Biosciences and Food Technology Discipline, School of Science, STEM College, RMIT University

Revolutionising Monitoring of Waterway Health in Merri Creek

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Galada Tamboore, Merri Creek *Image: C. Leigh, 2020*

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Executive Summary

This project aimed to assist agencies tasked with looking after Melbourne's waterways and improving stream health by helping them to better monitor, understand and manage stream water-quality, specifically turbidity. Managers need to know when and where turbid water events occur in streams as soon as possible in order for them to make informed and timely decisions on how to pinpoint, prevent and mitigate such disturbances. To this end, we have installed high-frequency turbidity, light and temperature sensors in two sites along Merri Creek of the Yarra River catchment in Melbourne's north-east suburbs in collaboration with the City of Whittlesea, City of Moreland, and the Merri Creek Management Committee. The in-situ sensors have been logging high-frequency data since December 2020. Telemetered turbidity sensors are expensive and thus prohibitive to distribute widely throughout stream networks. However, light and temperature sensors are relatively very low cost. We analysed the sensor data to explore the turbidity, light and temperature dynamics in Merri Creek and whether the light and temperature sensor data have the potential to act as individual or combined surrogates of turbidity.

However, the ability to perform such an analysis was constrained by the presence of anomalies and missing data within the turbidity time series. To overcome this, our efforts were redirected to predicting turbidity by creating a model based on publicly available data of known good quality using variables as similar as possible to those measured by the sensors: mean turbidity and the covariates maximum air temperature and total global solar exposure, all measured on a daily timestep, along with total daily rainfall and mean daily water level given their availability and the likely relationships that these latter two covariates have with in-stream turbidity.

The model where daily rainfall and daily water level were used as predictors provided the most accurate forecasts of turbidity. This accuracy was maintained when running a time-series cross validation process over 28 folds, predicting turbidity 7-days ahead in each fold. The model is expected to capture sudden spikes in turbidity associated with high rainfall and water level.

Solar exposure and air temperature data also showed some potential in predicting turbidity, indicating that low-cost light and temperature sensors may still hold promise as potential surrogate indicators for in-stream turbidity. Correspondence of light data with continuous turbidity data may help to reveal stronger relationships between underwater light levels and turbid and/or pollutant-rich discharges into and through stream networks.

We see benefit in continuing to monitor turbidity along with light and temperature data so that models can be refined, and anomalies can be better detected. Working on anomaly detection in the turbidity data is also a potential avenue for future research that may help to enhance the benefits that can be derived from the use of sensor-based monitoring in Merri Creek and other waterways in the region.

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1. Background

1.1 The project and objectives

This project developed out of an opportunity to bring practitioners working across government, industry, community and academia in the water space together to help identify needs, and collaborative opportunities to address those needs, regarding water-resource monitoring and management using emerging technologies.

The City of Whittlesea is interested in developing a network of sensors to help monitor and raise awareness of waterway health – especially in Merri Creek, which flows through their municipality.

The City of Whittlesea agreed to participate in this project and provide funds to support a 12-month trial of one turbidity sensor, along with the installation and retrieval of the turbidity sensor and two temperature-light ('Hobo') sensors, plus the remote dashboard monthly access to the data at the selected Merri Creek site.

The objectives of this project are therefore to develop and trial a pilot water-quality monitoring project at Galada Tamboore, a site along Merri Creek, focussing on the remote collection of high-frequency light, temperature and turbidity data from in-situ sensors.

1.2 Merri Creek

Merri Creek flows south from the Great Dividing Range for about 60 km to its confluence with the Yarra River at Dights Falls in Abbotsford, Victoria. Water along some channels is now piped and some wetlands and swampy areas have been drained and converted into channels or drains. Much of the catchment has been cleared of its native grassland and woodland. Land use in the catchment is mainly rural, but does change from upstream to downstream, going from pastoral to industrial to urban and residential.

Several ecologically sensitive restoration and revegetation projects are being undertaken in the catchment by the Wurundjeri people, local governments including the City of Whittlesea, and other organisations such as the Merri Creek Catchment Committee (https://www.mcmc.org.au/parkland-management). The endangered growling grass frog, *Litoria raniformis*, has been heard in several places along the creek.

