* 2012). The sensitivity of the SWCM to changes in the weather was examined in Barker *et al.* (2019), where it was found that an increase of 0.8 °C in average annual maximum temperature or a decrease of 420 mm in total annual rainfall would result in an increase of approximately 2% in total consumption.

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 GCMs 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 GCMs used were the CCCMA CGCM3.1(T74),

Downloaded from http://iwa.silverchair.com/jwcc/article-pdf/12/4/1168/896194/jwc0121168.pdf
by guest

CSIRO-MK3.0, ECHAM5/MPI-OM and MIROC3.2(medres) GCMs, hereafter the CCCMA3.1, CSIRO-MK3.0, ECHAM5 and MIROC3.2 GCMs. Three simulations were conducted for each period/climate model combination. Data are available on a 10 km × 10 km grid, which covers south eastern Australia, including the greater Sydney metropolitan area.

The choice of which GCMs were downscaled and the physical parameterisations used with WRF is detailed in Evans *et al.* (2014). Briefly, the GCMs were chosen based on the performance over eastern Australia (Evans *et al.* 2012) combined with a test of model independence proposed by Bishop & Abramowitz (2013). The GCMs were also required to span the range of future change simulated using the A2 emission scenario in terms of precipitation and mean temperature. Therefore, by design, the NARCLiM simulations attempt to span uncertainty in rainfall and temperature projections, rather than attempt to provide a smaller range of future projections that mask uncertainty. A large ensemble of WRF simulations was conducted and three configurations were selected that involved varying the convection, boundary layer, radiation and cloud microphysics schemes. The WRF configurations chosen reproduce observed storm events (Evans *et al.* 2012; Ji *et al.* 2014) and have independent model errors. This independence criteria ensure that the configurations differ in their overall climate biases (Olson *et al.* 2016a) and ability to capture the teleconnections with large-scale climate modes (Fita *et al.* 2017). It has been found that WRF multi-physics ensembles can have as much variability in terms of model performance as larger multi-model ensembles (Kotlarski *et al.* 2014). The NARCliM product has been used extensively to evaluate future climate change over south eastern Australia (e.g. Olson *et al.* 2016b; Evans *et al.* 2017), to assess changes in future wind energy (Evans *et al.* 2018) and the impact of urban expansion on temperatures (Argüeso *et al.* 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 have the same yearly averages as the Australian Water Availability Project data (Jones *et al.* 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.

We note the NARCLiM system implemented here does not allow the physical footprint of Sydney to change in time and therefore the representation of the impact of a growing city is not captured in terms of an urban heat island effect for example.

Stochastic weather generator

A stochastic weather generator developed by Barker *et al.* (2019) 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 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 were used to calibrate the stochastic weather generator. Each weather scenario contains data for the 11 financial years from 2014/2015 to 2024/2025 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 require 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.* (2019) was used to generate evaporation data as a function of precipitation and maximum temperature.

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 are estimated for each of the financial years

Downloaded from http://iwa.silverchair.com/jwcc/article-pdf/12/4/1168/896194/jwc0121168.pdf
by guest

between 2014/2015 and 2024/2025, allowing population to vary over this 10-year period. The weather data associated with a forecast are taken from a stochastic weather generator simulation based on data from an 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 2014/2015 and 2024/2025 with weather for the present, near future or far future. We therefore undertake three analyses, each for the present, near and far future:

1. 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;
2. isolate the effect of population change on water consumption. Here, population varies from 2014/2015–2024/2025 and the dwelling type mix uses population estimates;
3. isolate the effect of dwelling type mix. Here, population varies from 2014/2015–2024/2025 and the dwelling type mix varies between the dwelling type mix estimate, simulations with no single dwellings and simulations assuming all single dwellings.

RESULTS

Figure 2 shows the annual consumption for the present, near future and far future climates across all dwelling types projected using four GCMs each downscaled three times using different configurations of WRF. These simulations reflect population and dwelling configuration representative of 2019/2020 and therefore isolate 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 under the present climate to 484–494 GL under the near future climate and to 495–505 GL under the far future climate. 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) from the present to the far future. CCCMA3.1 displays higher variability in the near future (the range from the minimum to the maximum estimate is

