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Future projection of water resources based on digitalisation and open data in a water-rich region: a case study of the city of Klagenfurt

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ABSTRACT

Implementation of different strategies on the demand and supply side to deal with potential water scarcity is based on a comparison of future water demand and availability of water resources based on different scenarios of climate change and population growth. Especially, the Alpine region is characterised by many small and medium water supply systems (WSSs) having neither human resources nor time for advanced planning, requiring simple methods for estimating future development. Therefore, the aim of this work is to provide future projections of water demand, resource availability, and drinking water quality for an Alpine area based on simple approaches with minimal data requirements. As the results of the case study show, linear and polynomial regression with precipitation and temperature data can illustrate the temporal variation of system input and drinking water temperature with sufficient accuracy and is suitable for an estimation of future development. The groundwater modelling, however, requires the consideration of a non-linear term depending on the depth to obtain reasonable results. Due to the usage of open-access data and the easy approaches developed and applied, a good transferability to other case studies is expected which can provide stakeholders a first assessment of the future need for action.

Key words: resource availability, transferability, water demand, water quality, water-rich countries, water supply system

HIGHLIGHTS

- Simple regression analyses are used for future projections for water resources.
- Precipitation and temperature are utilised as input parameters.
- Water demand increases by 25–125% due to climate change and population growth.
- Increased availability of open-access data can help future planning.

INTRODUCTION

Water supply systems (WSSs) provide drinking water in sufficient quantity and quality to the urban population, representing an important part of today's urban environments. In particular, the combined effects of climate change and urbanisation are increasing the pressure on the WSS (Parkinson *et al.* 2016; Biswas & Gangwar 2020; Liang *et al.* 2020), requiring timely water management to avoid water scarcity.

In general, water management is based on a comparison of future water demand and availability of water resources based on different scenarios of climate change, economic development, and population growth (Dong *et al.* 2013). This information is afterwards used for the implementation of different strategies on demand and supply side to deal with potential water scarcity (Wang *et al.* 2014). As a large number of literature has shown, it usually requires a combination of different measures on the demand and supply side for sustainable future water management (Brown *et al.* 2019; Alemu & Dioha 2020; Terblanche *et al.* 2020; Daloğlu Çetinkaya *et al.* 2022). Additionally, it is beneficial to include a wide variety of scenarios to deal with uncertainties in future developments (Makropoulos *et al.* 2008; Asghar *et al.* 2019; Ayt Ougougdal *et al.* 2020; Saketa 2022; Sivagurunathan *et al.* 2022).

The experiences of the past years and forecasts showed, that the pressure on the WSS is also increasing in water-rich regions like Austria due to climate change, urban population growth, agricultural pollution, and over-extraction in future (Neunteufel *et al.* 2017). Subsequently, the Federal Ministry Republic of Austria (2021) recommended an early analysis of future water demand and availability of drinking water, as the duration from planning over approval procedures to commissioning of new sources takes approximately 20–30 years in Austria. However, there are many small and medium-sized water utilities in Austria, e.g., around 4,500 WSS companies (81% of all water utilities) supply less than 1,000 inhabitants (Neunteufel *et al.* 2012). Thereby, these small and medium-sized water utilities have neither monetary, human, or time resources for advanced planning (Oberascher *et al.* 2020), and appropriate future water management is a major challenge.

Therefore, developed models should be based on input variables, that can be easily measured to support a practical implementation (Donkor *et al.* 2014), but this requirement can also be extended to simple and explainable models for an easy application by the WSS operators. However, especially groundwater and water demand studies often use complex machine learning approaches and hydrodynamic modelling, whereas the application mentioned above regarding water management mainly applied the water evaluation and planning (WEAP) tool. These approaches have the disadvantages that a lot of input data are needed for the development (except simpler machine learning methods like a random forest or support vector machine), are time-consuming to implement and require expert knowledge.

Subsequently, the aim of this work is to develop and test simple methods to give future projections of water demand, resource availability, and drinking water quality, and thus provide decision-makers with a basis for further action (e.g., more detailed planning). In this context, data availability is significantly increasing through open data platforms (Cheval *et al.* 2020; Dautz *et al.* 2022), that can be utilised, therefore. The detailed objectives of this work can be described as follows:

- Utilisation and development of simple formulas for water resources planning and management that are comprehensible and based on open-access data to support easy transferability to other case studies.
- Showcase the developed approaches for water management for a water-rich area using the city of Klagenfurt (Austria) and forecast the future water demand, resource availability and drinking water quality to support local decision-makers to maintain the existing high reliability of the WSS in future.

MATERIALS AND METHODS

The aim of this work is to provide WSS operators with future projections of WSS data to support future water management. Therefore, the focus of this work is on long-term prediction (e.g., 30–50 years) of system input, groundwater levels, and water quality based on measurement data with a coarser resolution (e.g., monthly).

Future projections of WSS data

For the future projections, a three-step approach is chosen including identification of previous trends, model development and future predictions to assist decision-makers for future water resource planning and management (Figure 1).

Identification of previous trends

First, the temporal variation of the historical WSS data is visually analysed to identify previous trends (e.g., differences over time, in seasons), which will have an impact on future development. Afterwards, the historical WSS data are correlated with the weather and population data to analyse the influence of climate and urban development on the historical system behaviour. For developing simple models, the influence of the weather is described using only temperature and precipitation data. Temperature and precipitation data are selected because these parameters are relatively easy to measure, are available over large areas and are also basic output data of climate change models. Subsequently, the identified parameters that have an influence on the historical behaviour are used as input in the utilised model.

