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A Probabilistic Decision Support Tool for Prediction and Management of Rainfall-Related Poor Water Quality Events for a Drinking Water Treatment Plant

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Abstract

A data-driven Bayesian Network (BN) model was developed for a large Australian drinking water treatment plant, whose raw water comes from a river into which a number of upstream dams outflow water and smaller tributaries flow. During wet weather events, the spatial distribution of rainfall has a crucial role on the incoming raw water quality, as runoff from specific sub-catchments usually causes significant turbidity and conductivity issues, as opposed to larger dam outflows which have typically better water quality. The BN relies on a conceptual model developed following expert consultation, as well as a combination of different types (e.g. water quality, flow, rainfall) and amount (e.g. high-frequency, daily, scarce depending on variable) of historical data. The validated model proved to have acceptable accuracy in predicting the probability of different incoming raw water quality ranges, and can be used to assess different scenarios (e.g. timing, flow) of dam water releases, for the purpose of achieving dilution of the tributary's poor-quality water and mitigate related drinking water treatment challenges.

Introduction

Continuously producing consistent and high-quality treated water for consumers is one of the main goals of water utilities. While drinking water treatment plants (DWTPs) often achieve this goal under normal operation, extreme weather events, predicted to increase in frequency and magnitude (Khan et al. 2015), can impact the quality and quantity of water, and strain the capacity of unprepared DWTPs. This leads to decreased water quality after treatment during extreme events, potentially resulting in poor water aesthetics (e.g., colour and odour), public health (e.g., gastrointestinal illnesses) and economic (e.g., interruption in water supply) issues, as well as damage to water utility reputation. Such events have frequently occurred in the past (Carberry et al. 1984, Clancy 2000) and continue to occur in the present, as a result of a combination of unexpected weather/water quality changes, poor monitoring, and reactive operation and maintenance of assets.

While DWTPs that rely on raw water from lotic sources (i.e., reservoirs) usually deal with more stable water systems (especially for deeper reservoirs, less affected by wind), DWTPs collecting raw water from lentic sources, particularly large rivers with several tributaries, must cope with more dynamic and sudden changes in water quality and quantity. In contrast to most lotic systems, changes in water quality in lentic systems are more sensible to point-source pollution and rapid and intense weather events due to their variable flow nature and limited ability to store and diffuse pollutants (Meyer et al. 2019). The dynamic nature of lentic systems results in complex interactions (e.g., variable time delays between heavy rain and poor water quality), adding further challenges to DWTPs relying on lentic systems to proactively respond to extreme events.

River water quality forecasting is only rarely attempted (Loos et al. 2020), especially when compared to lakes and reservoirs. Of particular concern are high flow events, which can cause several water quality parameters to exceed guidelines thresholds. This includes turbidity (Lee et al. 2016), organic matter (Lambert et al. 2016), pathogens (Bertone et al. 2019) but also less expected ones for such conditions, such as phytoplankton (Somma et al. 2021). The literature presents countless data-driven or hybrid water quality prediction models for reservoirs (e.g. Bertone et al. (2015), Park et al. (2021), Wang et al. (2022)), while for river systems, or integrated river-reservoir systems, process-based models seem to be more common (e.g. Ferreira and Fernandes (2022)), potentially due to a lower amount of high-frequency monitoring stations/tools compared to reservoirs. Despite their advantages, process-based models might not be able to capture the site-specific features of complex catchments. This could potentially affect process-based models' accuracy and robustness, depending on their end goal. Process-based models usually require extended time to run simulations, which is not ideal in time-constraint situations such as in preparation to potential flood events. When large datasets are available, it is argued that data-driven models may be a more cost-effective modelling option. The recent advancements in new in-situ water quality sensing technologies, mainly optical and electrochemical (Silva et al. 2022a) and including metals monitoring (Silva et al. 2022b), despite the need for substantial reliability checks and site-specific calibrations (Choo et al. 2019, de Oliveira et al. 2018, Silva et al. 2022a), offer new unique opportunities for a much deeper understanding of certain aquatic systems. The availability of real-time monitoring, recently emphasized in other studies (Meyer et al. 2019), and related large amounts of data can be used to develop such data-driven predictive and optimisation models to assist operators and decision makers to more proactively respond to high flow events in river systems in a time-efficient manner.

Mt Crosby DWTP, which produces treated drinking water for Brisbane, Australia, uses as water source the Mid-Brisbane River, located downstream to Wivenhoe Dam. The efficacy of Mt Crosby DWTP conventional treatment process (i.e., coagulation, flocculation, sedimentation, filtration and disinfection) was challenged at times (Colasimone 2022, Khan et al. 2017), especially during heavy rain resulting in high flows at upstream locations (e.g., South East Queensland flooding events in 2010-2012). The specific location of heavy rainfall can greatly affect the resulting water quality downstream, as certain Brisbane River tributaries (e.g., Lockyer's and England Creek) are believed to be the main turbidity sources, while others (e.g., Black Snake Creek) are known to be the source of high conductivity in the raw water reaching Mt Crosby DWTP. In recent years, a number of high-frequency water quality and flow monitoring stations have been installed and deployed at different locations along the Brisbane River, thus opening opportunities to better understand of the dynamics of the overall system, and to subsequently model it, to support proactive operation during extreme events, including controlling Wivenhoe Dam discharges for dilution of poor water quality downstream at Mt Crosby DWTP intake.

Previous research tried to predict and optimise dilution flows to ensure the assimilation capacity of the river is not exceeded, such as Farhadian et al. (2015); however, it was based on scenarios where river pollution is controllable, rather than when the source of poor water quality is a direct consequence of runoff from a certain section of the catchment. Other studies looked at the effect that controlled discharges from a dam has on assimilation capacity of a downstream river (Hashemi Monfared et al. 2017) but those were limited to the theoretical level, without validation and observation in the field (i.e., behavior of a specific pollutant in a specific location with multiple dams, rivers and creeks entering a catchment). In this context, the work described herein represents a novel research opportunity, i.e., extracting value from a large (both spatially and temporally) dataset to develop a unique data-driven water quality modelling tool, where stakeholders can assess multiple scenarios (of e.g. amount of water released from Wivenhoe dam) and devise the most suitable treatment/management strategy to adopt.

This has a substantial value for the water utility. First, the resulting predictive model would provide early warnings to Mt Crosby DWTP operators to inform adjustments on water treatment processes (e.g., chemical dosing). Second, due to the capacity of adjusting flow releases from the upstream Wivenhoe dam, there would be potential to adjust flow releases to effectively dilute poor-quality flows from tributaries based on the predictive model outputs. This proves to be a more sustainable and economical treatment solution during periods without shortage of water (i.e., no drought and strict water conservation measures in place, increasing the value of the stored water), by alleviating the water quality issue in the first place and in turn reducing the amount of chemicals used and sludge produced.

Materials and Methods

2.1 Study location

The Mount Crosby DWTP, which comprises two separate plants (East Bank and West Bank), collects raw water from the Mid-Brisbane River, and treats and supplies up to 800 ML/day of drinking water to the Brisbane and Ipswich regions, in South-East Queensland, Australia. Upstream to Mount Crosby DWTP, the Mid-Brisbane River receives water from many tributaries (Figure 1), and reservoirs, which significantly affect the overall water quality and quantity of the raw water prior to treatment. In addition to (depending on water level and operation strategy) Wivenhoe dam, the largest flow contributor is the main tributary, Lockyer Creek. Several other tributaries contribute to the Mid Brisbane River flow, such as England Creek and Black Snake Creek. While their flow are much smaller compared to Lockyer Creek during wet weather events, such tributaries' water quality can cause significant water quality issues in the raw water at Mount Crosby DWTP even after diluting into the Mid-Brisbane River. Seqwater, the main bulk water supplier in the region, manages both the water treatment plant and the operations of the Wivenhoe dam, and takes care of most of the water quality and flow monitoring of the catchment.

