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Probabilistic Water Demand Forecasting Using Projected Climatic Data for Blue Mountains Water Supply System in Australia

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Abstract Long term water demand forecasting is needed for the efficient planning and management of water supply systems. A Monte Carlo simulation approach is adopted in this paper to quantify the uncertainties in long term water demand prediction due to the stochastic nature of predictor variables and their correlation structures. Three future climatic scenarios (A1B, A2 and B1) and four different levels of water restrictions are considered in the demand forecasting for single and multiple dwelling residential sectors in the Blue Mountains region, Australia. It is found that future water demand in 2040 would rise by 2 to 33 % (median rise by 11 %) and 72 to 94 % (median rise by 84 %) for the single and multiple dwelling residential sectors, respectively under different climatic and water restriction scenarios in comparison to water demand in 2010 (base year). The uncertainty band for single dwelling residential sector is found to be 0.3 to 0.4 GL/year, which represent 11 to 13 % variation around the median forecasted demand. It is found that the increase in future water demand is not notably affected by the projected climatic conditions but by the increase in the dwelling numbers in future i.e. the increase in total population. The modelling approach presented in this paper can provide realistic scenarios of forecasted water demands which would assist water authorities in devising appropriate management strategies to enhance the resilience of the water supply systems. The developed method can be adapted to other water supply systems in Australia and other countries.

Keywords Water demand · Long term forecasting · Monte Carlo simulation · Water restrictions · Climate change

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1 Introduction

Water scarcity has become a major problem in many countries in the world due to increasing water demand and decreasing water resources as a result of growing population, economic development and changing climatic regime (Fan et al. 2014; Gain and Wada 2014). The water scarcity problem is more severe in regions experiencing reduced rainfall and increased temperature due to anthropogenic global warming. This has led to a need for better planning of water supply systems, implementing system expansion and developing and managing water resources (Padula et al. 2013). Water authorities have also considered alternative water resources such as rainwater tanks (Abdulla and Al-Shareef 2009; Imteaz et al. 2011) and desalination plants (El Saliby et al. 2009; Ghaffour et al. 2013) as a means of enhancing water security. Accurate prediction of long term water demand is a vital component in planning, development and management of water supply systems including desalination plants (Jain et al. 2001). Moreover, long term forecasting is helpful in assessing the impacts of various water conservation measures and making decisions on the development of policies and strategies for efficient demand management. Therefore, prediction of long term water demand is important in devising appropriate management alternatives to make a right balance between supply and demand.

Various demographic, socio-economic and climatic factors influence urban water demand (Slavíková et al. 2013). These factors change with time, in particular due to expansion of urban areas, economic growth and climate change (Koo et al. 2005; Schleich and Hillenbrand 2009). Demographic changes such as changes in population growth and lifestyle affect future water demand. Population growth is normally considered as the most important explanatory variable in the long term water demand forecasting (Polebitski and Palmer 2009). Socio-economic factors such as water usage price and economic growth also affect water demand forecasting (Tortajada and Joshi 2013). In addition, climate change is likely to have an impact on the future water demand, as this is more likely to alter temperature and precipitation patterns at many locations (Griffin and Chang 1991; Gato et al. 2007). Garden watering, swimming pool use, frequency and timing of bathing are likely to increase due to the increase in the temperature as a result of potential impact of changing climate. This is likely to increase the future water demand. Moreover, drought severity and length may increase due to the effect of climate change, which would have an impact on water consumption pattern (Meehl and Tebaldi 2004; Zargar et al. 2014).

Water demand forecasting can be categorized into short term and long term forecasting in terms of temporal scale (House-Peters and Chang 2011). For long term forecasting, prediction resolution is considered to be greater than 1 year, and for short term forecasting, the resolution is normally varies from 1 h to some days (Nasseri et al. 2011). Long term water demand can be forecasted by the deterministic and probabilistic models (Froukh 2001; Almutaz et al. 2012). Deterministic models normally forecast single value of water demand without considering the stochastic nature of the predictor variables. As water demand depends on different predictor variables which are stochastic in nature and are correlated among themselves such as population growth, household size, income, water usage price, climate change and conservation measures (Babel and Shinde 2011; Qi and Chang 2011), the usefulness of deterministic models in forecasting may be limited. If the associated uncertainties in the predictor variables are ignored, the forecasted water demands may not be realistic and adequate for efficient planning and management of water supply systems. Therefore, uncertainties associated with the predictor variables should be explicitly incorporated into demand forecasting models to allow decision makers to understand how uncertainties in the predictor variables may affect the future water demand. Incorporation of such uncertainties can be achieved by developing a probabilistic water demand forecast model using a Monte Carlo simulation. Another important aspect of water demand forecasting is to account for the correlations among the predictor variables as the predictor variables are often correlated.