Model development

In the second step, a model is created to simulate the historical system behaviour and the applicability is evaluated by comparing measurement and simulation data. In literature, a variety of approaches are applied to analyse and forecast timeseries data, ranging from statistical approaches (e.g., (S)ARIMA) (Donkor *et al.* 2014) to the wide field of machine learning (Ghobadi & Kang 2023). These techniques are very well suited to correctly reflect more complex relationships and timeseries

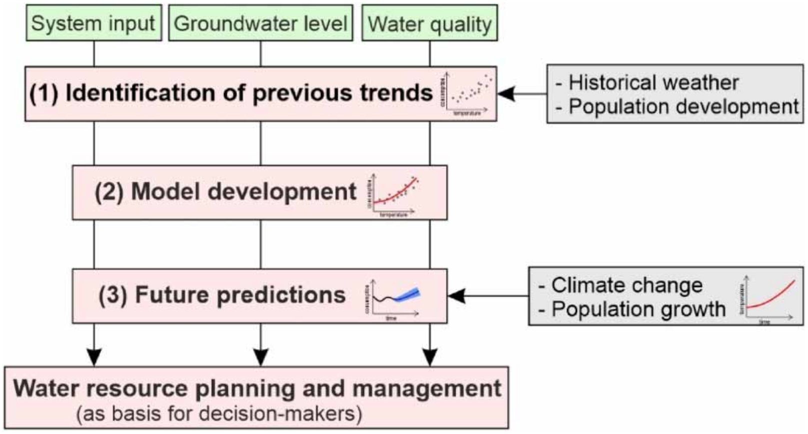

Figure 1 | Overview of the selected three-step approach to forecast the future system development.

data, however, they require expert knowledge and especially the results of machine learning techniques like artificial neural networks are often not comprehensible (Doorn 2021).

Therefore, we have intentionally chosen linear and polynomial regression in this work, as it allows a simple implementation (e.g., no hyperparameter tuning) and a transparency of the results. Due to their simplicity, these models will not be able to correctly illustrate all relationships and time patterns, but it is expected that they will be able to illustrate the approximate course and serve as a basis for future projections to assist WSS operators. In this regard, we extended the linear and polynomial regression with Bayesian statistics to deal with data uncertainties:

$$y = \beta_0 + \beta_1 * x + \beta_2 * x^2 + \ldots + \beta_n * x^n + \varepsilon \quad (1)$$

where y is the predicted value, x^n is the predictor variable with order n, β_n is the corresponding weight, and ε is the error term. For more details regarding the selection of input parameters, output, and utilised models, refer to the respective WSS data in the Results section. The presented approach is implemented in Python 3.9.13 using scikit-learn (Pedregosa *et al.* 2011).

The model is able to simulate a wide range of hydrological conditions with a limited dataset, as the focus is on long-term behaviour. Additionally, the applied regression analyses are not sensitive to overfitting (as would be the case with neuronal networks). Therefore, the whole dataset is utilised for model calibration and validation. The performance evaluation of the model is based on the mean absolute percentage error (MAPE):

$$\text{MAPE} = \frac{100}{N} * \sum_{i=1}^{N} \left| \frac{Y_i^{mod} - Y_i^{obs}}{Y_i^{obs}} \right| \quad (2)$$

in which Y_i^{obs} is the ith measured value, Y_i^{mod} the ith modelled value, and N refers to the number of values within the measured data.

Future predictions

Subsequently, the developed models from step two are used to estimate future system behaviour. Therefore, the relevant parameters for each model are taken from a specified climate change and population scenario for a specific future date, resampled to the applied time resolution (e.g., in this work monthly) and used as input parameters. The output of the model corresponds to the predicted value for the selected future time step. Afterwards, this process is repeated for all available future time points (e.g., influenced by the length of climate change forecasts) to obtain a timeseries for the selected climate change and population scenario. Furthermore, a wide range of climate change and population scenarios can also be defined to obtain multiple timeseries and make them available to the WSS operators as an ensemble output to reduce the impact of uncertainty.

Case study

The case study is the WSS of the city of Klagenfurt (Austria) located on the south side of the Alps having a size of around 120 km² and 103,000 inhabitants. The weather is characterised by four distinct seasons and can be assigned to the climate zone Dfb (D = cold climate, f = without dry season, and b = warm summer) according to the definition of Peel *et al.* (2007).

Water supply system

The WSS is designed as a central system with two groundwater wells (Straschitz and Zwirnawald) outside the city and the elevated tank Spitalberg in the city centre as daily balancing volume. The further supply of the city is provided through a gravity-driven pipe network. For the analysis, the following data were provided as primary data from the operator:

- For the water demand, the system input of the entire WSS is available on a monthly basis for the period 2010–2021. Thereby, the system inputs include domestic, industrial, and touristic water demand as well as water losses in the network.
- The groundwater level is measured for the two groundwater wells on daily time steps and is resampled to monthly values for the period 2010–2021.
- In accordance with official regulations, the water quality has to be measured at regular intervals by certified testing laboratories. Thereby, (nearly) monthly quality analysis reports are available for the two groundwater wells, the elevation tank and two measurement points (Magistrate and Limmersdorf) distributed in the network for the period 2016–2021. As chemical parameters obtained in laboratories are often only indicative or below the measurement limit, for this study, temperature, pH, and conductivity measured on-site are extracted from the reports.