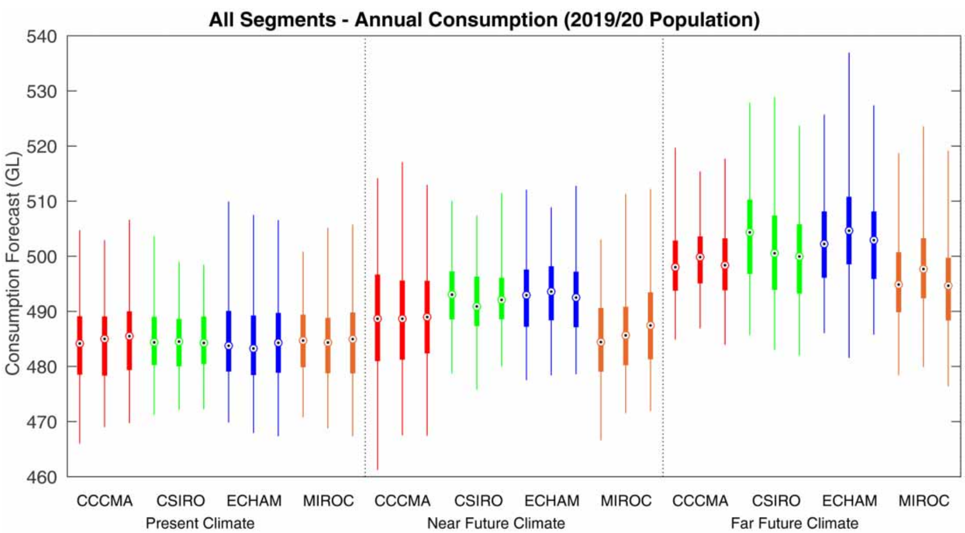

Figure 2 | Consumption forecasts by model (CCCMA3.1 – red, CSIRO-MK3.0 – green, ECHAM5 – blue and MIROC3.2 – orange) showing three ensemble members for each model. Total consumption for all dwellings types (includes single dwellings, units, town houses and non-residential). Each bar shows the median (open circle), the range derived using the stochastic weather generator. Three climate periods are shown: the present, near future and far future and assuming 2019/2020 populations. Please refer to the online version of this paper to see this figure in colour: http://dx.doi.org/10.2166/wcc.2020.230.

Downloaded from http://iwa.silverchair.com/jwcc/article-pdf/12/4/1168/896194/jwc0121168.pdf
by guest

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 exceed 1–2%.

We next examine how future changes in water consumption due to population growth compared to changes due to climate change. Figure 3 shows the total annual consumption forecasts for each level of population between 2014/2015 and 2024/2025 for the present day, near and far future weather. Figure 3 shows the total annual consumption increases with population (the overall trend from 2014/2015 to 2024/2025) 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 2014/2015 to 2024/2025 due to population increase over the same period is from 457.1 GL to 507.6 GL (50.5 GL, 11.0%) under the present climate, from 462.6 GL to 514.5 GL (51.9 GL, 11.2%) under the near future climate and from 471.2 to 524.2 GL (53 GL, 11.2%) under the far future climate. The increase in median consumption from the present to the far future due to climate change is between 14.1 GL (3.1%) in 2014/2015 to 16.6 GL (3.3%) in 2024/2025. 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.

The impact of climate change on consumption is affected by season and property type. Figure 4 shows the density of annual and quarterly 2019/2020 consumption forecasts across all NARCliM ensemble members for Single Dwelling and Units for each NARCliM period. Consumption for both Single Dwellings and Units increases from the Present to the Near Future and further to the Far Future. Consumption is higher and has greater variability in the hotter quarters, Q2 (OND) and Q3 (JFM) than in the colder quarters Q1 (JAS) and Q4 (AMJ). The magnitude and variability of Single Dwelling consumption are higher than that of Unit consumption. This is most likely explained by the greater amount of outdoor water use in Single Dwellings than in Units and the sensitivity of outdoor water use to the weather (Roberts et al. 2011; Athuraliya et al. 2012).

Figure 4 shows that Single Dwellings have higher consumption than units, but given that they also have more people we now consider how water demand would vary into the future if all population growth was accommodated

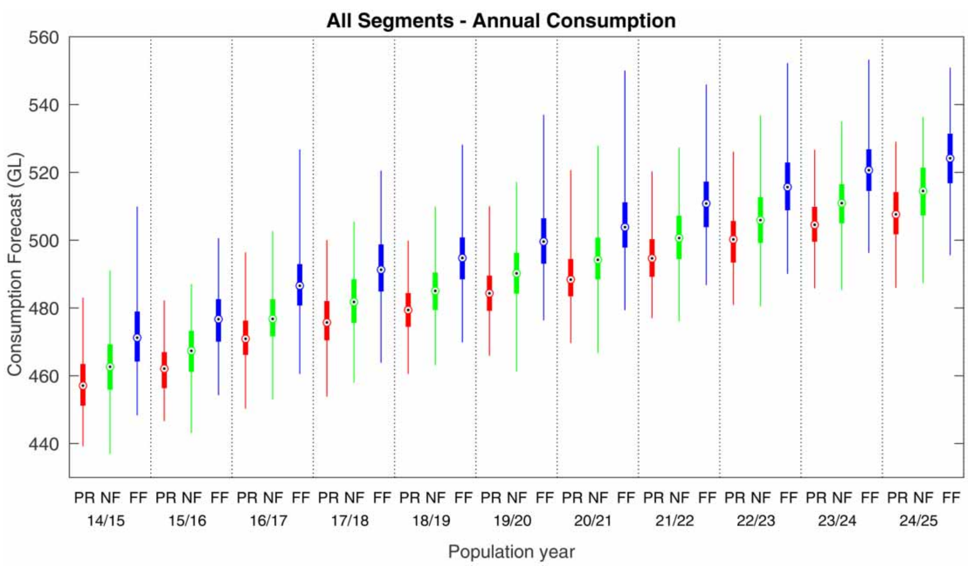

Figure 3 | Consumption forecasts across all dwelling types by year for each NARCliM period (Present Climate – red (PR), Near Future Climate – green (NF), Far Future Climate – blue (FF)) for population increases from 2014/2015 to 2024/2025. Each bar shows the range of consumption forecasts across 100 simulations from each of the 12 NARCliM ensemble members (four climate models, three configurations). Please refer to the online version of this paper to see this figure in colour: http://dx.doi.org/10.2166/wcc.2020.230.