In the literature, most of the long term water demand forecasting studies estimated future water demand by a deterministic approach (e.g. Babel et al. 2007; Mohamed and Al-Mualla 2010). On the contrary, there has been a limited research on the probabilistic forecast of long term urban water demand. Examples include studies by Almutaz et al. (2012) and Khatri and Vairavamoorthy (2009) who adopted a probabilistic forecasting method; however, the correlations among the predictor variables were not accounted for. The main contribution of this study is to develop a probabilistic long term water demand forecasting model considering the stochastic nature and the correlation structures of the predictor variables using a Monte Carlo simulation technique. This also examines how water demand in future would be affected by future climate change. The methodology developed in this paper can be adapted to other water supply systems in Australia and other countries.

2 Study Area

The study area is located in the Blue Mountains region, New South Wales, Australia (Fig. 1). In the Blue Mountains region, water is supplied by the Blue Mountains Water Supply System (BMWSS) that provides water to about 48,000 people residing between Faulconbridge and Mount Victoria (Sydney Catchment Authority 2009). Monthly metered water consumption data for the BMWSS were obtained from Sydney Water for the period of January 1997 to September 2011. It was found that in the BMWSS about 80 % of total water was used by residential sector and the remaining 20 % by non-residential (commercial and industrial) sector. It was also found that the single dwelling residential sector was responsible for about 94 % residential water consumption, while the multiple dwelling sector for the remaining 6 %.

Per dwelling monthly water consumption data during 1997 to 2010 for the residential sector comprising of single and multiple dwellings are presented in Fig. 2. It can be seen that water consumption shows a mild decreasing trend during the period 2003 to 2010 despite the increasing trend of number of dwellings, which is more likely to be attributed to the combined effect of imposed water restriction and conservation program adopted during that period. No mandatory water restrictions were applied in the Blue Mountains region before 2003. Level 1 (October 2003 to May 2004), Level 2 (June 2004 to May 2005) and Level 3 water restrictions (June 2005 to June 2009) were imposed when the dam levels dropped below 60, 50 and 40 %, respectively (Sydney Water n.d.). In June 2009, Level 3 restriction was lifted and water wise rules were introduced as dam storage level improved to around 60 % (Sydney Water n.d.). Details description of the water restrictions imposed in the Greater Sydney region during 2003 to 2009 can be found in Haque et al. (2013).

3 Materials and Methods

In this paper, future water demand for the Blue Mountains water supply system (BMWSS) was estimated for 2015–2040 time period for both the single and multiple dwelling residential sectors by adopting a Monte Carlo simulation technique. Monte Carlo simulation is a well-established method which plays an important role in many scientific applications, which can evaluate overall uncertainty in modelling (Rahman et al. 2002; Nash and Hannah 2011) due to