1.3 Water quality monitoring: Turbidity, light and temperature

In our efforts to analyse water quality at Merri Creek, we direct our analysis towards its turbidity. Turbidity is caused by particulate matter that may be suspended or settled in water, the presence of which gives water a cloudy or murky appearance. High turbidity may indicate the presence of substances or pollutants that adversely affect ecological productivity and quality, making the water intrinsically harmful for supporting organisms that rely on it. Turbidity may be caused by natural factors such bioturbation, or human-induced factors such as agricultural or industrial work that accelerates sedimentation and erosion (Leigh et al., 2019). It is commonly measured in Nephelometric Turbidity Units (NTU) using electronic turbidity meters that record light passing through water, Particles present in the water scatter light such that the more particles present, the higher the turbidity. Our work focuses on high-frequency NTU measurements recorded since December 2020 by an electronic turbidity meter installed underwater at the Galada Tamboore site in Merri Creek (Figure 1). A second turbidity meter was also installed at a site further downstream, at North Fitzroy (Figure 1), in collaboration with the City of Moreland, and we refer briefly to the turbidity data from that site also in this report.

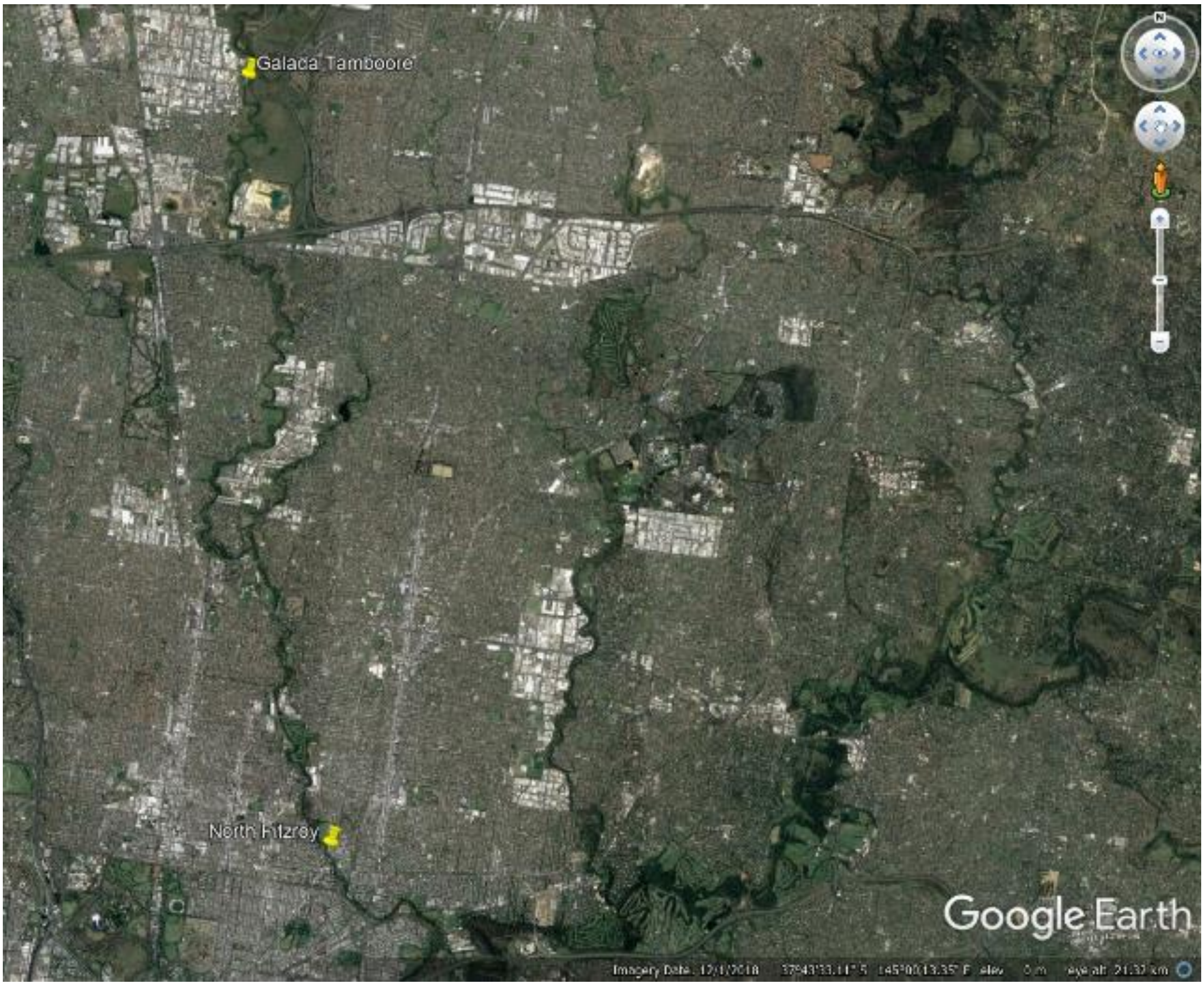

Figure 1: Location of turbidity sensors deployed in Merri Creek at Galada Tamboore and North Fitzroy, in the northeastern suburbs of Melbourne, Victoria.