Downloaded from http://iwa.silverchair.com/jwcc/article-pdf/12/4/1168/896194/jwc0121168.pdf
by guest

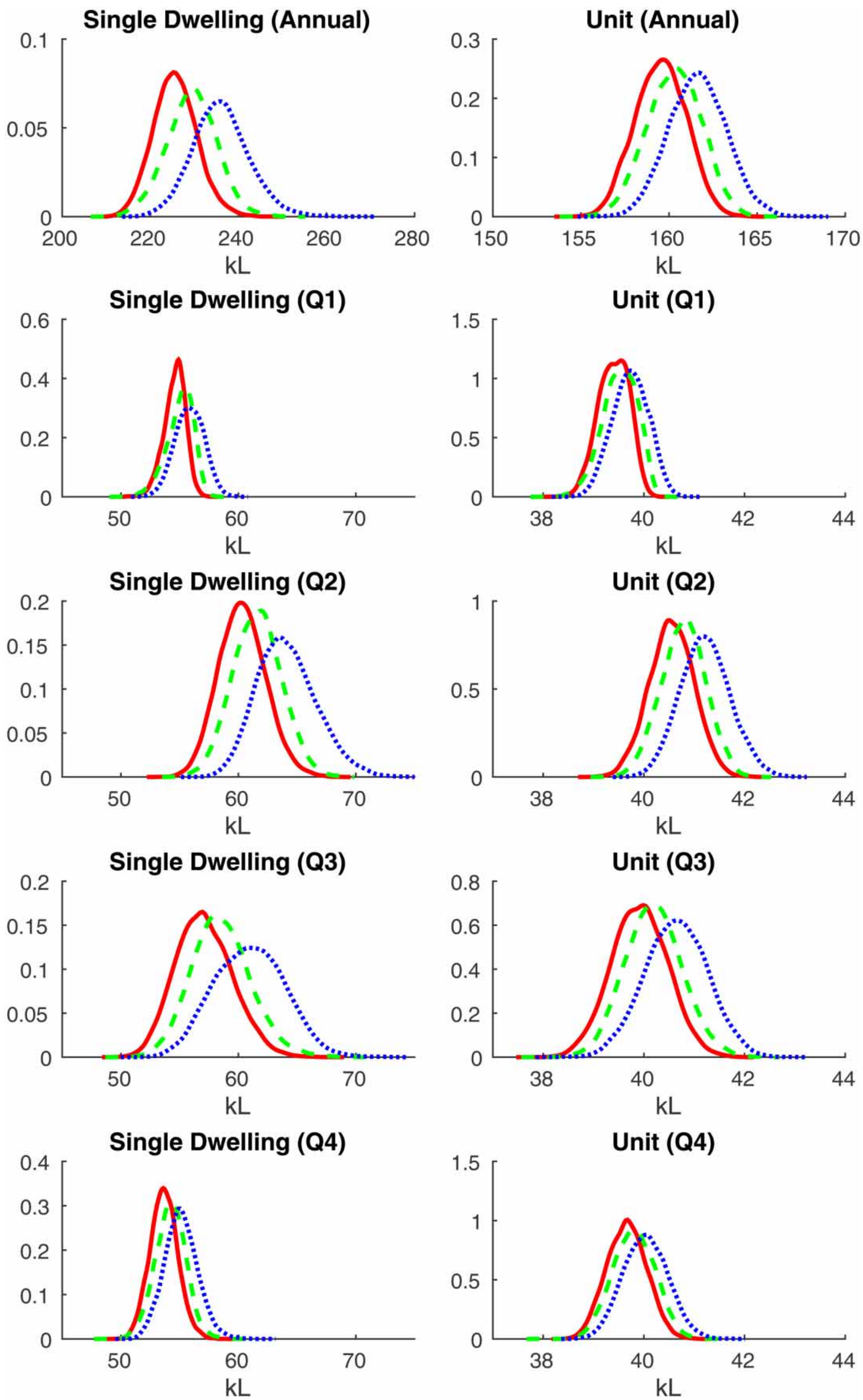

Figure 4 | Density of annual and quarterly per dwelling consumption forecasts across all NARCliM ensemble members for Single Dwelling and Units for each climate period (Present – red (solid), Near Future – green (dashed), Far Future – blue (dotted)). Please refer to the online version of this paper to see this figure in colour: http://dx.doi.org/10.2166/wcc.2020.230.

Downloaded from http://iwa.silverchair.com/jwcc/article-pdf/12/4/1168/896194/jwc0121168.pdf
by guest

via single dwellings, or via a mixture of dwellings, or without any single dwellings. We assume that 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. In the present, all three planning options lead to similar median water consumption (Figure 5(a)) for a given year with the overall trend upwards between 2014/2015 and 2024/2025 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 5(b)), there are hints that the median increases as a function of the fraction of single dwellings, and this becomes clearer in the far future (Figure 5(c)). In addition, the variability increases markedly as the fraction of single dwellings increases. Intuitively, one might expect that moving people from Units to Single Dwellings should increase total water consumption due to the increased amount of outdoor water use. However, increasing the number of people per dwelling also provides economies of scale in the use of washing machines, etc. which contributes to a reduction in per capita consumption (Troy *et al.* 2005; Roberts *et al.* 2011; Athuraliya *et al.* 2012).