Open data

The primary data from the network operator were supplemented by the following publicly available data as secondary data:

- There is high-resolution groundwater monitoring in Austria, and monthly groundwater levels are publicly accessible under https://ehyd.gv.at/#. Therefore, the groundwater level data provided by the operator is extended by nearby monitoring sites, resulting in groundwater series from 1992 to 2021.
- Information about population development is provided by the city government of Klagenfurt at the website https://www.klagenfurt.at/stadtinfo/statistik (accessed on 18.11.2022). The data are available on an annual basis and scaled down linearly to months for this work. The city had 94,383 and 103,003 inhabitants in 2010 and 2021, respectively, which corresponds to an increase of about 0.8% per year in the last decade.
- Meteorological data are freely available on the datahub https://data.hub.zamg.ac.at/ (accessed on 18.11.2022) operated by the Central Institute for Meteorology and Geodynamics (ZAMG) (Dautz *et al.* 2022). The data hub includes station data as well as raster and grid data for a wide range of parameters. For this work, mean temperature and precipitation sum per month are utilised for the station Klagenfurt-Flughafen (ID 48) within the city boundaries. The annual mean temperature was between 8.1 and 11.2 °C and annual precipitation was between 730 and 1,350 mm in the period 1990–2021 (black line in Figure 2). Additionally, daily grid data for evapotranspiration and temperature were extracted for the nearest grid point to the case study.
- For Austria, the output of regional climate models is provided within the dataset 'ÖKS15' publicity available on the Climate Change Center Austria (CCCA) Data Server https://data.ccca.ac.at/en/ (accessed on 18.11.2022). The dataset includes future projections for daily mean temperature and precipitation sum in a 1 km grid raster, which are also bias corrected (Chimani *et al.* 2020). In total, the output of 13 climate change models is available for scenario RCP 4.5, whereby the data from the grid point closest to the before-mentioned weather station is sampled for months and used for the ensemble. Figure 2 shows the annual projections for mean temperature and precipitation sum, whereas the blue line represents the mean of all climate change models, and the hatch shows the minimum and maximum values of the considered climate change models. As can be seen, the average annual temperature increases by about 2.5 °C (from 8.9 °C in 1990 to 11.4 °C in 2100), whereby the difference between the predicted maximum and minimum is approximately 2.0 °C each. In contrast, the average precipitation sum stays relatively constant between 800 and 900 mm, however, also annual precipitation sums of around 500 mm are projected (corresponds to a decrease of about 35% compared to the past decades).

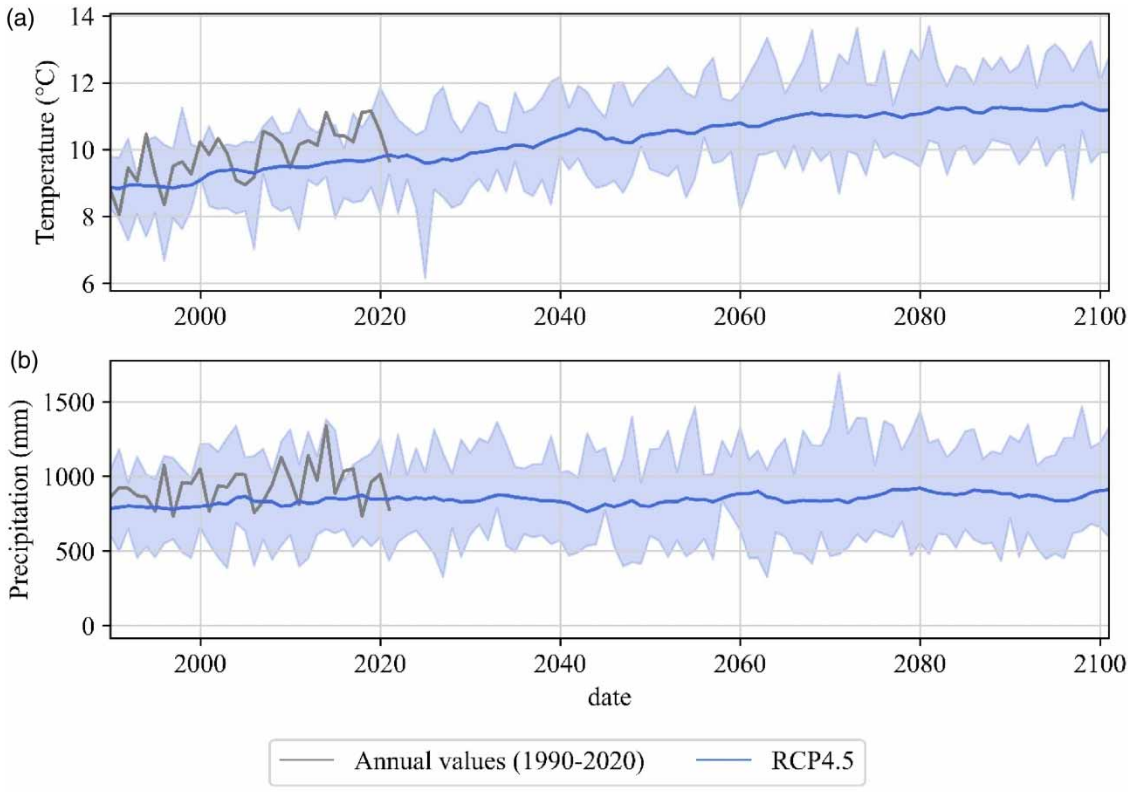

Figure 2 | Measurements (1990–2021) and projections for RCP4.5 for the following parameters: (a) mean temperature and (b) precipitation sum on yearly basis.