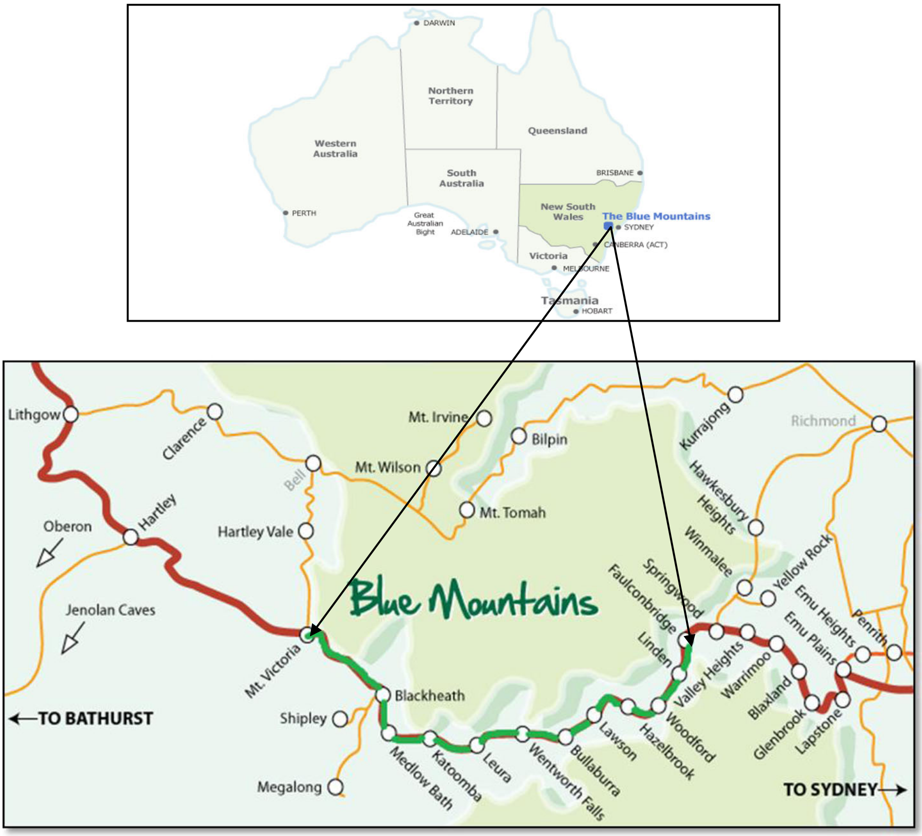

Fig. 1 Blue Mountains region in Australia and Cascade and Greaves creeks water supply area (Bluemountainsaustralia.com n.d.)

the associated uncertainties in the predictor variables. Using three different future climatic scenarios (A1B, A2 and B1) and four possible water restriction conditions, 12 possible water demand scenarios were simulated. In the generated 12 scenarios, water usage price and water conservation variables were kept the same. The uncertainty in the forecasted demand was expressed by developing 90 % confidence intervals from the generated 10,000 forecasts. From the 90 % confidence intervals, it can be interpreted that 90 % of all the possible forecasts would fall within this interval for a given forecast year.

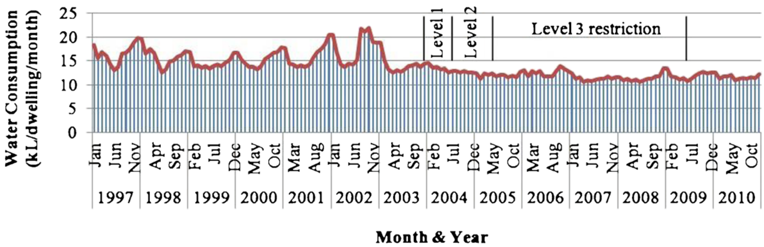

Fig. 2 Per dwelling monthly water consumption of residential sector (1997–2010) in the Blue Mountains Water Supply System, Australia

To develop a probabilistic forecasting model, a deterministic model needs to be developed first. In this study, the deterministic water demand model was developed by multiple linear regression technique to forecast per dwelling monthly water demand (Y). A total of five independent/predictor variables were used: monthly total rainfall in mm (X_1), monthly mean maximum temperature in °C (X_2), water usage price in AUS $/kL ($X_3$), water savings from conservation programs in kL/dwelling/month (X_4) and water restriction savings in kL/dwelling/month (X_5). The regression coefficients were estimated using method of ordinary least squares based on the observed data during 1997–2009. Modelling was done by three forms of multiple regression techniques, namely Raw-Data, Semi-Log and Log-Log. The Semi-Log model was adopted as final deterministic model as it outperformed the two other models. The functional form of the Semi-Log model is given by Eq. 1.

$$\log_{10} Y = \alpha + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_k X_k \tag{1}$$

Where α is the model intercept β's are the regression coefficients, and k is the number of independent/predictor variables.

Data of monthly water demand (Y) and water usage price (X_3) were obtained from Sydney Water for the period of January 1997 to September 2011. The climatic data (X_1 and X_2) were collected from Sydney Catchment Authority. Data on approximate average yearly water savings for each of the water conservation programs (e.g. rain water tank, WaterFix (installation of new showerheads, flow restrictions and minor leak repairs undertaken by a licensed plumber (Abrams et al. 2012)), DIY (Do-It-Yourself) kits (self installed flow restrictors), water efficient washing machines and toilets) implemented in the study area during the study period were obtained from Sydney Water. These average yearly savings were converted into monthly savings by dividing it with 12. Data on the numbers of household that participated in the conservation programs were also collected in the monthly steps from Sydney Water. Then total monthly water savings from conservations programs were estimated by multiplying the average monthly savings with monthly participated household number. These monthly total savings were divided by the total number of household in that month to get the 'per dwelling saving' (X_4) from the conservation programs.