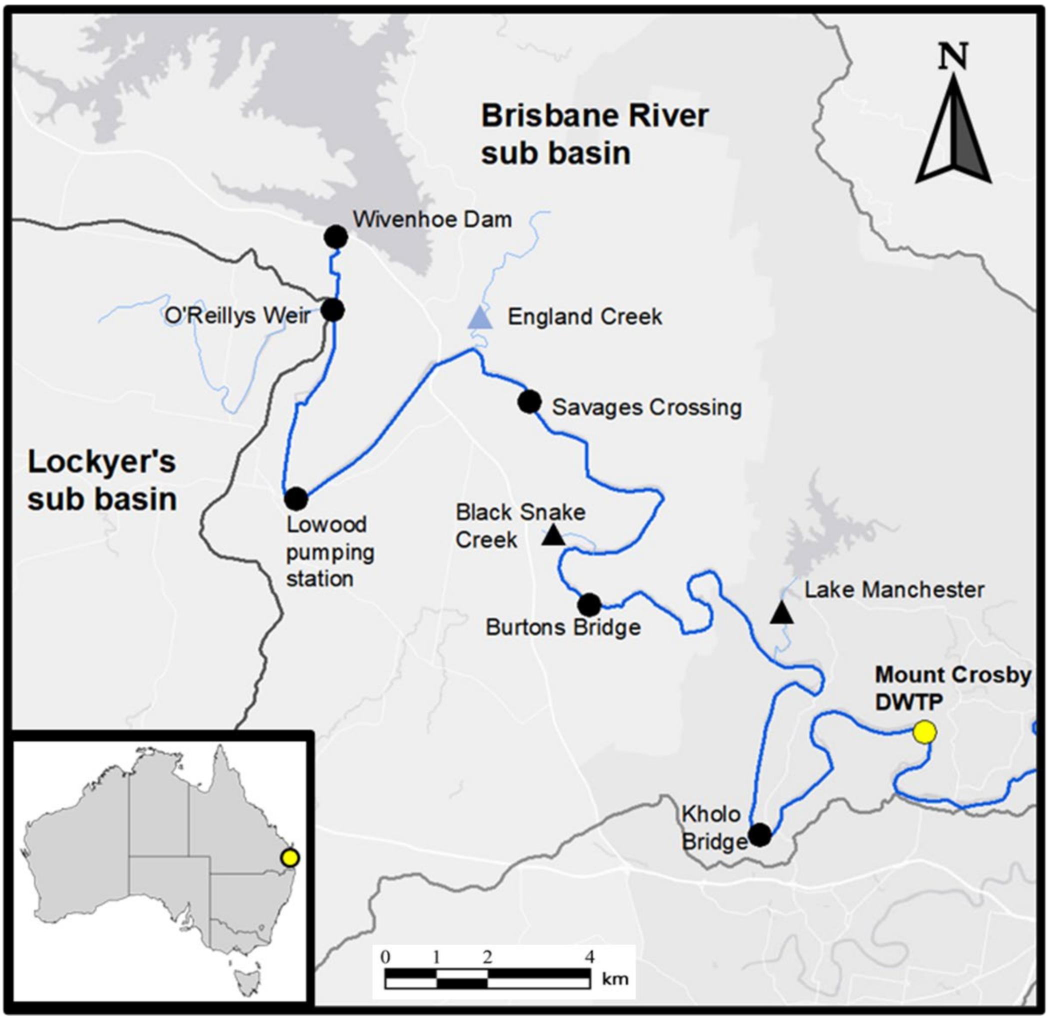

Figure 1 – Main water quality/flow monitoring locations

2.2 Data collection and pre-processing

Following a stakeholder workshop, which assisted in refining project goal and scope, system behavior and data sources, historical data was collected and pre-processed. Turbidity, water colour, conductivity and bromides were identified as the target water quality parameters because they historically affected Mount Crosby DWTP operation. Based on stakeholders' experience (later validated by data, when available), Black Snake Creek has been the major source of high conductivity (and often bromides) water, while other tributaries (e.g. England Creek and also Lockyer Creek) are the lead cause of high turbidity and organics.

Historical hourly flow data for seven river locations during a period ranging from 2009 to 2020 was collected from river monitoring stations (Figure 1), as well as hourly water quality data (with a focus on turbidity and conductivity) at six of these locations starting between 2012 and 2016. Data was collected by EXO2 sensors (YSI, Yellow Springs, USA). Aside for temperature, pH and dissolved oxygen, only turbidity and conductivity were monitored by sensors installed in those water quality stations: colour and bromides data were only available at lower frequencies for Mount Crosby DWTP. Rainfall data from several stations in the catchment were collected from Seqwater and the Australian Bureau of Meteorology (BoM). Data frequency ranged from hourly to daily.

Data was consolidated and filtered for time periods where data for most of the stations was available. Flow data, while overall relatively complete and accurate, presented certain large periods with missing data, corresponding either to very low (i.e., below detection), or high (i.e., likely sensor failure) flow periods. Most of the water quality data from the river stations had a 10-minute frequency, which was averaged to hourly frequencies to match flow data frequency. Before this, data was inspected and pre-processed (i.e., removal of faulty measurements, outliers, missing data, standardisation of data frequency) in collaboration with Seqwater stakeholders. After pre-processing, it was found that conductivity showed the greatest lack of data, with 3 out of 4 stations in the Mid-Brisbane River having less than 50% of reliable data available. In terms of stations, O' Reillys Weir station (monitoring the Lockyer Creek close to the confluence with Wivenhoe dam outflows) was the most problematic, with several periods of missing or incomplete data.

Data for Mt Crosby DWTP were extracted from both the Seqwater's Water Quality Data Management System and operator log data, merged, and filtered to focus only on raw water data for both East and West treatment plant. Depending on the variable, data frequency varied from 3 times a day, to monthly. Data gaps, data reporting errors, as well as data from different instruments were noted.

2.3 Data analysis and modelling choice

The data analysis included visual inspection, time series analysis, and linear/nonlinear regression analysis. Turbidity/flow hysteresis loops (Evans and Davies 1998) were analysed, to characterize the type of runoff event.

An event identification algorithm was developed to extract, from the pre-processed dataset, periods of interest for water treatment issues and to train a related model. Specifically, the algorithm identified rainfall-runoff events analysing significant changes in the baseflow concurrently with rainfall. Events were then classified according to their probability of occurrence (quantiles of peak flows/turbidity throughout the data), and then grouped by their peak flow magnitude at Mt Crosby. Sources of data used in this analysis included flow, turbidity and conductivity data from sensors distributed along the Mid-Brisbane River, and rainfall data from multiple stations across the Brisbane River and Lockyer's Creek sub-basins. Rainfall data was grouped according to the basin in which they are located, and interpolated to hourly frequency using spline method and rounding values below 0.1mm/h to 0. A rainfall event was flagged whenever a station within the Brisbane River sub-basin registered precipitation greater than 0.1mm/h. Since rain is often intermittent, a lag of up to 6 hours between the sequential "rain flags" was considered to be the same event, to account for variable response time from rain to runoff (i.e., modification in river flow) between events, due complex interactions between preceding soil moisture, rainfall-runoff events, and subsequent precipitation. The determination of the end of an event was set according to the baseflow at Mt Crosby. The baseflow was calculated using the R package lfstat function *baseflow()* (Koffler et al. 2016). This function estimates the baseflow of a river for regular time series based on the turning points of events. Whenever the actual flow of the river matched the calculated baseflow, it was assumed that the precedent rain had no further influence on the hydraulic conditions of the river and thus the current event has ended. The following new event started whenever a rain flag was detected after the end of the preceding event.

In relation to flow analysis and prediction, initially several short-term flow forecasting models were developed, briefly outlined elsewhere (Bertone et al. 2020). Previous studies developed 6-week ahead flow prediction models using a probabilistic approach (Bertone et al. 2017). However, for this application, the final model had to overcome frequent missing data, high uncertainty, and integrate different types of data (e.g., high-frequency flow and water quality; spatially distributed rainfall; outputs from simpler models based on expert knowledge). For such circumstances, data-driven Bayesian Network (BN) models are recommended (Chen and Pollino 2012) and have been successfully developed in previous research (e.g., Bertone et al. (2019)). Therefore, BN was selected as the final modelling approach for this study.

For the validation and refinement of the models, data from 2021 and 2022, collected by Seqwater during the course of this project, were used. During this time, affected by persistent wet conditions, several high flow events were reported. Data comprised flow, turbidity, conductivity, and rainfall for the required locations. Pre-processing of data followed the similar procedure of event identification, which included summaries of maxima and totals for flow, turbidity, conductivity and rainfall for each event. Manual visual verification for each event was performed to identify sensor faults (e.g., leading to non-meaningful large or low values).

2.4 Bayesian Network Model Development

BNs are a type of statistical model, specifically a probabilistic graphical model, which achieve compactness by factoring the joint probability distribution (i.e. the probability of every possible event as defined by the combination of the values of all the variables) into local conditional probability tables (CPTs), making them very fast to run (Fenton and Neil 2018, Pearl 1988). Overall, BNs have been increasingly applied in the past two decades for environmental modelling problems, specifically in the ecological modelling/environmental management field (Marcot et al. (2001), Barton et al. (2012)) but also in the water sector (e.g. Rigosi et al. (2015), Bertone et al. (2019), Sahin et al. (2016), Mayfield et al. (2019)), with more recent applications including for drought monitoring (Ali et al. 2020) and drinking water quality risk assessment (Yu and Zhang 2021).