We next explain these results in terms of changes in weather variables. Figure 6 shows precipitation, number of days with more than 2 mm 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 6), 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 6(a) is considerable, with some models predicting decreases of 100 mm per year and others predicting increases of 200 mm per year. This range or uncertainty reflects the well-known challenge in climate modelling of constraining the regional projections of future rainfall and is an uncertainty that is very difficult to reduce. In our experiments, this range is 'by design' because NARCLiM intentionally downscaled models across a range of rainfall changes, To add to this uncertainty, Figure 6(b) shows projections of rainfall events exceeding 2 mm per day range from 70 to 85 days a year with almost no clustering among 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 6(c)) and days over 30 °C (Figure 6(d)) 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 among the models in terms of the maximum temperature change (Figure 6(c)). The number of days over 30 °C increase from 35–40 days 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.

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 SWCM via a stochastic weather generator. We can separate the impact of changes in climate from changes in population through to 2025. Based on our results, we find that population changes are the dominant driver of increases in future water demand, increasing demand by 51.9 GL (11.2%) per decade under a near future climate, with similar increases under present and far future climates. This contrasts with a far smaller impact from climate change from the present to the far future of between 2.0 GL (0.4%) and 2.4 GL (0.5%) per decade. 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 is much greater than the increase due to climate change in our simulations.

Downloaded from http://iwa.silverchair.com/jwcc/article-pdf/12/4/1168/896194/jwc0121168.pdf
by guest

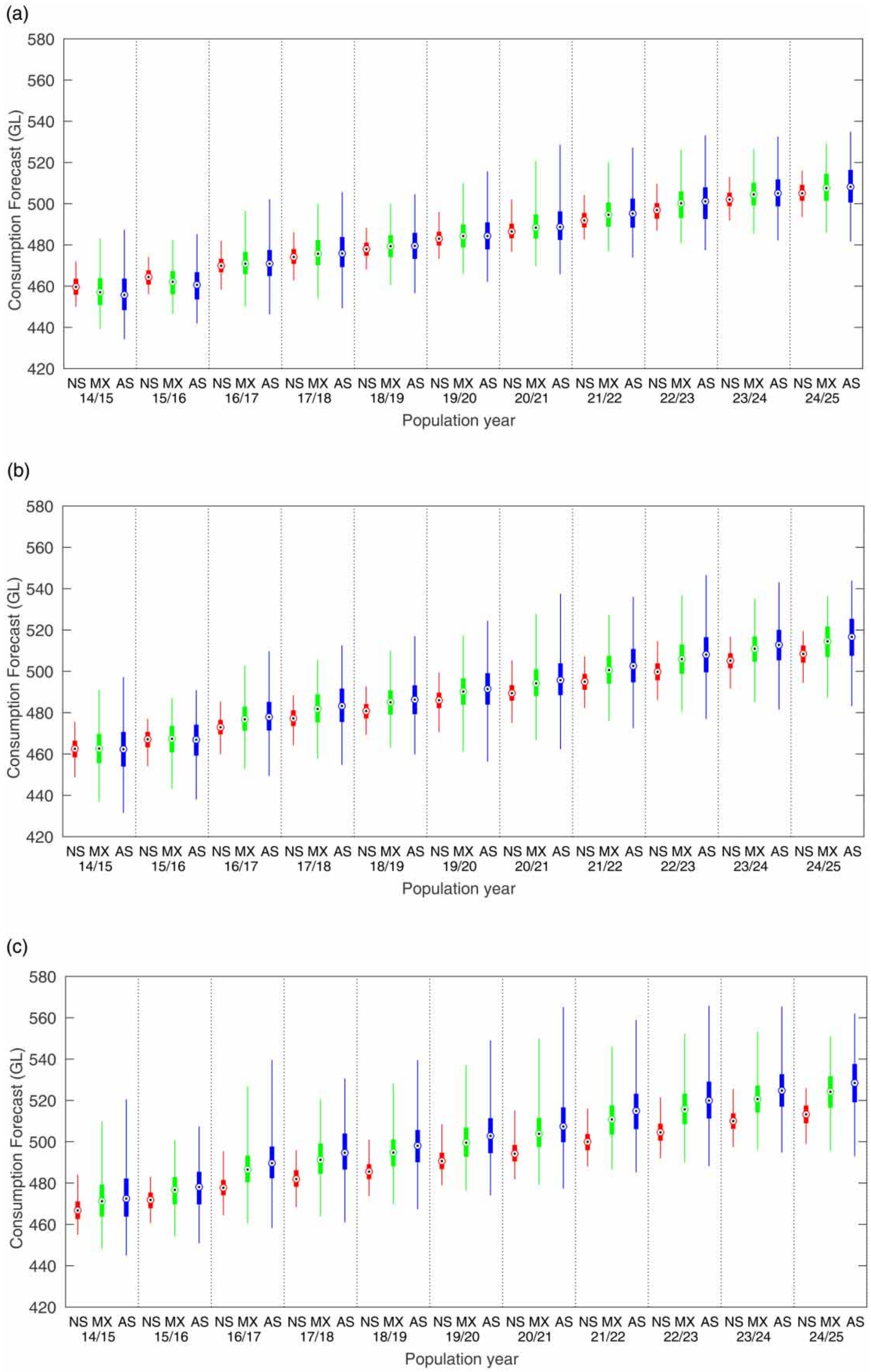

Figure 5 | Consumption forecasts for the (a) present, (b) near and (c) far future climate as a function of population growth and the nature of the dwelling type. Red bars (NS) indicate no single dwellings, green (MX) indicates the dwelling mixture and blue (AS) indicates where all properties are single dwellings. Please refer to the online version of this paper to see this figure in colour: http://dx.doi.org/10.2166/wcc.2020.230.