RESULTS AND DISCUSSION

System input

Previous trend

In the first step, the monthly water demand was divided by the population size and number of days per month to be independent of population development and month length. Following, water demand per capita was between 0.200 and 0.303 m^3/day during the period 2010 and 2021 (Figure 3(a)). As irrigation takes place in Austria mainly during the summer-half year (April – October) (Neunteufel *et al.* 2014), the water demand data was then classified according to summer and winter months, shown as orange and blue points, respectively. This shows clearly that the water demand per capita decreased in winter over the last decade, while it remained relatively constant during the summer months. A decrease in water consumption is also apparent in other industrialised countries such as North America (Rockaway *et al.* 2011; Parandvash & Chang 2016) as well as in previous research in Austria (Neunteufel *et al.* 2014). Possible reasons therefore could be more water-efficient appliances, careful use of drinking water and, in this case study, also a reduction of water losses in the WSS.

Subsequently, the system input per capita during the winter months was assumed as base water consumption (BWC), and the difference between BWC and water demand during the summer months represents the additional outdoor demand for the seasonal water consumption (SWC) (Figure 3(b)). The additional SWC is between −0.02 and 0.07 m^3/day, and showed a good correlation with mean temperature and number of hot days above an average temperature of 20 °C.

Model development

Summarised, the developed model to forecast system input consists of the following modules:

- The BWC is modelled by a linear regression, using the annual difference to the first available data point (here 2010) as the input variable. For the future forecast, it was assumed that the downward trend of BWC is limited by 0.2 m^3/day.