Water restriction savings during drought periods (2003–2009) were calculated by deducting monthly per dwelling water conservation savings from monthly per dwelling total water savings, which can be expressed by the following equation:

$$(WRS)_{ij} = (WS_T)_{ij} - (WCS)_{ij} \tag{2}$$

Where,

- WRS Per dwelling monthly water restrictions savings (kL/month/dwelling)
- WS_T Total water savings (kL/month/dwelling)
- WCS Per dwelling monthly water conservation savings (kL/month/dwelling)
- i drought year (2003, 2004, …, 2009); and
- j month (Jan, …, Dec).

Total per dwelling water savings were estimated by deducting observed water consumption for any month from the base water consumption of that month. In this study, the period 1997–2002 was chosen as the base consumption period as during these periods no water restriction was imposed in the study area. Moreover, no water demand management program was implemented during 1997–2000. However, little water saving (2 % of total water use) was achieved during the period 2001–2002 due to the introduction of the water conservation programs.

The developed deterministic models were validated by split-sample and leave-one-out cross validation (LOOCV) methods (Haddad et al. 2013). The available data set (1997–2011) was divided into two sub-sets, model development sub-set (January 97 to June 09) and validation sub-set (July 09 to September 11).

In order to forecast future water demand, the plausible future values of the predictor variables are needed. Population growth is considered in the modelling through the growth in the number of dwellings in future. It is assumed that life style of residents would remain unchanged in the forecast period. Number of single and multiple dwellings were estimated for the period of 2015–2040 in the BMWSS based on the monthly growth rate found in the dwellings data during the period 1997-201. From the water usage price data for the period of 1997–2011, it was found that water usage price increased in each year at the rate of 0.085 AUS $/kL per year. Water usage price for the forecasting period was estimated by considering this yearly growth rate. Number of participated household in water conservation programs were estimated based on the monthly growth found in the data of recent 2 years (September 2009 to September 2011). Thereafter, per dwelling monthly water savings from conservations programs were estimated by the method described earlier. In this study, four different water restriction conditions were considered being Level 1, Level 2, Level 3 and no restrictions. Per dwelling water savings due to imposed water restrictions were estimated as mentioned earlier. The average per dwelling water restriction savings for single and multiple dwelling residential sectors for different levels were used in the forecast period.

Projections of future climate are needed to estimate future water demand under various plausible climatic conditions. Due to highly uncertain future emission growth, a series of potential greenhouse gas emission scenarios were developed by the Intergovernmental Panel on Climate Change (IPCC) (Nakicenovic et al. 2000). These scenarios were grouped into four categories (A1, A2, B1 and B2) based on different economic and population growth rates, development pathways and use of technologies. In this study, future water demand was estimated under three future climate scenarios being B1, A1B and A2, which represent low, medium and high future emission scenarios, respectively. Climate projections by CSIRO Mark 3.0 global climate model (GCM) were used in this study. The statistically downscaled temperature and rainfall data under three emission scenarios were taken as input to the water demand forecast model to estimate the future water demand scenarios. These downscaled future climatic data of Katoomba weather station were obtained from Sydney Catchment Authority.

After estimating plausible future values of the predictor variables, a multivariate normal distribution (MVN) (Krzanowski 2000) was adapted to generate stochastic predictor variables data maintaining the correlation structure among the predictor variables. In applying the MVN, it was assumed that each of the predictor variables data can be described by a uni-variate normal distribution. The pair-wise correlations of the predictor variables to be used in the MVN were obtained from the observed predictor variables data set. Thereafter, a Monte Carlo simulation was carried out to obtain the distribution of total water demand for the forecasted period (2015–2040). A total of 10,000 simulations per scenario were undertaken. The simulation was carried out in two steps: (i) per dwelling monthly water demands (10,000 values) were estimated from the generated predictor variables; and (ii) estimated per dwelling monthly demands were multiplied by the projected values of the monthly dwellings (10,000 values) to get the monthly demands.

The Monte Carlo simulation scheme was programmed in MATLAB. Water demand was forecasted by the Monte Carlo simulation technique for the period 2021 to 2040. Projection of water demand for 2015 was estimated by interpolation method using the observed demand from 2000 to 2010 and predicted demand from 2021 to 2040, because the future meteorological data during 2014 to 2020 were not available for this study.