Despite reasonable accuracy of measurement, electronic turbidity meters are can be costly in terms of setup and maintenance. A possible alternative to using NTU sensors, is to develop a model that can predict turbidity using high-quality covariate data. Such data can be acquired from other, lower-cost sensors collocated in the monitoring sites, and/or from publicly available data sources. Such models can also be used to aid in validating the sensor measurements. There are numerous potential covariates of turbidity in water. For Merri Creek, we have focused on investigating the relationships between turbidity and rainfall, water level, light, solar exposure and temperature.

Heavy rainfall affects turbidity via erosion and runoff, thereby increasing sediment loads in streamflow, which itself rises together with water level, and leads to resuspension of sediments (Leigh et al., 2019). Hence, sudden peaks in turbidity are often expected following periods of high rainfall and increase in water levels. Underwater light can be measured in Lux, a unit that measures illuminance when light passes through or hits a surface. Therefore, we may expect high turbidity when we have low Lux measurements, given that less light passes through cloudy waters relative to clear waters. However, light is also affected by other factors, such as time of day and amount of cloud cover and shading of the stream from vegetation or other structures on the banks.

As such, the relationship between underwater light and turbidity may not be as straight forward as that between rainfall, discharge (or water level) and turbidity. Water temperature is commonly measured at the same time as other water quality variables by sensors that target those other variables. Thus, we also included temperature in the suite of covariates investigated for their potential to predict turbidity. However, suspended solids also absorb more heat than water molecules when exposed to solar radiation. Hence, high water temperature and solar exposure may also be associated with high turbidity as suspended particles raise water temperatures more than water molecules do when exposed to sunlight (Paaijmans et al. 2008).

2. Methods

2.1 Sensor data: Turbidity, light and water temperature

One Observator turbidity sensor was installed by Bio2Lab (https://bio2lab.com.au/) at Galada Tamboore and another at the North Fitzroy site on 14th December 2020, with each set up to record turbidity (NTU) every 2 minutes. In addition to the turbidity sensors, two HOBO (Pendant MX2202 - Temperature/Light Bluetooth Data Logger) sensors measuring both light (lux) and temperature (°C) were also deployed at each site, in the same location as the turbidity sensor. The HOBO sensors recorded underwater illuminance (lux) and temperature (°C) every hour, commencing 14th December 2020.Two HOBO sensors were installed at each site in order to determine if these low-cost sensors recorded comparable and therefore reliable data.

To date, turbidity data collected from Galada Tamboore span a 6-month period with some gaps (Figure 2) due to missing observations or incorrect measurements due to technical issues with the probes and/or the telecommunications software (pers. comm., Steve Marshall, Bio2Lab). Data collected from the North Fitzroy site was limited to a period of 3 months from December 2020 (sensor retrieved 17th March 2021), also with several periods of missing or anomalous data (Figure 2). Data collected from the HOBO sensors at Galada Tamboore did not have any gaps and comprised hourly underwater light and temperature data available until 2nd September 2021 when the turbidity sensor was removed for maintenance along with the two HOBO sensors; however the HOBO sensors at North Fitzroy did have periods of anomalous data associated with storm disturbance and removal of the sensors during maintenance of the turbidity sensor at that site (Figures 3-4). Another two HOBO sensors were deployed at Galada Tamboore on 7th September 2021, just upstream and downstream of the original deployment site, and continue to record light and temperature data there every hour. Bio2Lab will notify the team when the Galada Tamboore turbidity sensor is ready to be re-deployed and have indicated that they will continue to monitor turbidity until a full 12 months' worth of data have been provided.