Depending on the features of a modelling project, BNs can provide a number of advantages compared to other models. In addition to the aforementioned fast computational speed, they are suitable for data sets with missing data (Uusitalo 2007), such as for some of the historical timeseries data from the Mid-Brisbane River. BNs can also be “fed” with different sources of data: probabilities can manually be entered through expert knowledge in case numerical data is limited. Thus, hybrid sources of data (historical data and expert knowledge, or also other models' outputs) can be used to overcome historical data limitations or to enhance the model performance (Uusitalo 2007). Due to their graphical nature, they are also very user-friendly and ideal for both top-down (i.e., scenario analysis/prediction) and bottom-up (e.g., optimisation) tasks.

As per any modelling tool, BNs also have limitations which needed to be accounted for when undertaking the model development stage of this study. For instance, variables must be discretised, with states potentially providing only a coarse representation of the actual variable's condition, especially if a variable is discretised into only a very limited number of states (Uusitalo, 2007). This is however the case only if CPTs are derived from experts or from limited datasets: if the relationships among certain nodes were accurately identified from other (e.g. regression) models or by means of large datasets, related nodes can be discretised with several states. BNs are also intrinsically not dynamic, e.g. they cannot be used to run temporal simulations; they can however be modified accordingly over a number of time-steps ahead (Bertone et al. 2019), or temporal attributes can be predicted as individual child nodes (e.g. lag between two locations) such as in this work, as explained later. Finally, feedback loops, which could be informative in understanding how the system operates (Sahin et al. 2015) are not easily supported in BN. If they are extremely important in the modelled system, or they cannot be eliminated by changing the BN structure, then other model categories must be explored (Uusitalo 2007); however in this case, significant temporal feedback loops were not identified.

For this project, the BN comprised only key variables selected through data analysis, and a number of algorithms were developed to identify rainfall/runoff events and in turn develop the events database use to train/validate the BN. BNs were developed and trained with the Netica 5.18 64Bit software (Norsys Software Corp.). The main target parameters of the BN models were flow, turbidity and conductivity at Mt Crosby. Whenever appropriate (i.e., very high accuracy), regression models were used to generate the CPTs through the 'Equation to Table" Netica function. "Dynamic" components were also included by predicting relevant time delays for key variables/locations. The structure of the model for flow and turbidity prediction is illustrated in Figure 2, while the model for conductivity prediction is shown in Figure 3.

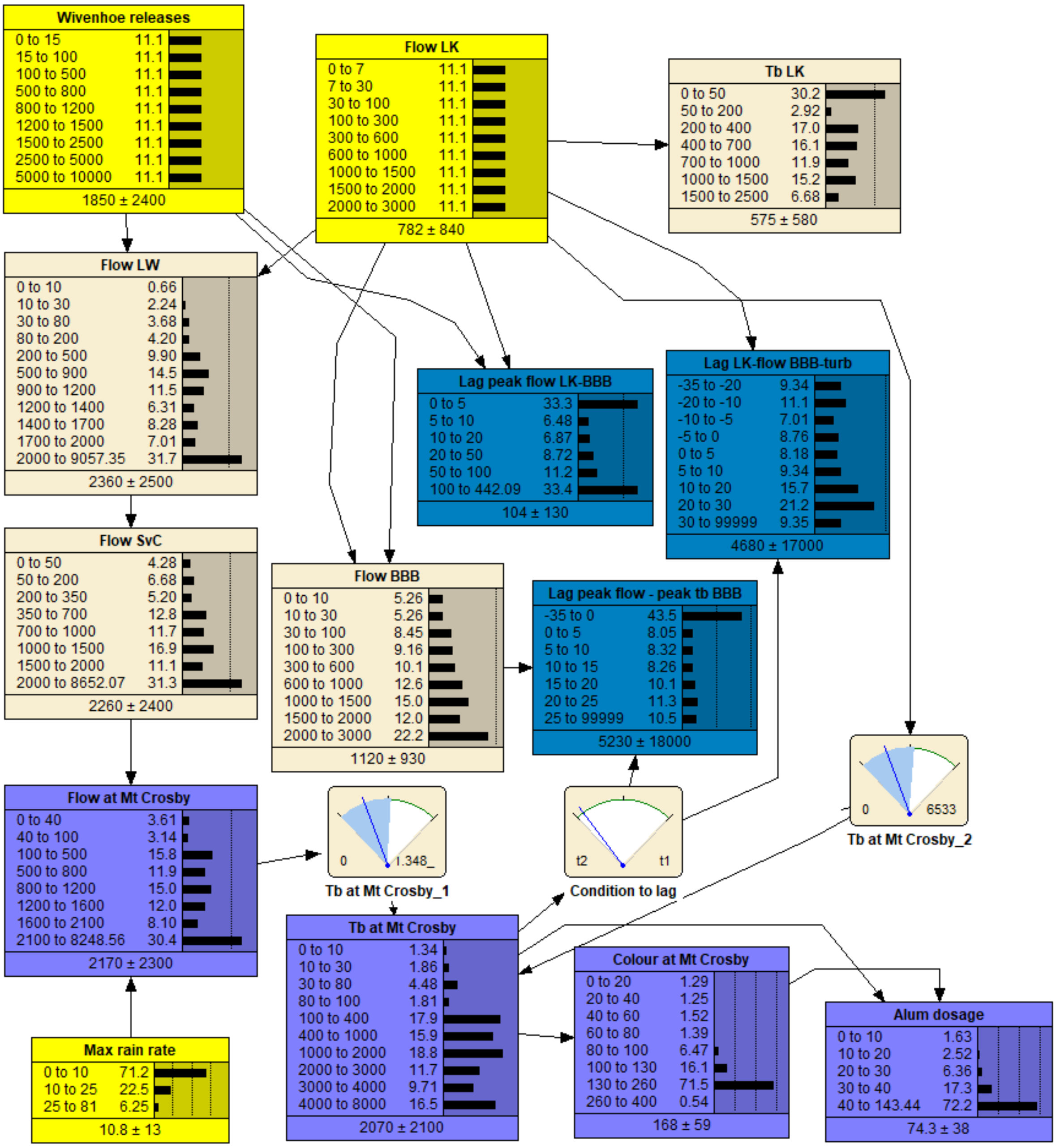

Figure 2 – Final BN for flow and turbidity prediction.

(Bright Yellow nodes=Inputs; Yellow nodes=intermediate outputs; Purple nodes=main outputs; Blue nodes=lag related outputs LK=Lockyer's Ck at O' Reillys Weir; LW=Lowood; SvC=Savages Crossing; BBB=Burtons' Bridge; Tb or turb=turbidity; meter-looking nodes: calculations)

The logic of the model revolves around a sequential flow prediction moving downstream; thus, by knowing peak flows coming from Wivenhoe dam and the Lockyer's Ck, the model predicts the peak flow at Lowood, and in turn at Savages Crossing and Mt Crosby. The last flow prediction (i.e. at Mt Crosby) is enhanced by adding "max rain rate" as input, i.e. the expected or recorded maximum hourly rainfall for any of the nearby rainfall stations in the Mid-Brisbane River Basin. The CPT population relied on regression models developed among the peak flows at subsequent dowsnstream stations during the identified events. As a consequence, it was possible to discretise the variables by keeping several different states (i.e. between 8 and 11), which could be also modified at a later date based on operators' preferences. Given the high (R^2>0.95) accuracy of each flow model, even after accounting for individual uncertainty, it was deemed (and later confirmed through model validation, see Results) that the error/uncertainty propagation to the final, Mt Crosby node, would have been limited.

Turbidity at Mt Crosby was predicted through a weighted average (weights proportional to accuracy) of two regression models: the first based on the predicted peak flow at Mt Crosby (which relies on peak flow from both O' Reillys Weir and Wivenhoe), and the second based directly on the measured flow at O' Reillys Weir. Combining these two modelling options better accounted for the detrimental effect of Lockyer's Ck flow (and related turbidity) on increasing the turbidity at Mt Crosby, as opposed to using models relying exclusively on Wivenhoe flow. Finally, a temporal prediction component to the BN was provided by two separate pieces of information. First, the model predicts the lag (in hours) between the peak flow at O' Reillys Weir, and the peak turbidity in Burtons' Bridge. Alternatively, the timing of the peak turbidity at Burtons' Bridge can be also calculated by summing the predicted lag between peak flows at those two locations and the predicted lag between peak flow and peak turbidity at Burtons' Bridge. The "condition to lag" node dictates whether the lag has to be calculated (i.e., if a turbidity event is predicted at Mt Crosby) or not: if the latter, a lag of 999999 would be assigned. The lag was predicted at Burtons' Bridge due to the availability of hourly turbidity data as opposed to Mt Crosby (every 8 hours). Operationally, since the peak in turbidity at Burtons Bridge always anticipated the one at Mt Crosby by several hours or days during extreme events, this prediction would provide an early warning and extra time for proactively adjusting treatment operations.