4 Results and Discussion

4.1 Single Dwelling Residential Sector

The 50th percentile of the forecasted water demand from the Monte Carlo simulation is presented in Table 1 for single dwelling residential sector. As can be seen in Table 1, for A1B climatic scenario and under different restriction levels, forecasted water demands vary from 2.66 to 3.39 GL/year in 2040. In comparison to water demand in 2010 (base year), the water demand is expected to rise by 4 to 33 % in 2040 under A1B climatic scenario and different restriction levels (i.e. under no water restriction and Levels 1, 2 & 3 water restrictions conditions water demand is expected to rise by 33, 18, 7 and 4 %). For A2 climatic scenario under different restriction levels, forecasted water demands would be in the range of 2.63 and 3.34 GL/year in 2040, which is 3 to 31 % rise as compared to base year. The water demand is expected to rise by 2 to 30 % in 2040 under B1 climatic scenario and different restriction levels as compared to the water demand in 2010 as forecasted water demand ranges 2.60 to 3.31 GL/year.

Though water demand characteristics vary from city to city across different countries, the results obtained in this study are found to be quite comparable with other similar studies. For example, Babel et al. (2007) predicted a 20 % increase in water demand in Kathmandu, Nepal by 2015 as compared with 2001. Mohamed and Al-Mualla (2010) predicted that water demand would rise by 50 % in 2020 in Umm Al-Quwain, UAE. Dziegielewski and Chowdhury (2011) found that water demand would rise by 36–54 % in 2050 in North-eastern Illinois, USA.

Table 1 50th percentile (expected value) of the forecasted water demand values for single dwelling residential sector

	No restriction	Level 1	Level 2	Level 3
Climatic scenario: A1B (50th percentile water demand in GL/year)				
2015	2.75	2.59	2.47	2.44
2021	3.19	2.83	2.57	2.51
2025	3.23	2.86	2.60	2.54
2030	3.31	2.93	2.66	2.60
2035	3.23	2.87	2.60	2.54
2040	3.39	3.00	2.72	2.66
Climatic scenario: A2				
2015	2.77	2.61	2.49	2.46
2021	3.25	2.88	2.61	2.55
2025	3.27	2.90	2.63	2.57
2030	3.24	2.88	2.61	2.55
2035	3.34	2.96	2.69	2.63
2040	3.34	2.97	2.69	2.63
Climatic scenario: B1				
2015	2.77	2.60	2.48	2.45
2021	3.24	2.87	2.61	2.55
2025	3.26	2.89	2.62	2.56
2030	3.30	2.93	2.65	2.59
2035	3.32	2.95	2.67	2.61
2040	3.31	2.94	2.66	2.60

Forecasted per dwelling monthly water demands in 2040 under Level 1 restriction and all three climatic conditions were found to be quite similar with 2010 water demand (base year). Overall, it was found that rainfall had a decreasing effect on the demand, temperature had an increasing effect, and water usage price, water conservation and water restrictions had decreasing effects on water demand. This result indicate that future water demand in the BMWSS would not be significantly affected by the projected climatic conditions as the increasing effects of the climatic variables on water demand are likely to be minimized by the decreasing effects of increasing water usage price and conservation variables. However, the rise in the total future water demand under Level 1 restriction and all three climatic conditions were found to be about 18 % in 2040; this increase was mainly associated with the increase in the dwelling numbers in future i.e. the increase in total population.

As can be seen in Table 1, the effect of water restriction on future demand is rather more important than various climatic scenarios. The projected water demands in 2040 were found to be 3.39, 3.34 and 3.31 GL/year for A1B, A2 and B1 climatic scenarios, respectively under no water restriction (representing 29 to 33 % increase in forecasted demands as compared with the base year, 2010). On the other hand, the forecasted water demands in 2040 were found to be 3.39, 3.00, 2.72 and 2.66 GL/year for no restriction and Levels 1, 2 & 3 restrictions, respectively under A1B climatic scenarios (representing 4 to 33 % increase in the forecasted demands as compared with the base year 2010). Hence, it can be stated that the variations in the forecasted water demands are much higher due to the different levels of water restrictions than those for different climatic scenarios. A similar result was noted by Khatri and Vairavamoorthy (2009) who showed that future climatic scenarios would have a minimal impact on future water demand in Birmingham, UK. Also, Slavíková et al. (2013) found that the future climatic scenarios would not have any significant effect in explaning water demand variability in two municipalities located in Central Bohemia, Czech Republic.