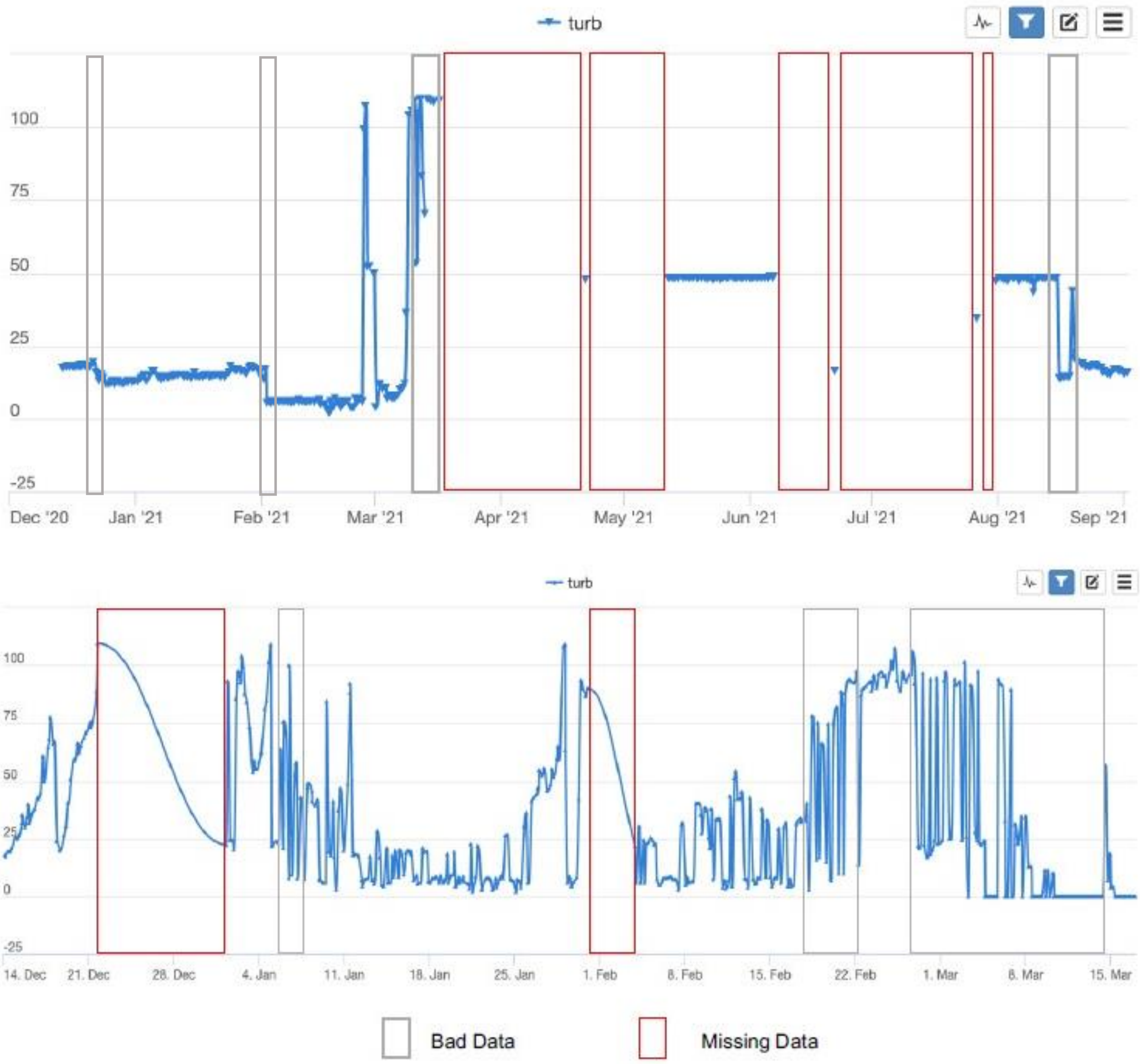

Figure 2: Turbidity (NTU) recorded at Galada Tamboore (upper plot) and North Fitzroy (lower plot). Periods of missing data are outlined in red boxes. Examples of data of potential bad or uncertain quality are outlined in grey boxes; these include, for example, sudden and large negative fluctuations between subsequent time points (typically, high turbidity tapers off gradually, as opposed to falling drastically in value between subsequent time points).