Finally, based on an historical data analysis showing a strong nonlinear correlation between turbidity and colour (R^2 = 0.67), the latter was also predicted by the model. An estimation of the alum dosage based on Mt Crosby empirical equations reported by Seqwater, which depends on both turbidity and colour of the raw water, is also provided by the model.

Operationally, the model only requires as inputs the recorded/forecasted maximum hourly rainfalls, the peak flow at O' Reillys Weir (which can be predicted by existing Seqwater hydrological models, based on forecasted rainfall) and peak release from Wivenhoe. However, the latter, while being an input, is also one of the target parameters: operators can run scenarios with different hypothetical water releases, to assess changes in water quality downstream, and in turn optimise the amount of such outflow.

Data scarcity from critical locations (i.e. Black Snake Creek, which did not have flow data) limited the accuracy for the conductivity prediction model, based on pre-2020 only events. Nevertheless, the addition of several high conductivity events post-2020 allowed to improve underlying correlations and the structure of the final BN conductivity model (Figure 3).

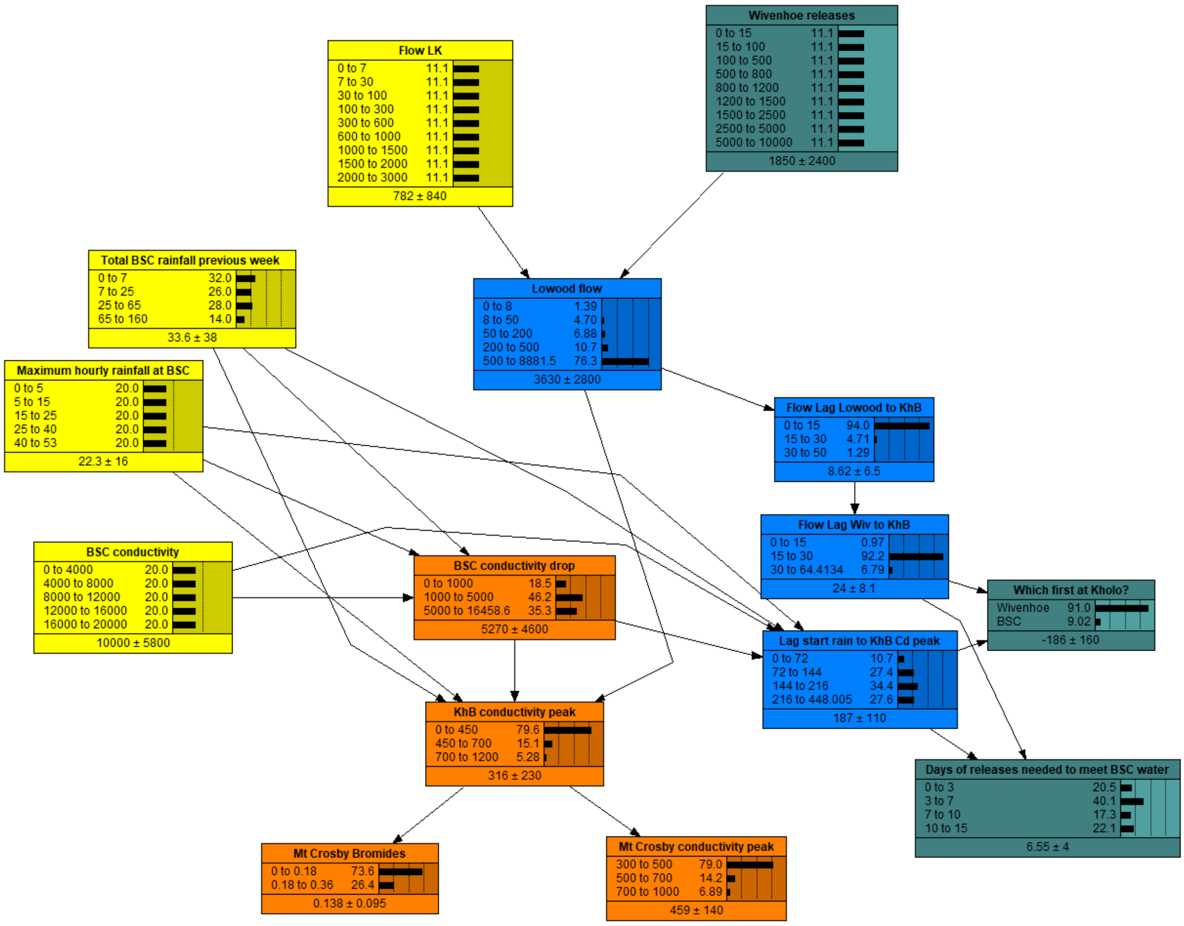

Figure 3 – Final BN for conductivity prediction; 3-state target node version.

(Yellow nodes = inputs; Orange nodes = water quality outputs; Blue nodes = flow and lags outputs; Dark green nodes = Operational input/output nodes (BSC = Black Snake Creek. KhB = Kholo Bridge. LK= Lockyer's Creek at O' Reillys Weir. Wiv=Wivenhoe).

From the data anaalysis, it was noticed that a drop in conductivity values at Black Snake Creek (BSC) was quite consistently followed by a spike in conductivity in the downstream section of the Mid-Brisbane River. This, based on stakeholder consultation, was hypothesised to be due to the runoff from wet weather events flowing into BSC and flushing high conductivity stagnant waters, resulting in drop in readings at BSC (due to the dilution with runoff water) and high readings downstream. A multivariate regression model was used as the starting point to generate the CPT for the conductivity drop at BSC. The best compromise between accuracy and complexity was achieved by having three input variables, namely (1) the weekly preceding rainfall total, (2) maximum hourly rainfall predicted for the next day, and (3) current conductivity level recorded at BSC (the higher, the higher the potential for a larger drop). The advantage of the BN and its discrete structure is that issues with the regression fit (e.g. less accurate across certain input ranges) are reflected with different uncertainty levels for specific CPT rows ("scenarios"). As a consequence, such generated CPT can also be manually refined to reflect expert input and compensate lack of data for specific scenarios. This approach was applied to this node and all similar nodes where an equation was used as starting point for CPT population.

A relatively accurate multiple linear regression model was also developed for Kholo Bridge (KhB) conductivity prediction, relying on the same rainfall inputs, but also on the predicted BSC conductivity drop (the higher, the larger the expected peak at KhB due to a likely higher flow of very high-conductivity waters from BSC) and flow from Lowood (i.e. as a proxy for cleaner waters from the upstream sections of the Mid Brisbane River). It was noticed that, for certain maximum hourly rainfall ranges, the regression was consistently under- or over-predicting. Thus, the equation and resulting CPT was adjusted appropriately in the BN. The isolated causal impact of the BSC conductivity drop on KhB conductivity was assessed with the "do-calculus" approach, by removing the "back-door paths" among the two cause-effect nodes (Pearl and Mackenzie 2018). The relationship between KhB and Mt Crosby conductivity peaks was developed directly from historical data; while for bromides, due to more limited data, an equation-to-table approach, building from a regression model, was applied. The main target variable, i.e. Mt Crosby conductivity peak, was discretised in three states, in what could be classified as "normal" (300-500 μS/cm), "moderate" (500-700 μS/cm) and "extreme" (700-1000 μS/cm) conductivity events. From an operational, "early warning" point of view, it may be enough to know whether "above normal" conditions can be expected. In this case, the accuracy of a model with only two states would be higher.

The blue variables represent estimations of time delays (e.g. from the start of a rain event around BSC and the peak in conductivity at KhB; or between the peak flow at Lowood and at KhB). These were all based on, initially, regression models developed with limited datasets. CPTs were adjusted to reflect experts' understanding of the system and the uncertainties explained above. As such, resulting posterior probabilities may be relatively uniform in some cases. This reflects the current accuracy of the model and can be updated in the future. Regardless, and importantly, it was noticed that, in most cases, the time delay between rainfall and the conductivity peak at KhB is much higher than the water travel time from Wivenhoe dam to KhB. This implies that, if a conductivity event were to occur, operators should have plenty of time to plan for potential releases from Wivenhoe dam to achieve a certain degree of dilution.