The 90 % confidence intervals of forecasted total yearly water demands for A1B climatic scenario for single dwelling residential sector under different restriction levels are presented in Fig. 3a-d. Similar results were obtained for the A2 and B1 climatic scenario. As can be seen in Fig. 3a-d, there is 90 % possibility that water demands would be in the range of 2.8 GL to 3.2 GL, 2.6 GL to 2.9 GL, 2.5 GL to 2.8 GL and 3.2 GL to 3.6 GL in 2040 under Levels 1, 2 & 3 and no restriction conditions, respectively for A1B climatic scenario. From the forecasted results of all of the 12 scenarios, uncertainty bands were found to be in the range of 0.3 to 0.4 GL/year in 2040, which represent 11 to 13 % variation around the median forecasted demand. On the contrary, the deterministic model predicted a single water demand value. For example, the forecasted water demands in 2040 from the deterministic models were found to be 2.77, 2.74 and 2.72 GL/year under Level 1 restriction and A1B, A2 & B1 climatic conditions (representing median 7.4 % increase from the base year, 2010). Under the same conditions, the Monte Carlo simulation predicted an increase in water demand in 2040 by 9 to 25 % (median 17 %) as opposed to a fixed increase by 7.4 % by the deterministic model. Since the Monte Carlo simulation accounts for the stochastic nature of the predictor variables and their correlation structures, it provides a more realistic demand prediction under different plausible conditions that might arise in future.

It is also found that the highest forecasted value of water demand for single dwelling residential sector is 3.6 GL in 2040 under no restriction condition and A1B climatic scenario. The lowest forecasted value is 2.4 GL in 2040 under Level 3 restrictions and B1 climatic scenario. As with more strict water restriction, the residents will tend to conserve more water, and hence smaller value of forecasted water demand was obtained under Level 3 water restriction. Moreover, B1 climatic scenario is considered to be low impact emission scenario which has been reflected in the lowest value of forecasted demand.

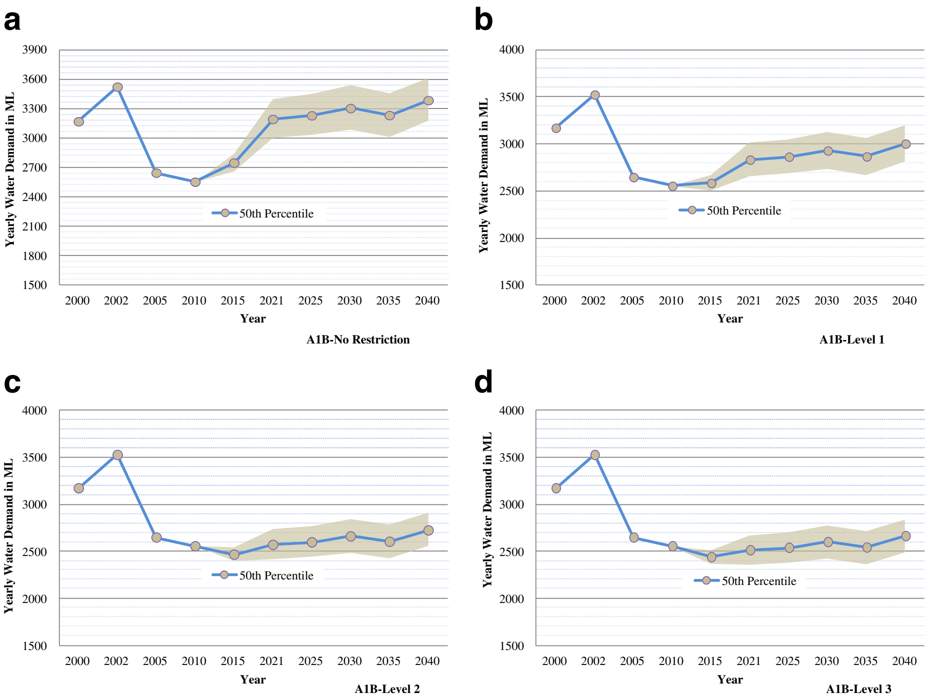

Fig. 3 Ninety percent confidence intervals for total yearly water demand from 2015 to 2040 for A1B scenarios under different restriction levels for single dwelling residential sector