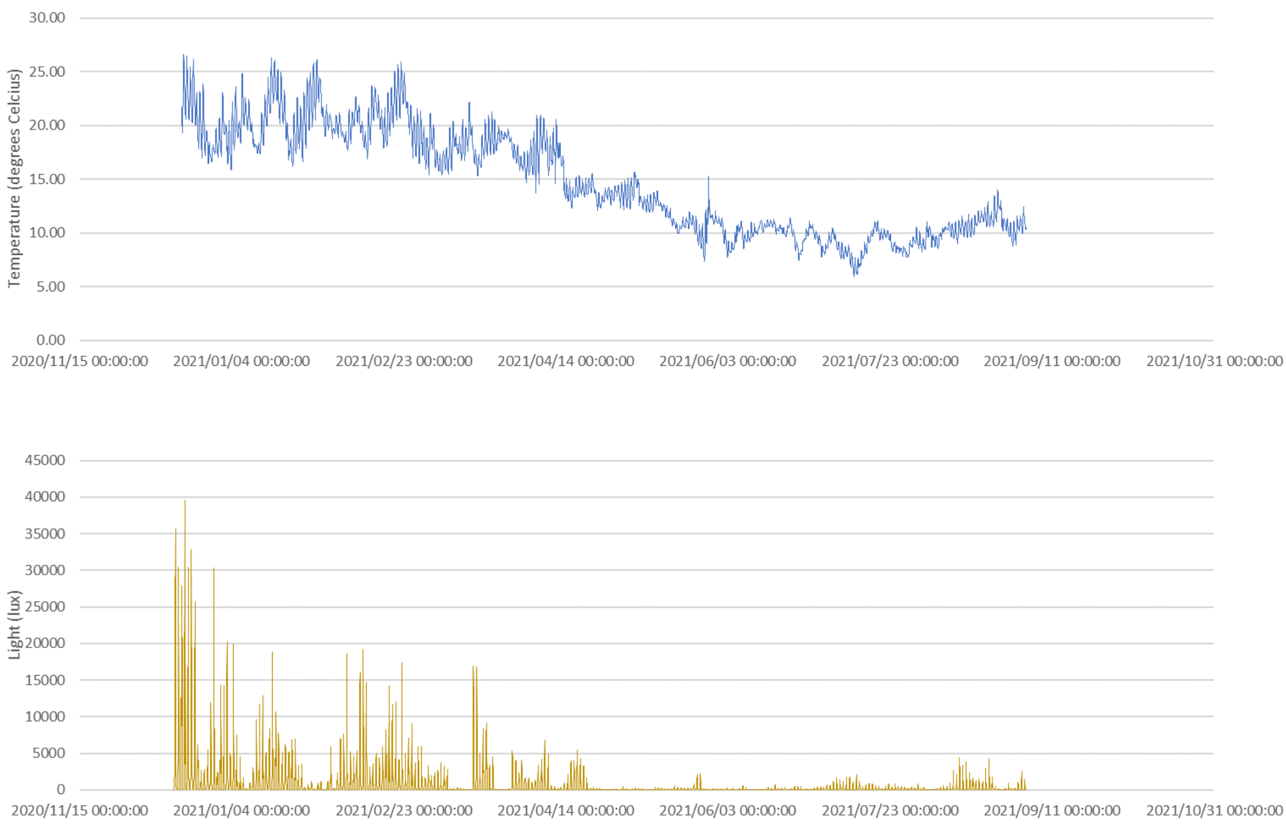

Figure 3: Water temperature (°C; upper plot) and light (lux; lower plot) recorded at Galada Tamboore from 14th December 2020 to 2nd September 2021.