Downloaded from http://iwa.silverchair.com/jwcc/article-pdf/12/4/1168/896194/jwc0121168.pdf
by guest

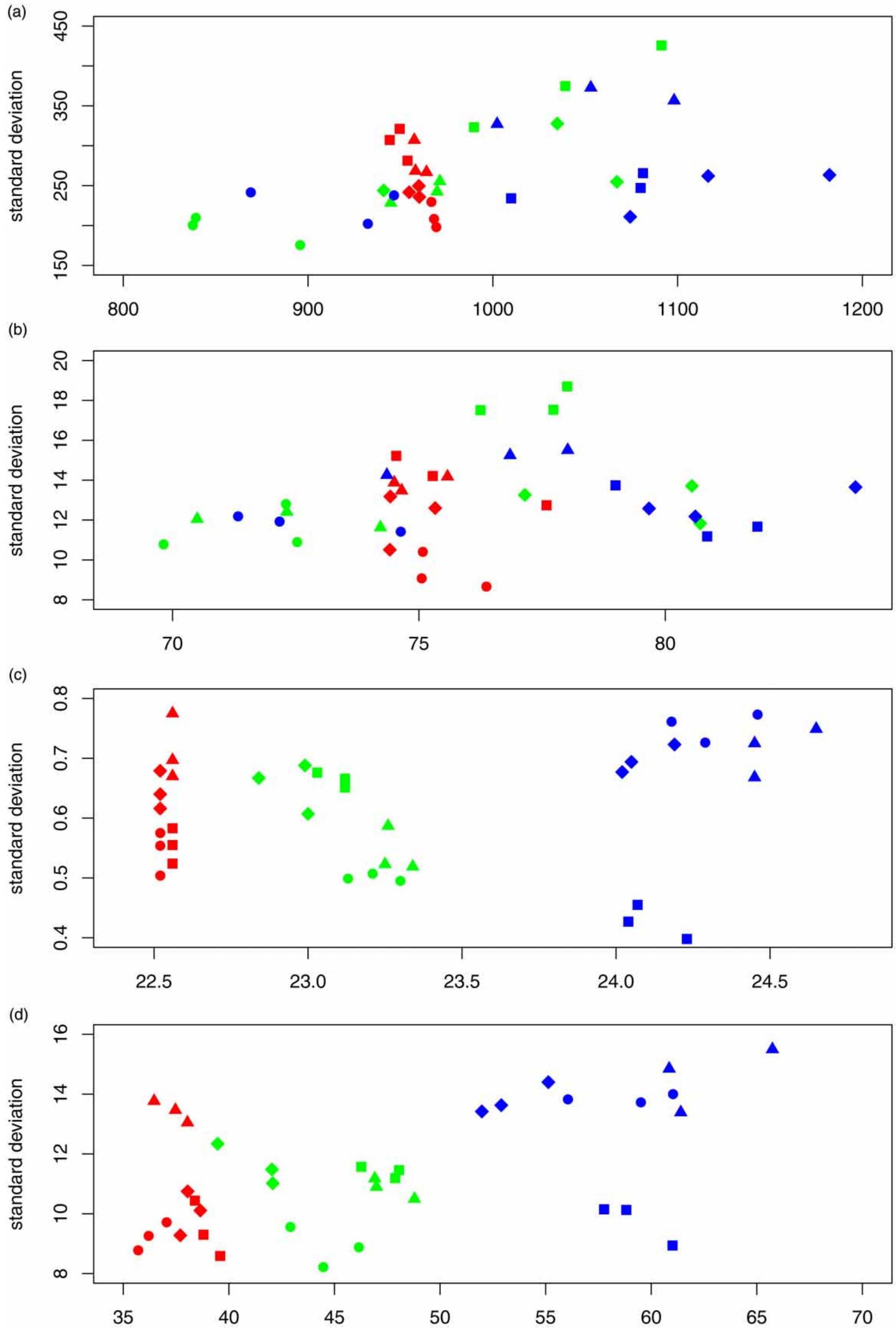

Figure 6 | Plots of annual standard deviation versus annual mean of weather variables for each of the NARCliM ensemble members. (CCCMA3.1 – square, CSIRO-MK3.0 – circle, ECHAM5 – triangle and MIROC3.2 – diamond), (Present Climate – red, Near Future Climate – green, Far Future Climate – blue). (a) Precipitation (mm), (b) number of days >2 mm, (c) maximum temperature (°C) and (d) number of days >30 °C.