The dark green variables are those of interest to decision-makers concerned with releases from Wivenhoe dam. Different scenarios can be considered with the "Wivenhoe release" node. This will automatically run through the model and estimate which water (whether from Wivenhoe dam or BSC) would reach KhB first and also how long releases should persist for, to ensure dilution can be achieved by the time BSC waters reach KhB.

The other colour codes include orange for the water quality outputs (described before) and yellow for the required inputs. Rainfall data can be accessed from Seqwater stations (total rainfall for the past seven days) and the Australian Bureau of Meteorology (maximum hourly rainfall that can be expected over the next 24 hours in the BSC area). The predicted peak flow for O' Reillys Weir (via other existing hydrological models) should be used, as well as the latest conductivity readings from BSC.

2.5 Bayesian Network models validation

Following an evaluation of model accuracy over the calibration dataset in order to refine the models, the final BN was tested with the most recent data, used as validation dataset (2020-22). To estimate the accuracy, we used a variation of the more commonly used Brier score (Fenton and Neil 2018) as illustrated in Equation 1, and called it "Performance" or PF:

$$PF = \frac{\sum_{i=1}^{n} p_i}{n} \tag{1}$$

Where p_i is the predicted probability of the correct range for event i, and n is the total number of events in the independent test set of data. Unlike R^2 values, a PF of just over 50% can be considered acceptable, because such value is equivalent to a model predicting the correct range for all events with a probability of over 50%; given that, as a consequence, this will unavoidably be the most likely range (as no other range would possibly have a prediction probability of over 50% too), it implies that such model would be always accurate. In practice, models with an overall PF of 51% will have often higher correct probabilities for individual events, which may however be compensated with wrong predictions (hence having small p_i); however, overall, a PF > 50% would still imply, in most cases, a well-performing model, as this index is essentially quantifying the average predicted probability of the correct range.

3 Results

3.1 Data analysis

Regarding all the high flow events occurring at Mt Crosby within the analysed calibration period (2010-20), the following common features were identified. A numerical estimation of peak flow values at different monitoring stations for the high (> 800 m^3/s) flow events in the training dataset is provided in Table SM1.

1. The sum of peak flows from Wivenhoe dam and recorded at O' Reillys Weir correlates very well, expectedly, with the immediately downstream Lowood peak flow. There is usually no or minimum time delay, and the peak is slightly lower.
2. While there is always a big drop in flow recorded at the downstream Savages Crossing, the flow increases again at Burtons Bridge, at very similar peak levels to Lowood with a lag of 2-8 hours.
3. Mt Crosby flow correlates well with Burtons Bridge flow. Peak levels were in a similar range to Burtons Bridge's peaks, with delays of 3-11 hours. Figure 4 summarises the identified lags between peak flows at different locations and Mt Crosby. It can be noticed, importantly, that the lag is usually quite consistent (i.e. limited variance) up to Lockyer's Creek at O' Reillys Weir, with only a slight increase in variability moving upstream (i.e. farther away from Mt Crosby). The larger variability in the lags for Wivenhoe flow is likely due to it being a controlled release flow, often without a clearly identifiable peak.

4. The difference between peak flows at different locations have correlations with rain-dependent variables (e.g., total rain in the past 6 months; rainfall heterogeneity within the catchment).

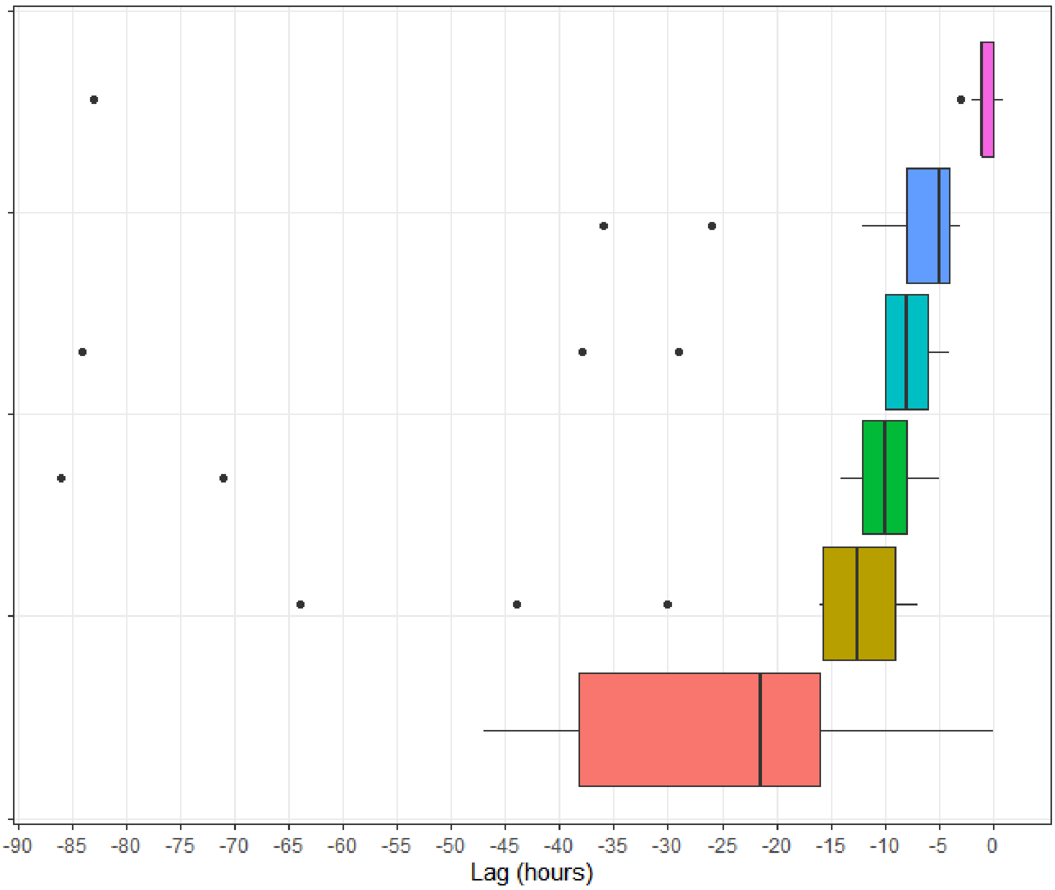

Figure 4 – Lags (hours) between flow peaks in monitoring stations along Mid Brisbane River and Mt Crosby during extreme events. Red = Wivenhoe dam, Yellow = Lockyer's Creek at O' Reillys Weir, Green = Lowood pumping station, Cyan = Black Snake Creek, Dark blue = Burtons Bridge, Pink = Kholo Bridge. Interquartile range (i.e. box) goes between lower and upper quartile, and contains median. Whisker goes from highest to lower value. Black dots = outliers.

From a water quality perspective, from the analysed data (2008-20) the following conclusions were achieved. A detailed numerical estimation of peak water quality values for all relevant events is provided in Table SM2.

1. True colour data is only available at Mt Crosby water treatment plant; however, they correlate strongly with turbidity data, which is better monitored throughout the catchment.
2. During colour peaks, $SUVA_{254}$, typically representing the more aromatic (Hua et al. 2015) and thus treatable (Shutova et al. 2016) part of the dissolved organic matter, also increases. Therefore, though the overall organic matter amount increases, the fraction recalcitrant to removal might not necessarily increase considerably.

3. For the identified high turbidity events at Mt Crosby, such turbid flow usually did not originate from the most upstream part of the Mid-Brisbane River. Both flow and turbidity incrementally increased moving downstream, highlighting potential for using Wivenhoe releases for dilution, if such events can be predicted well in advance.
4. All the Mt Crosby turbidity peaks were preceded by a peak at Burtons Bridge, whose peak value was often correlated to the value of the peak flow of the event. Given the 3-11 hours lag between the peak flows at the two locations, a prediction based on Burtons Bridge was deemed to be reliable and to provide enough warning time.
5. In contrast with Point #4, the peaks in turbidity and river flow do not match, with the lag strongly correlated with the peak flow for Burtons Bridge. Importantly, since the water quality data at Mt Crosby had a lower resolution (3 times a day to daily), the evaluation of such lag for Mt Crosby could not be accurately completed.
6. There was a strong relationship between drops in conductivity at Black Snake Ck and peaks in conductivity at Burtons Bridge. However, if a large flow was also recorded from the upper mid-Brisbane River, this acted as an effective dilution strategy, avoiding conductivity peaks at Burtons Bridge and subsequently at Mt Crosby.
7. The peaks in flow and turbidity at any given location usually did not match, however from hysteresis analysis there was no sufficient clarity on such behaviours (mainly due to limited/incomplete data).