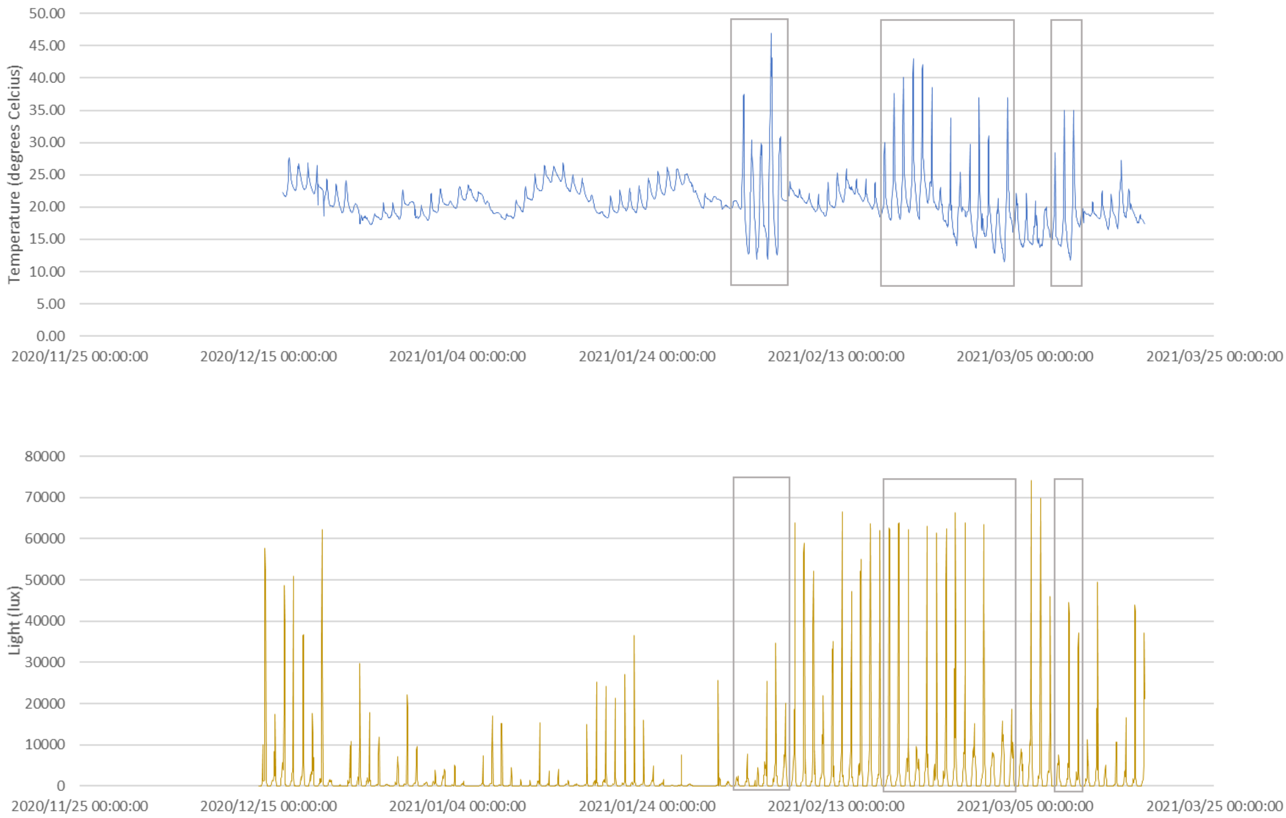

Figure 4: Water temperature (°C; upper plot) and light (lux; lower plot) recorded at North Fitzroy from 14th December 2020 to 17th March 2021. Data likely to be of bad or uncertain quality are outlined in grey boxes, these capture periods when temperatures were recorded as being above 30 °C, most likely during periods when the sensors were not submerged in the water (e.g. during turbidity sensor maintenance times).

2.2 Publicly available data: rainfall, water level, solar exposure and temperature

Hourly turbidity and water level data for Merri Creek, for the years 2013-2014, was sourced online from the Water Measurement Information System data portal (Department of Environment Land Water & Planning, 2021). This is one of the only publicly available datasets on turbidity for Galada Tamboore that consists of good quality values for a full year. Mean rainfall (mm), maximum air temperature (°C) and total global solar exposure data (MJ/m^2) were sourced online from the Bureau of Meteorology (2014), the minimum frequencies of which were daily. The rainfall data was recorded at the Somerton Epping weather station, the nearest upstream station to Galada Tamboore, while the temperature and total solar exposure data was recorded at Melbourne Airport, the closest and only such weather station to Galada Tamboore. Being the closest weather stations to Galada Tamboore, they are expected to have similar fluctuations to data that could have been recorded on site during those periods.

The temperature and solar exposure measurements are above-water measurements. Ideally, temperature and light measurements taken underwater would be better predictors for turbidity, and align more closely to the water temperature and light data that the HOBO sensors measure. However, data on underwater measurements of these covariates are not publicly available.

Therefore, it was deemed reasonable to approximate these values, by assuming temperature and light measurements above water behave similarly to measurements underwater (beyond the diel fluctuations expected in light and temperature being less extreme in water, we can also expect water to be warmer on warmer days, and more light to propagate through water on sunnier days).

Finally, we pooled all the data into a single dataset by matching their frequencies. Hence, the hourly turbidity and water level data were averaged by day to provide daily means. The final dataset consisted of daily data of known good quality from January 2013 to January 2014.