4.2 Multiple Dwelling Residential Sector

The 50th percentile of the forecasted water demand from the Monte Carlo simulation is presented in Table 2 for multiple dwelling residential sector. As can be seen in Table 2, forecasted water demands vary 0.31 to 0.35 GL/year in 2040 for A1B climatic scenario under different restriction levels. For both the A2 and B1 climatic scenarios, forecasted water demand in 2040 also falls in the range of 0.31 and 0.35 GL/year. In comparison to water demand in 2010 (the base year), the water demand is expected to rise by 72 to 94 % in 2040 for all of the scenarios. As can be seen in Table 2, there is no remarkable variation in the forecasted values for all of the scenarios in any year for multiple dwelling residential sector since water demand of this sector is very low in comparison to water demand of single dwelling residential sector. Moreover, multiple dwellings normally consume less water in outdoor purpose due to smaller outdoor area. As water restriction mainly targets outdoor water use, the effect of water restriction is less in this sector in comparison to single dwelling residential sector.

The 90 % confidence intervals of forecasted total yearly water demand for A1B, A2 and B1 climatic scenarios under different restriction levels for multiple dwelling residential sector are presented in Fig. 4a-d. Since a very similar results were obtained for other scenarios, the graphs of confidence intervals for A2 and B1 climatic scenarios under different restriction levels are not presented here. As can be seen in Fig. 4a-d, there is 90 % possibility that water demands would be in between 323 and 344 ML/year, 308 and 328 ML/year, 304 and 323 ML/year, and 340 and 362 ML/year in 2040 under Level 1, Level 2, Level 3 and no restriction conditions, respectively for A1B climatic scenario. From the forecasted results of all of the 12 scenarios, uncertainty

Table 2 50th Percentile of the forecasted water demand values for multiple dwelling residential sector

	No restriction	Level 1	Level 2	Level 3
Climatic scenario: A1b (Water demand in ML/year: 50th percentile values)				
2015	204	198	193	192
2021	238	226	215	212
2025	258	244	233	230
2030	286	271	259	255
2035	312	296	282	279
2040	351	333	317	313
Climatic scenario: A2				
2015	205	199	194	193
2021	239	227	216	214
2025	259	246	234	231
2030	284	269	256	253
2035	317	301	286	283
2040	349	331	316	312
Climatic scenario: B1				
2015	204	199	194	193
2021	239	227	216	214
2025	259	245	234	231
2030	286	271	258	255
2035	316	300	286	282
2040	347	330	314	310

bands were found to be about 20 ML/year in 2040, which represent 6 % variation around the median forecasted demand. It is found that the confidence band increases with the increase of forecast year. From the confidence intervals of all the scenarios, the highest forecasted value of water demand for multiple dwelling residential sector were found to be 362 ML/year in 2040 under no restriction condition and A1B climatic scenario, and the lowest forecasted value were found to be 300 ML/year in 2040 under Level 3 restrictions and B1 climatic scenario.

From the effect of different water restriction levels on forecasted water demand (Fig. 5a-b), it is found that the impact of Level 2 and Level 3 restrictions is quite similar. As Level 3 water restriction was imposed on the top of Level 2 by adding an additional day in a week in the restriction limit, its effect was not that high as compared to a shifting from Level 1 to Level 2. Abrams et al. (2012) reported that Level 3 water restriction had only 2 % incremental effect of water savings as compared to Level 2 restriction for the Sydney region in Australia.

5 Conclusion

This paper develops a methodology to incorporate uncertainty in the predictor variables and various climatic scenarios explicitly into the water demand forecasting model using a Monte Carlo simulation technique. The method is applied to the Blue Mountains water supply system in New South Wales, Australia. Using five predictor variables, three different future climatic scenarios (i.e. A1B, A2 and B1) and four different water restriction conditions (Levels 1, 2 & 3 and no restriction), twelve different plausible scenarios is generated. It is found that the median