Downloaded from http://iwa.silverchair.com/jwcc/article-pdf/12/4/1168/896194/jwc0121168.pdf
by guest

However, for any single year and any single climate period, changes in the weather can produce a wide range of consumption forecasts (Figure 3). Density functions of the difference in consumption forecasts from 2019/2020 to 2020/2021 (Figure 7) show that while the median of these differences is a measure of the increase in consumption due to the increase in population from 2019/2020 to 2020/2021, 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 30–35% 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 7 shows that using the median estimates is very likely a poor basis for managing risk.

The NARCliM product provides estimates of near future and far future climate from four climate models, each

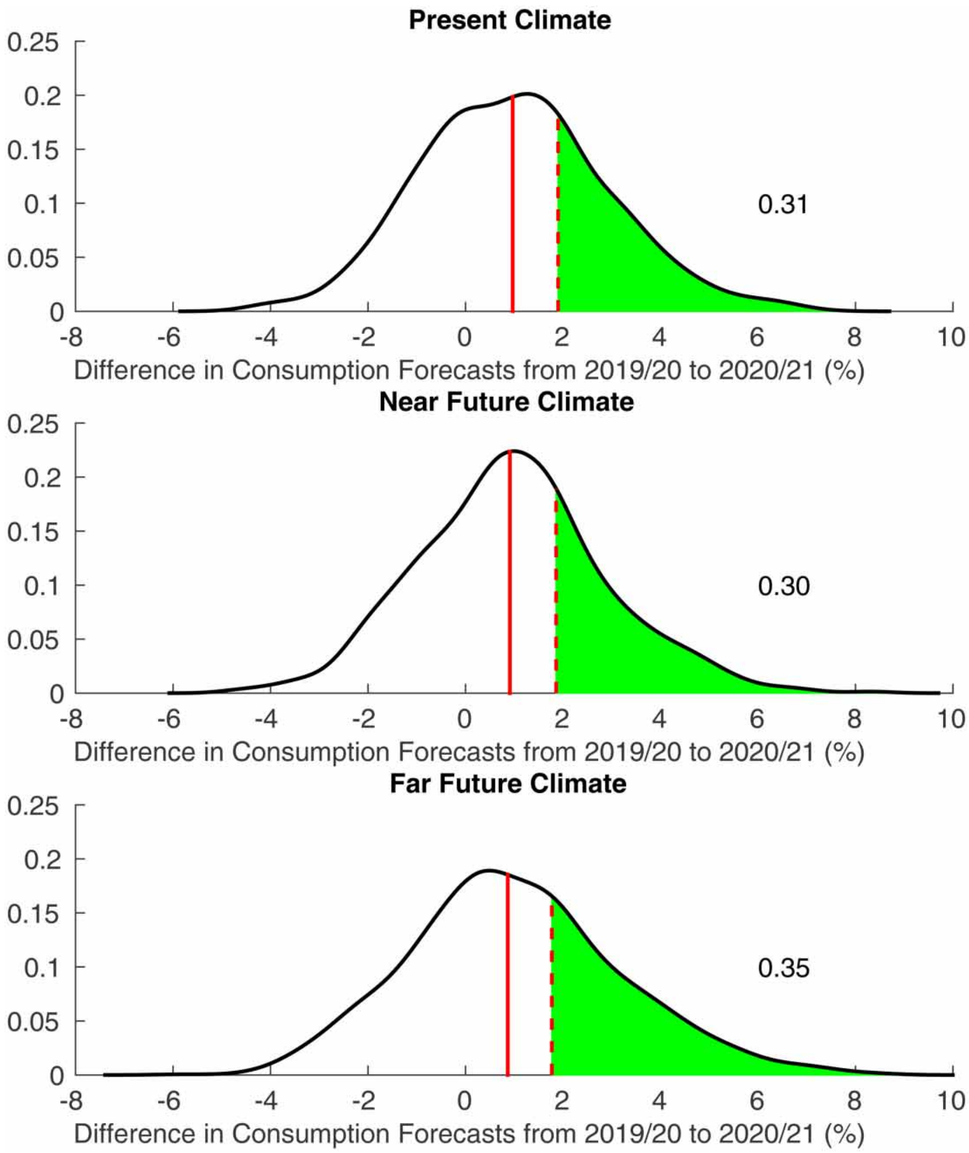

Figure 7 | Density function of percentage difference in consumption forecasts from 2019/2020 to 2020/2021 for the present, near and far future climates. Solid vertical line is at the median of the consumption forecast differences and the dashed vertical line is at twice that median. The filled region 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 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.

Downloaded from http://iwa.silverchair.com/jwcc/article-pdf/12/4/1168/896194/jwc0121168.pdf
by guest

downscaled three times. While the NARCLiM product is the only downscaled product designed for New South Wales and the Sydney Basin, and great care was taken in the development of this system, no single methodology of this type can ever be definitive. However, there are attributes of the NARCLiM product that provides some confidence around the value of the projections. 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 6). 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 future, increases by about 100 mm 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 very likely occur non-linearly with time. Better characterisation of uncertainty in projecting climate-related water demand requires more GCMs to be downscaled as a priority over downscaling individual climate models multiple times.