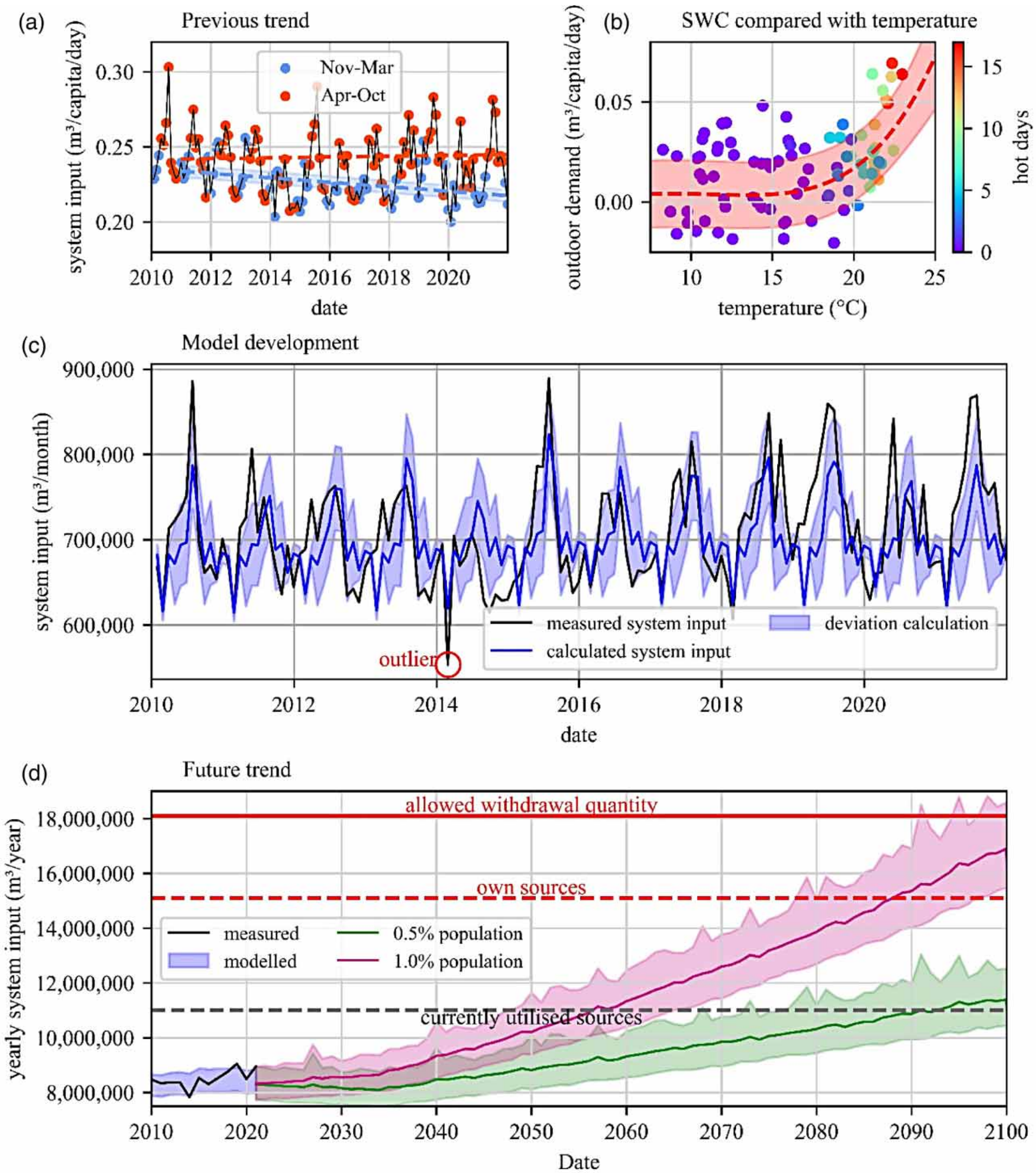

Figure 3 | (a) Water demand per capita during the period 2010 and 2021 classified into winter (blue) and summer (orange) months, (b) outdoor demand based on mean temperature and number of hot days (above average temperature of 20 °C), (c) comparison of modelled and measured monthly system input for 2010–2021, and (d) forecasted annual system input for a 0.5 and 1% increase in population until 2010.

- The additional SWC is modelled for the summer months by a polynomial regression with an order of 4 using the mean temperature as the input variable.

Both regression lines are shown in Figure 3(a) and 3(b), while Figure 3(c) compares the modelled and measured monthly water demand for the entire WSS. As the functions are relatively simple, there is always a deviation between the real system input, but the approximate course can be reflected very well (MAPE = 5.5%). Subsequently, the model was considered suitable for forecasting the future water demand.

Future predictions

As shown by the results, the climate change increase of the SWC could be quantified by about 2%, which is lower compared to the literature. For example, Opalinski *et al.* (2019) quantified the temperature-dependent increase by 3.7% per 1 °C, whereas a total increase of 4–15% can be expected due to higher outdoor temperatures until 2050 (Rasifaghihi *et al.* 2020; Fiorillo *et al.* 2021). These differences may be due to regional effects and boundary conditions, however, the results are in accordance with the findings of Stelzl *et al.* (2021) predicting a 3.5% increase in the peak water demand for Austria until 2050.

Afterwards, the total water demand is determined by multiplying the BWC and SWC by the number of inhabitants. Currently, two of three groundwater wells (Zwirnawald and Straschitz) are used having an allowed withdrawal quantity of 11 million m³ per year, whereby the system input is on average 8.5 million m³ per year. For resource planning, the maximum annual withdrawal quantities are specified by the authorities to 18 million m³ for the city of Klagenfurt, of which 83% are own sources and 17% can be taken from a joint water board. Therefore, the annual system input is relevant, and in consultation with the decision-makers, it was assumed that the population will continue to grow at 1% in the future. Following, future system input would be between 9.5 and 11.5 million m³ (+ 10 to 35%) in 2050 and would increase to 15.5 and 18.5 million m³ (+80 to 120%) in 2100 (Figure 3(d)). Therefore, the forecasted water demand could be covered almost entirely by utilising the allowed withdrawal quantities, although the future system input would exceed the operator's own resources from around 2080 onwards. However, this would also imply that in case of a disturbance, e.g., failure or contamination of a source, no reserves for system failures would be available. Subsequently, an additional source would be required from around 2050 to provide the high reliability of the WSS in the city of Klagenfurt in future, while the period is around 20–30 years until a new source is operational. For comparison, the future water demand was determined for a population growth of 0.5% per year, which significantly reduces the projected water demand to 10.5 and 12.5 million m³ (+25 to 50%) in 2100. However, also in this scenario, an additional source would be required around 2080 onwards as a reserve to maintain the current reliability.

Groundwater level

Previous trend

The comparison with runoff data of neighbour river sites (extraction from https://ehyd.gv.at/#, last accessed on 21.11.2022) showed a high interaction between the two rivers Glan and Glanfurt with the two groundwater wells Zwirnawald and Straschitz, similar behaviour can also be observed in the literature (e.g., for the Rhine (Wunsch *et al.* 2021)). Figure 4(a) illustrates the trend of the river Glan and the distance of groundwater level to ground surface for Zwirnawald over a period of 7 months, whereby the trend of the groundwater level follows with approximately 2 days delay. For the groundwater source in Straschitz, a weir system is located within 500 m of Straschitz, which very probably influences the groundwater level. Therefore, the groundwater level in Straschitz is excluded and further analyses are based only on the groundwater level in Zwirnawald.

Figure 4(b) shows the difference in the groundwater level compared to the previous month based on precipitation sum and mean temperature, whereby the decrease in groundwater level increases with higher temperature and lower precipitation. This situation is confirmed by the literature, a change in precipitation patterns and rising temperatures leads to a temporal and quantitative change in groundwater recharge (Larocque *et al.* 2019; Amanambu *et al.* 2020; Liang *et al.* 2020). Following, precipitation and temperature were used to build a model (Equations (3) and (4)).