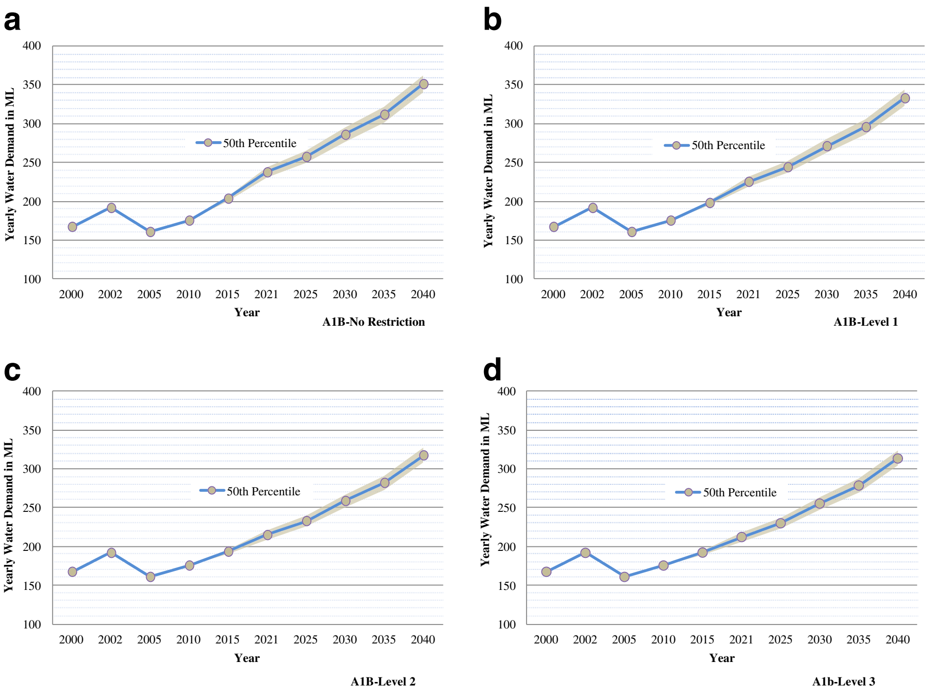

Fig. 4 Ninety percent confidence intervals for total yearly water demand from 2015 to 2040 for A1B scenarios under different restriction levels for multiple dwelling residential sector

water demand for the Blue Mountains water supply system in 2040 is expected to rise by 2 to 33 %, and 72 to 94 % for single and multiple dwelling residential sectors, respectively in comparison to water demand in 2010 (base year). It is also found that growth rate of water demand in multiple dwelling residential sector is much higher than the single dwelling residential one as growth of multiple dwelling sector is higher than the single dwelling residential one in the study area. Forecasted water demand values are found to be the highest during no water restriction condition and the lowest during Level 3 water restriction as

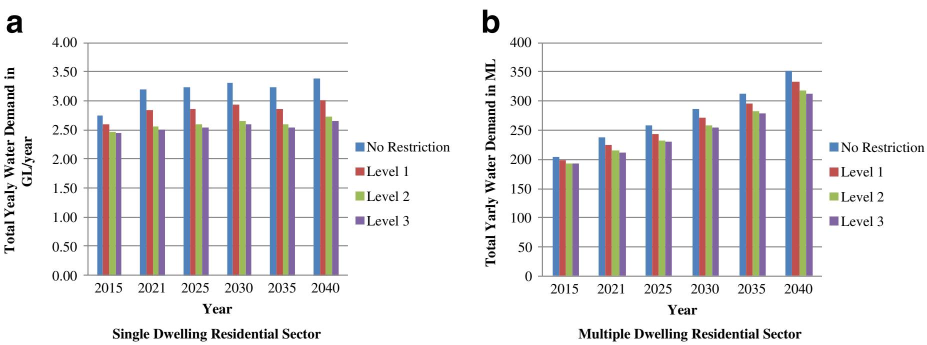

Fig. 5 Forecasted water demand under A1B climatic scenario and different restriction levels for the period of 2015–2040

expected. Moreover, effect of Levels 2 & 3 water restrictions on forecasted water demand is found to be quite similar.

It is found that the effects of different levels of mandatory water restriction conditions in water demand forecasting are more significant than the effects of various climatic scenarios. It is also found that the increase in future water demand is not notably affected by the projected climatic conditions but by the increase in the dwelling numbers in future i.e. the increase in total population. From the 90 % confidence intervals of the forecasted values, it is found that the uncertainty band varies about 11 to 13 % and 6 % around the median forecasted demand for single and multiple dwelling residential sectors, respectively. The highest and lowest forecasted water demands for both the single and multiple dwelling sector are found to be for A1B and no restriction scenario, and B1 and Level 3 restriction scenario, respectively.

The modelling approach presented in this paper can provide realistic scenarios of forecasted water demand which would assist water authorities in devising appropriate management strategies to enhance the resilience of the water supply systems. The developed method can be adapted to other water supply systems in Australia and other countries.

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