We now combine the changes in climate variables (Figure 6) with the changes in water demand (Figures 2 and 3). Figure 8 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 6(a)) affects water consumption, forecasts remain between 484–494 GL that is the forecasts are relatively insensitive to the precipitation change (Figure 8). 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 6(a) showed changes in rainfall to be uncertain. However, we remind the reader that the SWCM does not currently include some higher-order rainfall statistics, such as dry spells. It is conceivable that given climate change, the length of dry spells will change in ways that increase water demand and this is not reflected in our results. In contrast to the insensitivity to the change in rainfall, 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 2019/2020 population levels. Sydney's water supply is considerable and at maximum capacity is of the order of 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

Downloaded from http://iwa.silverchair.com/jwcc/article-pdf/12/4/1168/896194/jwc0121168.pdf by guest

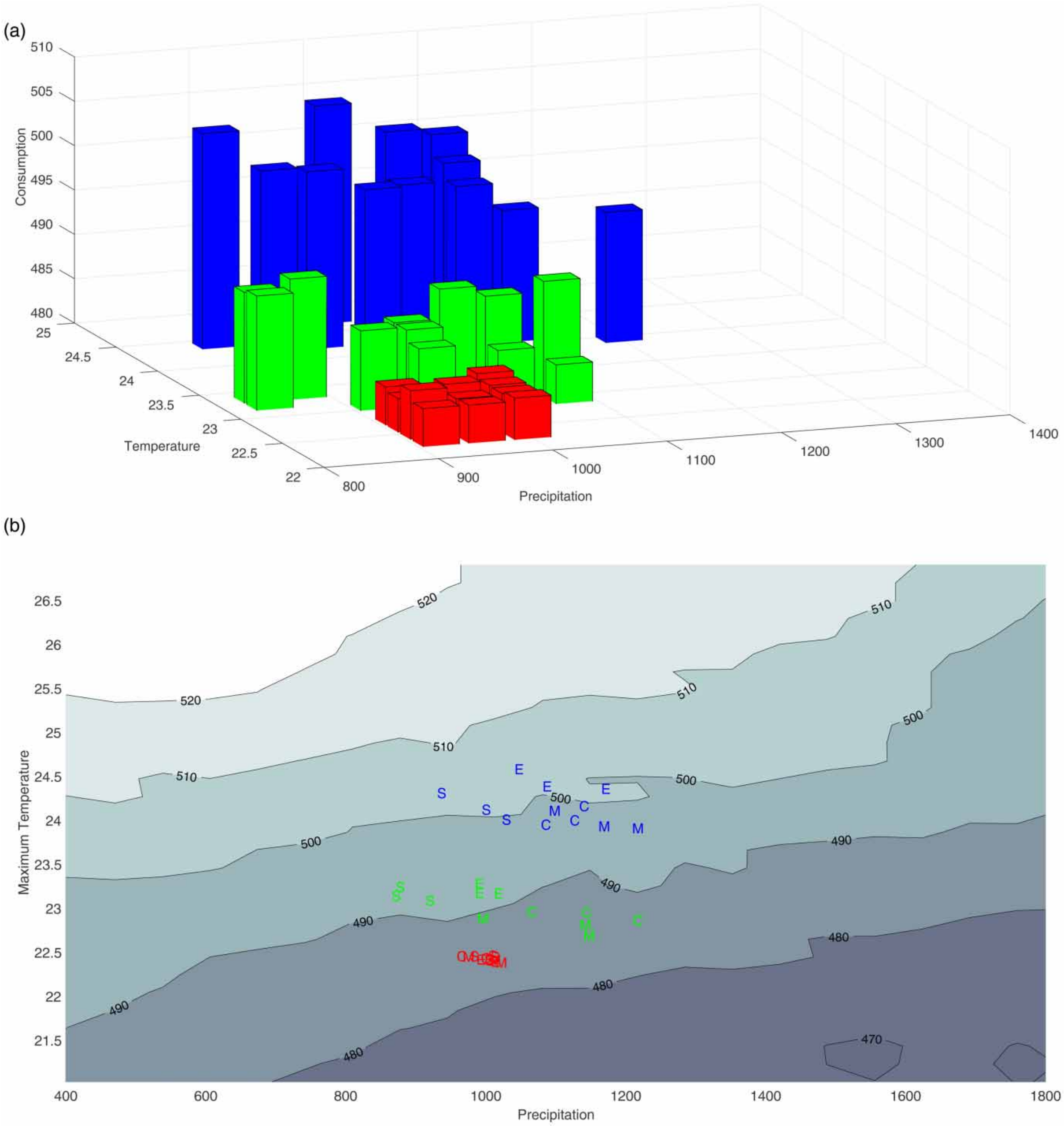

Figure 8 | (a) 3D bar chart map of consumption forecasts from all NARCliM ensemble members for the financial year 2019/2020 as a function of precipitation and maximum temperature. The climate periods are indicated by red for the present, green the near future and blue for the far future; (b) Contour 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.