Model development

All attempts with linear and polynomial regression did not lead to practical results for the groundwater level, as a groundwater level of 100 m below the surface was predicted until 2100, requiring an additional non-linear term depending on the actual groundwater depth to consider non-linear and non-stationary characteristics of groundwater levels (Maheswaran & Khosa 2013). Therefore, the differences in groundwater level (ΔGW) were estimated using the following equation based on mass balance:

$$\Delta GW = \propto_P * P - (SI + \propto_L * L) \tag{3}$$

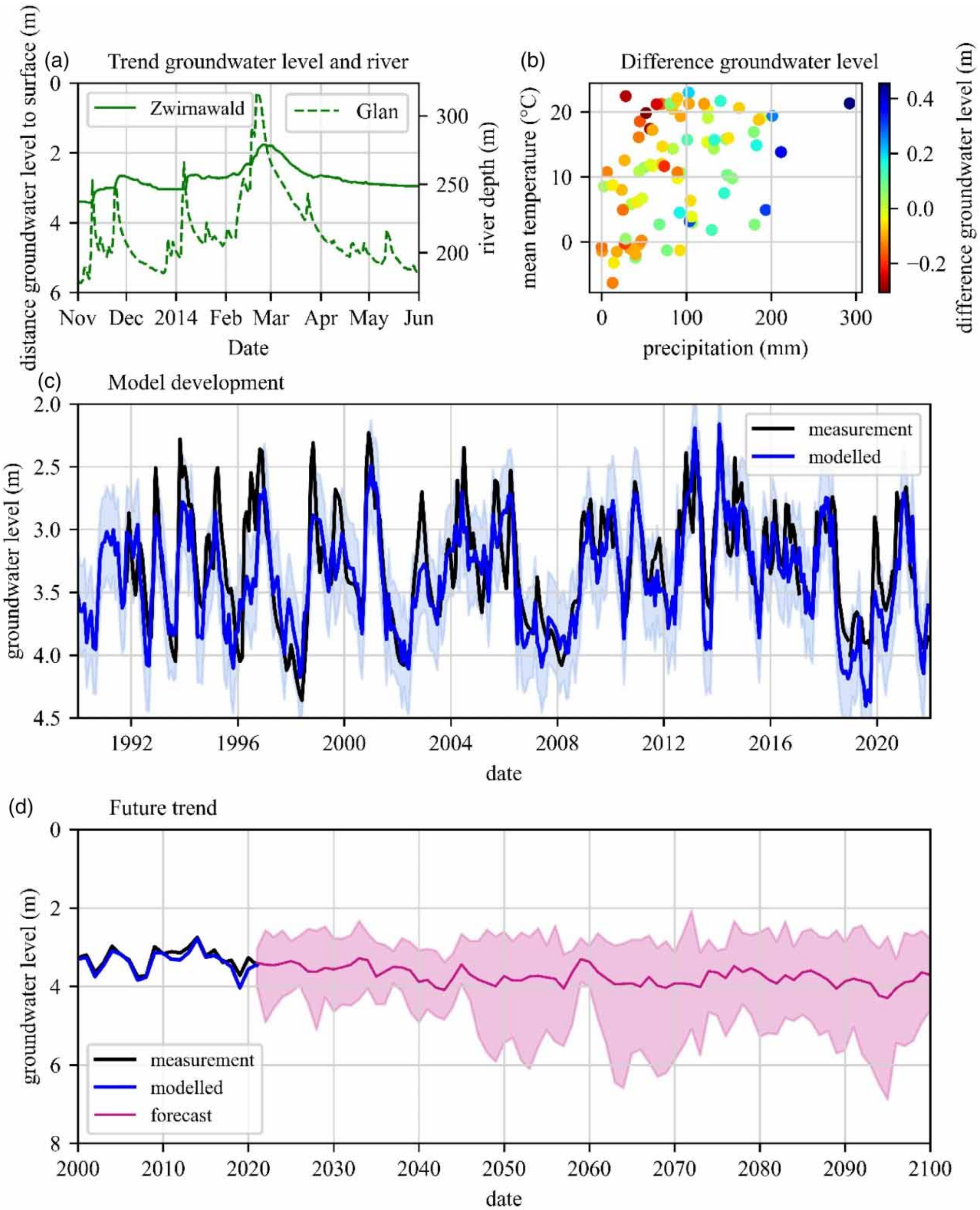

Figure 4 | Analyses of the groundwater level at Zwirnawald for (a) comparison of trend in groundwater level and neighbouring river, (b) difference groundwater level based on precipitation sum and mean temperature compared to previous month, (c) comparison of modelled and measured distance of groundwater level to surface for 1991–2021, and (d) forecasted distance of groundwater level to surface until 2100.

in which α_i represent adjustment factors, P is the precipitation sum as an independent variable, and SI and L are the dependent variables as the total water demand (corresponding to the system input) divided by aquifer area and the losses through exfiltration and evapotranspiration based on the actual groundwater depth, respectively. To calculate L, it was assumed that the total losses can be estimated similarly to evapotranspiration as a function of soil depth: (1) evapotranspiration increases with higher temperature and can be simplified modelled by using a linear regression with monthly temperature as input data

(Komatsu *et al.* 2012), and (2) the decrease follows approximately an e-function for different soil types as can be seen in the modelling results of Soylu *et al.* (2011). Subsequently, L can be expressed by the following equation:

$$L = \left(\sum_{i=1}^{n} \beta_i * T^i\right) * (e^{-GW_{prev} * \gamma_1} * \gamma_2 + (1 - \gamma_2)) \tag{4}$$

Here, β_i and γ_i are adjustment factors, T is the independent variable temperature, and GW_{prev} depends on the previous groundwater level. The adjustment factors for the evapotranspiration depending only on temperature data were determined by using daily grid data for evapotranspiration and temperature available at the datahub https://data.hub.zamg.ac.at/ resampled to months and an order of 3.