The data analysis revealed that flow predictions could achieve higher accuracy than water quality predictions, mainly due to better data availability and arguably a simpler prediction modelling task (as water quality is also affected by complex chemical and biological processes). The data analysis also allowed the conceptualisation of the system and the identification of key variables and their correlations (Figure 5), which informed the subsequent BN conceptualisation and CPTs population.

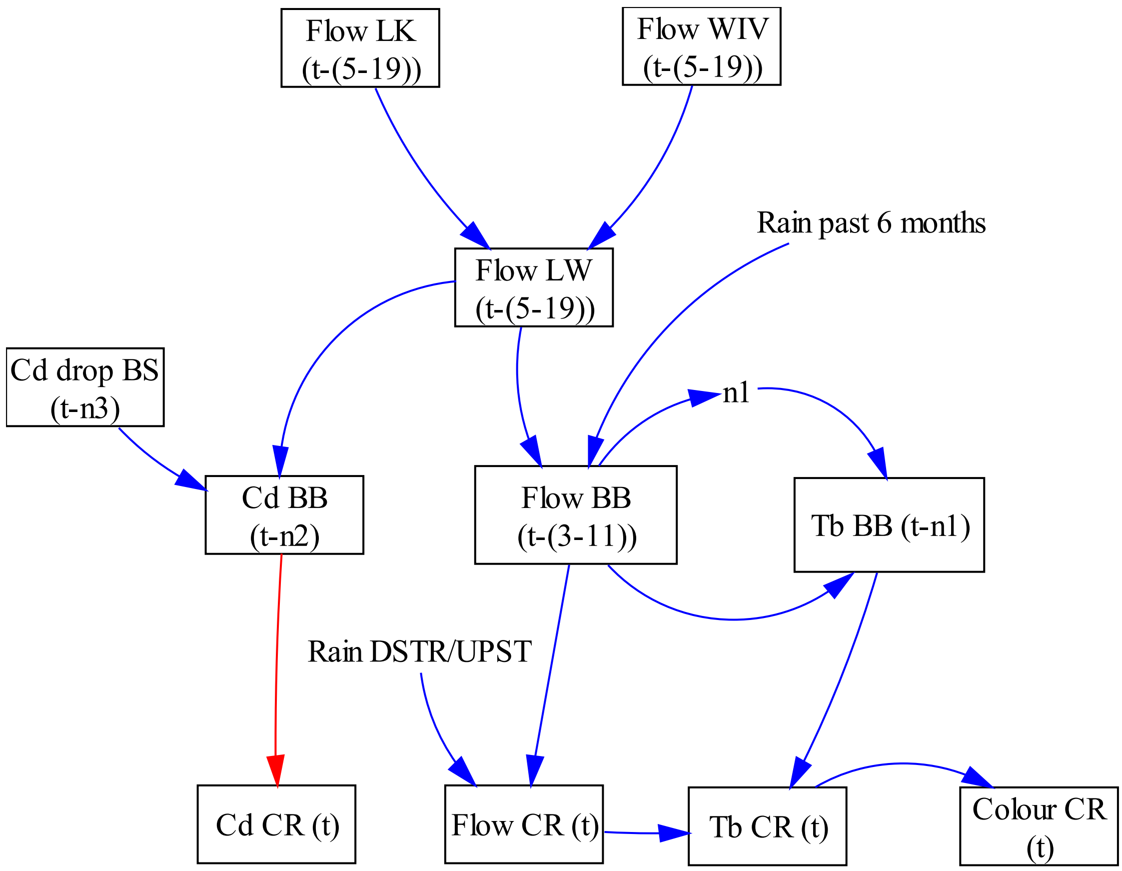

Figure 5 – Conceptual model for Mt Crosby water quality/quantity prediction. Cd= conductivity, Tb=turbidity, CR=Mt Crosby, BB=Burtons Bridge, BS=Black Snake Ck, LW=Lowood, LK=Lockyer's Ck at O' Reillys Weir, WIV=Wivenhoe, n=lag time. Red arrows = not evident correlation from data though expected

3.2 Bayesian network accuracy

Model predictions were highly accurate compared to observed flows, turbidity peaks and lags for the identified events in the calibration dataset (Supplementary Material Tables SM3 to SM5). All model components performed well, with under- and over-estimations usually limited to the next immediate interval. There were a limited number of poor predictions (e.g. 10% for turbidity and <3% for lags predictions), for events where it is hypothesised that turbidity might have originated from smaller tributaries than Lockyer's Creek; however, it was not possible to verify these assumptions due to the lack of data at those locations, or of calibrated process-based model simulations, which could further refine the BN in the future if available.

With regards to further validation of the turbidity prediction model, for most of new 2021-22 events there was no flow data available for Lockyer Ck at O' Reillys Weir. As a result, predictions were far more uncertain across different potential turbidity ranges due to the lack of information of one of the key inputs, which led to the simulations to run on the assumption of a uniform probability distribution for O' Reillys Weir peak flow. However, for the three identified events with flow data fully available, the likely turbidity range was correctly predicted. All the reported events codes were assigned sequentially by the event identification algorithm (Table 1).

Table 1 – Accuracy assessment, BN Tb model (test set events)

Event	Peak Flow Wivenhoe [m^3/s]	Peak Flow Lockyer's' Ck at O' Reillys Weir [m^3/s]	Tb peak at Mt Crosby [NTU]	Most likely Tb prediction range [NTU]
531-1	350	51.0	50	30-70 (29.5%)
541-1	375	88.4	100	100-400 (36.1%)
541-2	375	380.7	200	100-400 (43.7%)

The validation performance, overall conductivity prediction results and predicted values for each model sub-component showed very good agreement in most cases (Supplementary Material Tables SM6 to SM8). The *PF* (quantified as per Equation 1) of each component was always higher than 50%, and specifically was as follows:

- <u>Predicted conductivity drop at BSC: 68.3%</u>
  Often, prediction errors were due to either the observed value being just above the threshold of the predicted range (e.g., event 329: predicted between 1000-5000 μS/cm, observed 5948 μS/cm) or in a mid-range which the model could not predict "sharply" but it still assigned a quite large likelihood of occurrence (e.g. event 307-3: 50%/50% prediction for less than 1000 μS/cm and up to 5000 μS/cm, observed 2890 μS/cm). The only evident errors were related to atypical events. Event 325 was characterised by moderate rainfall and minimum flow from the Mid-Brisbane River, leading the model to predict a moderate drop, but there was no observed drop in the data; event 541-1 was instead characterised by very heavy rainfall and only limited flow from the Mid-Brisbane River, in line with other events which were correctly predicted as extreme drops; however in this case, only a minor drop (1164 μS/cm) occurred (Table SM6). This could be due to unmonitored variables related to e.g. more localised rainfall, saturation and runoff factors.
- <u>Predicted conductivity peak at KhB: 67.7%</u>
  Errors in this component usually were due to error propagation from the previous modelling components. When assessing the individual performance of this component, i.e., assuming perfect predictions for the BSC conductivity drop (Table SM7), *PF* increased to 72.5%. The only wrong prediction was evident in event 329-1, where a

"moderate" peak was predicted (450-700 μS/cm) but, despite some flow from the Mid-Brisbane River, which typically dilutes outflowing BSC conductivity, an extreme peak value (i.e. 1034 μS/cm) was observed. All other extreme events were correctly predicted. Event 541-3 was just above (714 μS/cm) the range which was predicted as the most likely (450-700 μS/cm). The isolated causal impact of the BSC conductivity drop on KhB conductivity was assessed to be strong: for instance the probability of high (> 700 μS/cm) conductivity peak at KhB in case of high (> 5,000 μS/cm) BSC conductivity drop was still 6% under the "do" scenario (e.g. after cutting the backdoor paths and removing the effect of the confounder "Maximum hourly rainfall at BSC"), though in the uncut BN this was 11%. In the opposite, "low-low" case, the "do" scenario leads to a 82.3% probability of low (< 450 μS/cm) conductivity peak at KhB compared to 91.6% of the uncut BN, thus displaying a strong causal role in both cases.