~57 GL per year of unmetered consumption or any water loss due to evaporation. They are also not adjusted to account for the desalination plant, opened in 2010, which has a current capacity of about 90 GL per year and the ability to be extended to 180 GL per year. These estimates do not account for any technological changes that improve water use or any consequences of a larger physical footprint of Sydney and possible amplification of the urban heat

Downloaded from http://iwa.silverchair.com/jwcc/article-pdf/12/4/1168/896194/jwc0121168.pdf by guest

island effect. The SCWM is designed to incorporate state government policy which requires all newly built properties to have higher water use efficiencies. The SCWM does not capture increasing efficiency in existing dwellings due to the replacement of fittings and appliances, such as showerheads and washing machines with more efficient models. This does not imply the SCWM cannot be used to estimate the incremental effect of climate change on demand; end use associated with climate change is significantly driven by outdoor watering which is not affected by increased efficiency in showers, toilets, etc. Despite these limitations and 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 note that throughout this discussion, we have highlighted ranges in future demand and a water manager might ask 'but which one should be used.' There is no answer to this question because uncertainty is inherent in the climate projections, the population changes, the technological innovation and so on. At this time, each of the water demand estimates is equally probable. Whether a water manager takes a precautionary approach and uses the worst scenario or hopes for the best and uses the least confronting scenario is not something we can recommend. We note that the trajectory for climate science projections is toward much larger ensembles and our recommendation is that the software engineering linked with water demand modelling should enable water planners to use all forthcoming climate simulations and explore how changes in individual variables drive water demand sensitivity. This knowledge can then inform decision making using an evidence-based approach and utilising all available information.

We conclude by noting that, based on our results, 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 unfeasible given the likely impact of technological innovation on water demand and supply management.

ACKNOWLEDGEMENTS

We acknowledge the NSW Office of Environment and Heritage backed NSW/ACT Regional Climate Modelling Project (NARCliM) project for providing the climate projection data. This work was supported by the ARC Centre of Excellence for Climate Extremes (CE170100023).

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.

Arbués, F., García-Valiñas, M. A. & Martínez-Espiñeira, R. 2003 Estimation of residential water demand: a state-of-the-art review. *Journal of Socio-Economics* **32**, 81–102.

Argüeso, 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), e0117066. doi:10.1371/journal.pone.0117066.

Athuraliya, A., Roberts, P. & Brown, A. 2012 *Yarra Valley Future Water – Residential Water Use Study Volume 2 – Summer 2012*. Yarra Valley Water, Melbourne, Australia.

Barker, A., Pitman, A. J., Evans, J. P., Spaninks, F. & Uthayakumaran, L. 2019 Probabilistic forecasts for water consumption in Sydney, Australia from stochastic weather scenarios and a panel data consumption model. http://doi.org/10.26190/5d534d6145702.

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: *The Oxford Handbook of Panel Data* (B. H. Baltagi, ed.). Oxford University Press, Oxford, pp. 76–110.

Downloaded from http://iwa.silverchair.com/jwcc/article-pdf/12/4/1168/896194/jwc0121168.pdf
by guest

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.
Ekström, 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., Ekström, 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., Argüeso, D. & Fita, L. 2014 Design of a regional climate modelling projection ensemble experiment – NARCliM. *Geoscientific Model Development* **7**, 621–629.
Evans, J. P., Argüeso, 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., Kay, M., Prasad, A. & Pitman, A. 2018 The resilience of Australian wind energy to climate change. *Environmental Research Letters* **13**, 024014.
Fita, L., Evans, J. P., Argüeso, D., King, A. & Liu, Y. 2017 Evaluation of the regional climate response in Australia to large-scale climate modes in the historical NARCliM simulations. *Climate Dynamics* **49**, 2815–2829.
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**, 053002.
House-Peters, L. A. & Chang, H. 2011 Urban water demand modeling: review of concepts, methods and organizing principles. *Water Resources Research* **47**, W05401.
Ji, F., Ekström, M., Evans, J. P. & Teng, J. 2014 Evaluating rainfall patterns using physics scheme ensembles from a regional atmospheric model. *Theoretical and Applied Climatology* **115** (1–2), 297–304.
Jones, D. A., Wang, W. & Fawcett, R. 2009 High-quality spatial climate data-sets for Australia. *Australian Meteorological and Oceanographic Journal* **58**, 233–248.
Kotlarski, S., Keuler, K., Christensen, O. B., Colette, A., Déqué, M., Gobiet, A., Goergen, K., Jacob, D., Lüthi, D., van Meijgaard, E., Nikulin, G., Schär, C., Teichmann, C., Vautard, R., Warrach-Sagi, K. & Wulfmeyer, V. 2014 Regional climate modeling on European scales: a joint standard evaluation of the EURO-CORDEX RCM ensemble. *Geoscientific Model Development* **7** (4), 1297–1333.
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, Cambridge, UK.
Olson, R., Evans, J. P., Di Luca, A. & Argüeso, D. 2016a The NARCliM project: model agreement and significance of climate projections. *Climate Research* **69**, 209–227.
Olson, R., Fan, Y. & Evans, J. P. 2016b 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**, 012010.
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.
Roberts, P., Athuraliya, A. & Brown, A. 2011 *Yarra Valley Future Water – Residential Water Use Study Volume 1 – Winter 2010*. Yarra Valley Water, Melbourne, Australia.
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.
Troy, P., Holloway, D. & Randolph, B. 2005 *Water use and the Built Environment: Patterns of Water Consumption in Sydney*. City Futures Research Report No. 1, City Futures Research Centre, Faculty of Built Environment, UNSW.
WaterNSW 2016 *WATHNET Water Supply System Model Independent Review 2016*.
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, Cambridge, MA.

First received 16 October 2019; accepted in revised form 22 May 2020. Available online 7 August 2020

Downloaded from http://iwa.silverchair.com/jwcc/article-pdf/12/4/1168/896194/jwc0121168.pdf
by guest