Figure 4(c) compares the modelled and the measured groundwater level for the period 1991–2021, and the pattern of the groundwater level can be modelled quite well (MAPE = 7.1%). Therefore, the model was used further to estimate the future pattern of the groundwater level.

Future predictions

The future groundwater level is strongly influenced by the considered climate change models, as indicated by the hatching in Figure 4(d), and predicted patterns range between no change and a decrease of 3 m. Therefore, the mean value from all climate change shows a slight decrease over time and the groundwater level is expected to decrease by around 0.75 m until the end of the century. For example, other studies show a decrease in groundwater level by 1.5 m in the next 20 years (Dehghani *et al.* 2022), whereby the difference is due to regional conditions. In the case of the city of Klagenfurt, this decrease in the groundwater level does not represent a major impact from a resource perspective. However, as there is a high interaction between groundwater bodies and neighbour rivers, it should be ensured that changes in the two streams will maybe also cause a change in the groundwater level. From an integrative perspective, the discharge head will increase due to higher elevation differences resulting in a higher energy demand for the pumps.

The implemented model for the simulation of the groundwater level showed good and plausible results for the case study. However, the transfer to other case studies will be only possible to a limited extent, as it entails some simplifications in the mass balance that contradict the specified goals with easy and understandable models. It is expected to work reasonably well with groundwater wells with the same catchment area sizes and characteristics (e.g., the catchment area for the case study is approximately. 500 km² and has an altitude between 400 and 1,800 m). However, some adjustments are required for larger catchment areas with longer flow times and higher influence from snow or glacier melt and should be addressed by future research.

Drinking water temperature

Previous trends

Conductivity and pH showed only slight changes over time and were almost constant between 500 and 600 μS/cm and 7 and 8, respectively. Therefore, the focus was on the drinking water temperature, which showed a good correlation with the monthly mean temperature (Figure 5(a)) with an increase in temperature during the summer months and a decrease in temperature during the winter months. Additionally, there is a relation to flow time noticeable. For example, the water temperature in the sources Straschitz and Zwirnawald showed only minor changes over time, while the water temperature in the measurement sites Limmersdorf and Magistrate located in the network reached up to 20 °C during the summer months.

Model development

Subsequently, the drinking water temperature was modelled by a linear regression (order of 1), using the air temperature as the input variable. The linear regression lines are shown in Figure 5(a), while Figure 5(b) compares the modelled and measured drinking water temperature for all investigated measurement sites. MAPE ranges between 7.4 and 17.2% for the measurement sites distributed over the network (Spitalberg, Limmersdorf, and Magistrate). Despite the simple models, the trajectories and the peaks are well reproduced and were therefore used for the long-term forecast. In contrast, the two sources (Straschitz and Zwirnawald) show only minor changes throughout the year (MAPE is 6.2 and 3.7%, respectively). Therefore, the source Straschitz is included in the further analyses only for comparison.