- <u>Predicted bromides at Mt Crosby: 68.4%</u>
  The choice of the threshold for the two acceptable/nonacceptable ranges (i.e., 0.18 mg/L), based on operational reasons, affected the individual model performance (Table SM8) because the majority of data was within the same, higher, range (i.e., > 0.18 mg/L). While a data-based CTP creation led to a very accurate bromide model based on available data, it was decided to rely on a regression model as starting point, to allow extrapolation towards potential scenarios with lower bromide concentrations. While this affected the performance for some scenarios, it can be considered a more robust prediction for future events. Alternatively, the thresholds values can be changed, or further data in the lower ranges, if made available, can be used to refine the model.
- <u>Predicted conductivity at Mt Crosby: 58.5%</u>
  Similar to aforementioned components, the performance was mainly affected by error propagating from other predicted nodes. When only the *PF* of this component was assessed, i.e. assuming perfect predictions of conductivity at KhB (Table SM8), this increased to 75.3%. Remaining errors were minimal, mainly due to observed values close to the mid-range threshold of 500 μS/cm. Even when looking at the overall performance, only one extreme event (event 329-1, 909 μS/cm) was not correctly predicted. As explained, however, this is also due to having this variable discretised into three states (i.e. normal, moderate, extreme). If, operationally, the main modelling goal would be knowing if an "above-normal" (i.e. > 500 μS/cm) event is expected, the aforementioned event would have been correctly (p=83.6%) predicted too.

Due to the limited number of relevant events, the performance of the flow's time delays components was not evaluated on an independent set of data, as this would have been too small to provide a meaningful assessment. The model relies on overall relationships observed across all the available dataset. Further work to reduce the uncertainty of this model component, requires complete flow data from future events, or simulations from existing, reliable process-based hydrologic models.

4 Discussion

As shown in Results, peak and timing of turbidity were predicted accurately: the correct peak turbidity range was predicted for 87% of analysed events, and the peak time delay range was correctly predicted for >97% of analysed events. Few exceptions were related to "atypical" events where turbidity might have originated from other unmonitored areas in the catchment (e.g., smaller tributaries) compared to the typical source.

By using the 2021-22 data as independent test set the overall high accuracy of the flow/turbidity model was confirmed, and the conductivity model also predicted the correct range in the majority of cases. A robust, reliable prediction of water travel time from Wivenhoe dam to the downstream Kholo Bridge was not possible due the limited amount of high-quality data and peak events. However, related predictions, whilst often uncertain, are provided by the model. Data-driven water travel time prediction with limited data is difficult and not often attempted (few exceptions include Jobson (1997) and (Jobson 2000)), thus the proposed approach, currently providing probabilistic predictions with large uncertainty but that can be refined in the future with further data collected, provides a different, novel attempt which adds to the limited relevant literature. In addition to water quality predictions, the model has a number of variables allowing the user to check the effects of different potential releases (flow, duration) from Wivenhoe dam on downstream water quality. Decision support systems, dealing with uncertainty and based on scenario analysis, have been developed in the past (e.g. Pallottino et al. (2005)) but they typically focused on water quantity only; when water quality was also considered (see Candido et al. (2022) for a recent, comprehensive review)), often the models were process-based and did not deal with case studies with diverse data features and large uncertainty, such as in this application.

The models rely on predicted peak flow at certain locations, which assumes the ability of the operators to run existing hydrological models to predict such peak flow (or at least, the most likely flow range) based on predicted rainfall amount and spatial variability. Hydrological models would be also important to run hypothetical events or fill missing data for historical events. This would help improve the accuracy for certain model components, in particular flow lags, and thus to obtain a better understanding of dilution effectiveness from Wivenhoe dam flow.

In addition, better use/maintenance of existing sensors/stations, would improve data collection and the future potential for more accurate data-driven models for the Mid-Brisbane River. While comprehensive modelling studies are typically performed for the spatial optimisation of water quality sensors (Jiang et al. 2020), this study highlighted, as a co-benefit, potential improvement options for the location of the monitoring stations. Despite its strategic location, the O' Reillys Weir station seems to be particularly problematic, with missing data being the norm. Ways to improve the reliability and reduce issues with data collection at this station should be considered. On the other hand, the presence of multiple flow/water quality stations between O' Reillys Weir and Mt Crosby seems redundant, and it is recommendable to instead improve the monitoring coverage of critical tributaries.

As previously mentioned, BNs present a number of potential limitations. For instance, variables are not continuous, but discretised in a number of ranges (Uusitalo 2007). While current ranges were selected to be operationally useful and are appropriate to fulfil the model objectives, future extra data can be used to increase the number of intervals considered by the models.

While the model can be used to assess potential water quality impacts due to upcoming wet weather, and to evaluate how Wivenhoe dam flows can help alleviate such poor water quality events via dilution, it is recommended to use this model jointly with other modelling tools to support decisions on Wivenhoe dam releases. This is due to other factors affecting the decision-making of dam releases such as the marginal value of water (Hoffmann et al. 2006, Khadem et al. 2018) to be released, flood risks, and environmental impacts. Future work should integrate these other components to provide a holistic decision about Wivenhoe dam flow releases. With one of the main features of BNs being their ability to deal with different types of data and interdisciplinary problems, an updated BN able to concurrently estimate all the costs (e.g. value of that water, depending on drought conditions) and benefits (e.g. avoided extra treatment costs) of water releases from Wivenhoe dam and in turn provide a comprehensive evaluation and prediction of the optimal release would be valuable.

Other modelling techniques were developed (Bertone et al. 2020); however, the final BN modelling choice was justified as being an appropriate compromise between accuracy, uncertainty representation, simulation runtime and user friendliness, the latter being crucial to ensure future deployment by stakeholders. While applied to a specific location and target optimisation problem, such data-driven BN approach can be applied to any environmental management problem where a combination of large datasets and incomplete/missing data are available, and where user-friendliness is sought after to ensure its deployment.

ConclusionsA number of Bayesian Network models were developed, based on available data and correlations found through data analysis, in order to predict flow, turbidity, colour, bromides and conductivity in the raw water of a drinking water treatment plant, with related peak flow time delays from the upstream part of the catchment. Over an independent test set of data, the flow and turbidity predictions proved to be highly accurate, with conductivity and bromides also predicted within the correct range in the majority of cases.

The model has a graphical user-friendly interface, which facilitates its deployment by relevant stakeholders. The main goal of this model is to use its predictions under different hypothetical scenarios, to understand the ideal release of water from a large upstream reservoir which minimises water quality issues at the treatment plant. Such prediction can be used by decision-makers in combination with other available information and priorities (e.g. the value of water released, flood mitigation), to take a more informed and proactive decision in relation to the combined dam/water treatment plant system operations.

Due to the flexibility of the model, future work can focus on integrating newly available data (both monitoring data or process-based model outputs) to refine model accuracy, and potentially on expanding the model scope to account for other important decision-making considerations.

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REFERENCES

Ali, Z., Hussain, I., Grzegorczyk, M.A., Ni, G., Faisal, M., Qamar, S., Shoukry, A.M., Wahab Sharkawy, M.A., Gani, S. and Al-Deek, F.F. (2020) Bayesian network based procedure for regional drought monitoring: The Seasonally Combinative Regional Drought Indicator. Journal of Environmental Management 276, 111296.

Barton, D.N., Kuikka, S., Varis, O., Uusitalo, L., Henriksen, H.J., Borsuk, M., de la Hera, A., Farmani, R., Johnson, S. and Linnell, J.D.C. (2012) Bayesian networks in environmental and resource management. Integrated Environmental Assessment and Management 8(3), 418-429.

Bertone, E., Juncal, M.L., Nguyen, K. and Kufeji, D. (2020) Data-driven modelling of high flow-related poor water quality events in the Mid-Brisbane River, p. 34.

Bertone, E., O' Halloran, K., Stewart, R.A. and de Oliveira, G.F. (2017) Medium-term storage volume prediction for optimum reservoir management: A hybrid data-driven approach. Journal of Cleaner Production 154, 353-365.

Bertone, E., Purandare, J. and Durand, B. (2019) Spatiotemporal prediction of Escherichia coli and Enterococci for the Commonwealth Games triathlon event using Bayesian Networks. Marine pollution bulletin 146, 11-21.

Bertone, E., Stewart, R.A., Zhang, H., Bartkow, M. and Hacker, C. (2015) An autonomous decision support system for manganese forecasting in subtropical water reservoirs. Environmental Modelling & Software 73, 133-147.

Candido, L.A., Coêlho, G.A.G., de Moraes, M.M.G.A. and Florêncio, L. (2022) Review of Decision Support Systems and Allocation Models for Integrated Water Resources Management Focusing on Joint Water Quantity-Quality. Journal of Water Resources Planning and Management 148(2), 03121001.

Carberry, W.L., Deffenbach, J.R., Schlender, G., Jensen, A., Wetzler, T.F. and DeWalle, F.B. (1984) The Leavenworth, Washington Case: Environmental concerns with a water treatment plant failure. Journal of Environmental Health, 10-14.