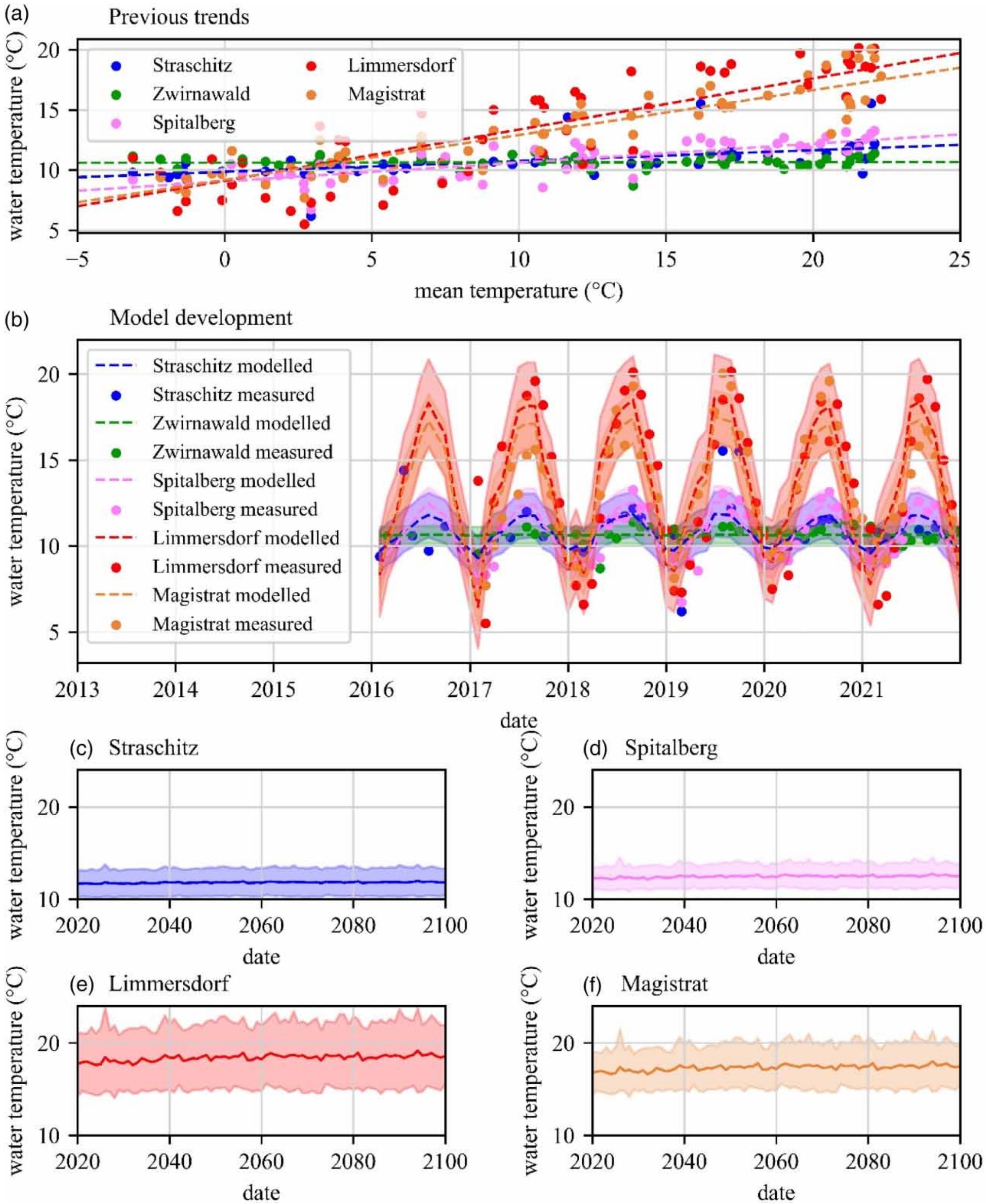

Figure 5 | (a) Correlation between mean temperature and water temperature for five measurement sites including regression analysis (the uncertainties obtained through Bayesian statistics have been removed for a better visualisation), (b) comparison of modelled and measured drinking water temperature for 2016–2021, and forecasted annual maximum temperature until 2100 for (c) groundwater well Straschitz, (d) elevation tank Spitalberg, (e) measurement site: Limmersdorf, and (f) measurement site: Magistrat.

Future predictions

The maximum annual drinking water temperature is illustrated in Figure 5(c)–5(f), whereby the line represents the mean of all climate change models and the hatches the corresponding minimum and maximum values. The temperature for the source Straschitz and the elevation tank Spitalberg will increase by 0.3 and 0.5 °C until the end of this century, being normally between 10 and 14 °C during the summer months. The projected temperature in the network will increase to a greater extent, being around 1 °C for Magistrat and Limmersdorf. Similar results can be derived from the literature, as the drinking water temperature is dependent on the air temperatures and the water age (Zlatanovic *et al.* 2017; Lai & Dzombak 2021), and is expected to increase by up to 2.3 °C until 2070 (Lai & Dzombak 2021). Furthermore, the maximum temperature predicted by the different climate change models will be up to 20 and 23 °C for the measurement site Magistrate and Limmersdorf, respectively. That is important insofar, as valid standards (e.g., ÖNORM EN 806-2 (2005)) specify, that the water temperature should not exceed 25 and 30 °C after full opening, as hot water favours the formation of bacteria, e.g., Legionella (Agudelo-Vera *et al.* 2020).

CONCLUSIONS

The WSS represents an important part of the infrastructure in urban areas, as its task is a sufficient supply of drinking water to the urban population. Due to climate change and urbanisation, urban water demand will continue to rise in future, thereby increasing the number of people living in urban regions exposed to water scarcity. As the experiences and forecasts show, the pressure on the WSS will also increase in water-rich countries like Austria due to climate change, urban population growth, agricultural pollution, and over-extraction in future. The aim of this work, was to provide future projections of water demand, resource availability and drinking water quality for the city of Klagenfurt (Austria), having sufficient drinking water up to now, to support decision-makers for the future development. Additionally, a special focus was on easy and explainable formulas based on meteorological open-access data to ensure a high transferability to other case studies. Based on the obtained results, the following conclusions can be drawn:

- The past development of system input and drinking water temperature as an indicator for water quality depends on air temperature, whereas the system input per capacity decreases over time.
- The groundwater level shows a high interaction with neighbouring rivers, and the changes in the groundwater level can be expressed by temperature and precipitation data.
- A linear and a polynomial regression are suitable approaches to model and estimate water temperature and system input, respectively, whereas the groundwater level requires additional non-linear terms to consider the non-linear decrease over the depth.
- In the case study, the future projections of water demand show an increase of 25–125% depending on population growth, a decrease in groundwater level of 0.75 m, and an increase in drinking water temperature of 1 °C until 2100.
- Depending on the population growth, additional sources will be needed in 2050 or 2080 to continue to maintain the high quality of the WSS in future. This is particularly important for the WSS operator, as it needs approximately 20–30 years to put a new source into operation.
- The usage of open-access data (meteorological data, results of climate change models) and the easy formulas applied allow a good transferability to other WSS for an initial assessment of future development.

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DATA AVAILABILITY STATEMENT

Data cannot be made publicly available; readers should contact the corresponding author for details.

CONFLICT OF INTEREST

The authors declare there is no conflict.

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