Chen, S. and Pollino, C. (2012) Good practice in Bayesian network modelling. Environmental Modelling & Software 37, 134-145.

Choo, F., Zamyadi, A., Stuetz, R.M., Newcombe, G., Newton, K. and Henderson, R.K. (2019) Enhanced real-time cyanobacterial fluorescence monitoring through chlorophyll-a interference compensation corrections. Water Research 148, 86-96.

Clancy, J.L. (2000) Sydney's 1998 water quality crisis. Journal-American Water Works Association 92(3), 55-66.

Colasimone, D. (2022) Why does Brisbane's water taste like dirt?, https://www.abc.net.au/news/2022-01-14/brisbane-water-disgusting-taste/100754040.

de Oliveira, G., Bertone, E., Stewart, R., Awad, J., Holland, A., O'Halloran, K. and Bird, S. (2018) Multi-Parameter Compensation Method for Accurate In Situ Fluorescent Dissolved Organic Matter Monitoring and Properties Characterization. Water 10(9), 1146.

Evans, C. and Davies, T.D. (1998) Causes of concentration/discharge hysteresis and its potential as a tool for analysis of episode hydrochemistry. Water Resources Research 34(1), 129-137.

Farhadian, M., Haddad, O.B., Seifollahi-Aghmiuni, S. and Loáiciga, H.A. (2015) Assimilative Capacity and Flow Dilution for Water Quality Protection in Rivers. Journal of Hazardous, Toxic, and Radioactive Waste 19(2), 04014027.

Fenton, N. and Neil, M. (2018) Risk assessment and decision analysis with Bayesian networks, Crc Press.

Ferreira, D.M. and Fernandes, C.V.S. (2022) Integrated water quality modeling in a river-reservoir system to support watershed management. Journal of Environmental Management 324, 116447.

Hashemi Monfared, S.A., Dehghani Darmian, M., Snyder, S.A., Azizyan, G., Pirzadeh, B. and Azhdary Moghaddam, M. (2017) Water Quality Planning in Rivers: Assimilative Capacity and Dilution Flow. Bulletin of Environmental Contamination and Toxicology 99(5), 531-541.

Hoffmann, M., Worthington, A. and Higgs, H. (2006) Urban water demand with fixed volumetric charging in a large municipality: the case of Brisbane, Australia. Australian Journal of Agricultural and Resource Economics 50(3), 347-359.

Hua, G., Reckhow, D.A. and Abusallout, I. (2015) Correlation between SUVA and DBP formation during chlorination and chloramination of NOM fractions from different sources. Chemosphere 130, 82-89.

Jiang, J., Tang, S., Han, D., Fu, G., Solomatine, D. and Zheng, Y. (2020) A comprehensive review on the design and optimization of surface water quality monitoring networks. Environmental Modelling & Software 132, 104792.

Jobson, H.E. (1997) Predicting travel time and dispersion in rivers and streams. Journal of Hydraulic Engineering 123(11), 971-978.

Jobson, H.E. (2000) Estimating the variation of travel time in rivers by use of wave speed and hydraulic characteristics, US Department of the Interior, US Geological Survey.

Khadem, M., Rouge, C., Harou, J.J., Hansen, K., Medellin-Azuara, J. and Lund, J. (2018) Estimating the economic value of interannual reservoir storage in water resource systems. Water Resources Research 54(11), 8890-8908.

Khan, S.J., Deere, D., Leusch, F.D., Humpage, A., Jenkins, M. and Cunliffe, D. (2015) Extreme weather events: Should drinking water quality management systems adapt to changing risk profiles? Water Research 85, 124-136.

Khan, S.J., Deere, D., Leusch, F.D., Humpage, A., Jenkins, M., Cunliffe, D., Fitzgerald, S.K. and Stanford, B.D. (2017) Lessons and guidance for the management of safe drinking water during extreme weather events. Environmental Science: Water Research & Technology 3(2), 262-277.

Koffler, D., Gauster, T. and Laaha, G. (2016) lfstat: Calculation of Low Flow Statistics for Daily Stream Flow Data. R package version 0.9.4. https://CRAN.R-project.org/package=lfstat.

Lambert, T., Teodoru, C.R., Nyoni, F.C., Bouillon, S., Darchambeau, F., Massicotte, P. and Borges, A.V. (2016) Along-stream transport and transformation of dissolved organic matter in a large tropical river. Biogeosciences 13(9), 2727-2741.

Lee, C.-S., Lee, Y.-C. and Chiang, H.-M. (2016) Abrupt state change of river water quality (turbidity): Effect of extreme rainfalls and typhoons. Science of The Total Environment 557, 91-101.

Loos, S., Shin, C.M., Sumihar, J., Kim, K., Cho, J. and Weerts, A.H. (2020) Ensemble data assimilation methods for improving river water quality forecasting accuracy. Water Research 171, 115343.

Marcot, B.G., Holthausen, R.S., Raphael, M.G., Rowland, M.M. and Wisdom, M.J. (2001) Using Bayesian belief networks to evaluate fish and wildlife population viability under land management alternatives from an environmental impact statement. Forest Ecology and Management 153(1), 29-42.

Mayfield, H.J., Bertone, E., Smith, C. and Sahin, O. (2019) Use of a structure aware discretisation algorithm for Bayesian networks applied to water quality predictions. Mathematics and Computers in Simulation.

Meyer, A.M., Klein, C., Fünfrocken, E., Kautenburger, R. and Beck, H.P. (2019) Real-time monitoring of water quality to identify pollution pathways in small and middle scale rivers. Science of The Total Environment 651, 2323-2333.

Pallottino, S., Sechi, G.M. and Zuddas, P. (2005) A DSS for water resources management under uncertainty by scenario analysis. Environmental Modelling & Software 20(8), 1031-1042.

Park, Y., Lee, H.K., Shin, J.-K., Chon, K., Kim, S., Cho, K.H., Kim, J.H. and Baek, S.-S. (2021) A machine learning approach for early warning of cyanobacterial bloom outbreaks in a freshwater reservoir. Journal of Environmental Management 288, 112415.

Pearl, J. (1988) Probabilistic reasoning in intelligent systems: networks of plausible inference, Morgan kaufmann.

Pearl, J. and Mackenzie, D. (2018) The book of why: the new science of cause and effect, Basic books.

Rigosi, A., Hanson, P., Hamilton, D.P., Hipsey, M., Rusak, J.A., Bois, J., Sparber, K., Chorus, I., Watkinson, A.J. and Qin, B. (2015) Determining the probability of cyanobacterial blooms: the application of Bayesian networks in multiple lake systems. Ecological applications 25(1), 186-199.

Sahin, O., Siems, R.S., Stewart, R.A. and Porter, M.G. (2016) Paradigm shift to enhanced water supply planning through augmented grids, scarcity pricing and adaptive factory water: a system dynamics approach. Environmental Modelling & Software 75, 348-361.

Sahin, O., Stewart, R.A. and Porter, M.G. (2015) Water security through scarcity pricing and reverse osmosis: a system dynamics approach. Journal of Cleaner Production 88(0), 160-171.

Shutova, Y., Baker, A., Bridgeman, J. and Henderson, R. (2016) On-line monitoring of organic matter concentrations and character in drinking water treatment systems using fluorescence spectroscopy. Environmental Science: Water Research & Technology 2(4), 749-760.

Silva, G.M.e., Campos, D.F., Brasil, J.A.T., Tremblay, M., Mendiondo, E.M. and Ghiglieno, F. (2022a) Advances in Technological Research for Online and In Situ Water Quality Monitoring—A Review. Sustainability 14(9), 5059.

Silva, G.M.e., Garcia, J.A., Garitta, J.d.A., Cunha, D.G.F., Finkler, N.R., Mendiondo, E.M. and Ghiglieno, F. (2022b) Smartphone-based spectrometry system as a prescreening assessment of copper and iron for real time control of water pollution. Journal of environmental management 323, 116214.

Somma, A., Bonilla, S. and Aubriot, L. (2021) Nuisance phytoplankton transport is enhanced by high flow in the main river for drinking water in Uruguay. Environmental Science and Pollution Research, 1-14.

Uusitalo, L. (2007) Advantages and challenges of Bayesian networks in environmental modelling. Ecological Modelling 203, 312-318.

Wang, X., Zhang, H., Bertone, E., Stewart, R.A. and Hughes, S.P. (2022) Hybrid three-dimensional modelling for reservoir fluorescent dissolved organic matter risk assessment. Inland Waters, 1-14.

Yu, R. and Zhang, C. (2021) Early warning of water quality degradation: A copula-based Bayesian network model for highly efficient water quality risk assessment. Journal of Environmental Management 292, 112749.