2.3 Data analysis

Information on maintenance dates (e.g. when sensors were taken out of the water) were provided by Bio2lab to assist with possible identification of technical anomalies (i.e. incorrect data due to technical errors) in the turbidity, temperature and light data collected from the Merri Creek sites However, there were more technical anomalies in the data than could simply be associated with the maintenance dates. This meant that in order to use the data from the turbidity sensors to build predictive models using surrogate covariates, we would first need to identify and possibly correct all the anomalies in the time series (e.g. as per Leigh et al. 2019). In other words, we would need to develop a model that could distinguish between valid and invalid measurements, and then correct the invalid measurements using additional statistical techniques; however, this was beyond the scope of the current project.

An alternative to using the sensor data collected from Merri Creek (given there were many technical anomalies present and differences in the timespans of the covariate data) was to develop a predictive model for turbidity using both turbidity and covariate data of known (good) quality from publicly available sources. The development of such a model would then provide support for using lower-cost water-quality covariates to predict turbidity at high-frequency and with reasonable accuracy. As the development of anomaly detection and correction methods was outside the scope of this project, we prioritised the prediction of daily turbidity using the good-quality publicly available data outlined in the section above. Given that each variable had a different unit of measurement, the data were also standardized prior to modelling, and then divided into a training and testing set to evaluate model generalizability.

We explored several modelling methods to predict turbidity: dynamic regression, dynamic harmonic regression, lagged predictor models and TBAT (Trial Balance Analysis Template) models. Basic time series regression models linearly predict a dependent variable using covariates, the errors of which are assumed to follow a white-noise process. In dynamic regression, dependent variables are predicted in the same way, with one key difference: their errors follow an Autoregressive Integrated Moving Average, or ARIMA, process. This allows the errors from the regression to contain autocorrelation, an inherent feature of water-quality time series data, and thus account for more information in the model. The regression therefore produces two errors – regression errors and errors from the ARIMA process. Only the latter is assumed to follow a white noise process (Hyndman & Athanasopoulos, 2021). The models were created in R using the Forecast and Fable packages (O'Hara-Wild et al., 2021). Usually, ARIMA models require stationary variables. The existence of a single non-stationary variable would require the dataset to be differenced to ensure the estimated coefficients are consistent. However, the 'auto.arima()' function from the ARIMA package eliminates the need for this, as it carries out the appropriate differencing on its own (Hyndman, 2010). The function chooses an ARIMA process for the errors that minimises its residuals.

Models were constructed on all possible subsets of predictor variables and then compared using the Akaike's Information Corrected Criterion, or AICc, of each model (Hyndman & Athanasopoulos, 2021). The model with the lowest AICc and best residual diagnostics was then selected for forecasting.

We then ran a time series cross validation to observe the best model's accuracy over several testing sets. The predictors in the initial training set (1st fold) were used to predict the next seven turbidity values. The actual turbidity values were then added to the next training set (2nd fold), that was used to predict the seven subsequent turbidity values. Hence, in every fold, the training set increased in size and the testing set was pushed forward by seven time points. We selected a forecast horizon of seven days (ie. one week of data) as a reasonable timespan in which to capture accurate forecasts, given that accuracy tends to decrease the further we forecast into the future. Furthermore, the first training set was specified to end at the 160th observation in order to include at least one spike in turbidity in the first fold. Therefore, the initial training set ranged from 2013-01-02 to 2013-06-20 and was used to predict turbidity from 2013-06-21 to 2013-06-27 in the first fold. The actual turbidity values from 2013-06-21 to 2013-06-27 were then added to the training set to predict turbidity from 2013-06-28 to 2013-07-04, in the second fold. Hence, the model forecasts the next seven turbidity values at each fold, over 28 folds. Across all folds, a root mean square error (RMSE; a unit free measurement commonly used for model comparison) that was similar to the RMSE of the selected model would indicate that it has good generalizability (Hyndman & Athanasopoulos, 2021). In general, the lower the RMSE the better the model fit.

3. Results

3.1 Relationships among variables

The visualised time series indicate that rainfall, water level and turbidity fluctuate together, especially noticeable in terms of the coinciding spikes; this phenomenon was not visually discernible in the temperature and solar exposure time series (Figure 5). Scatterplots of data for each pair of variables indicated that temperature and solar exposure, and turbidity, rainfall and water level appeared to have reasonably strong positive relationships (Figure 6).

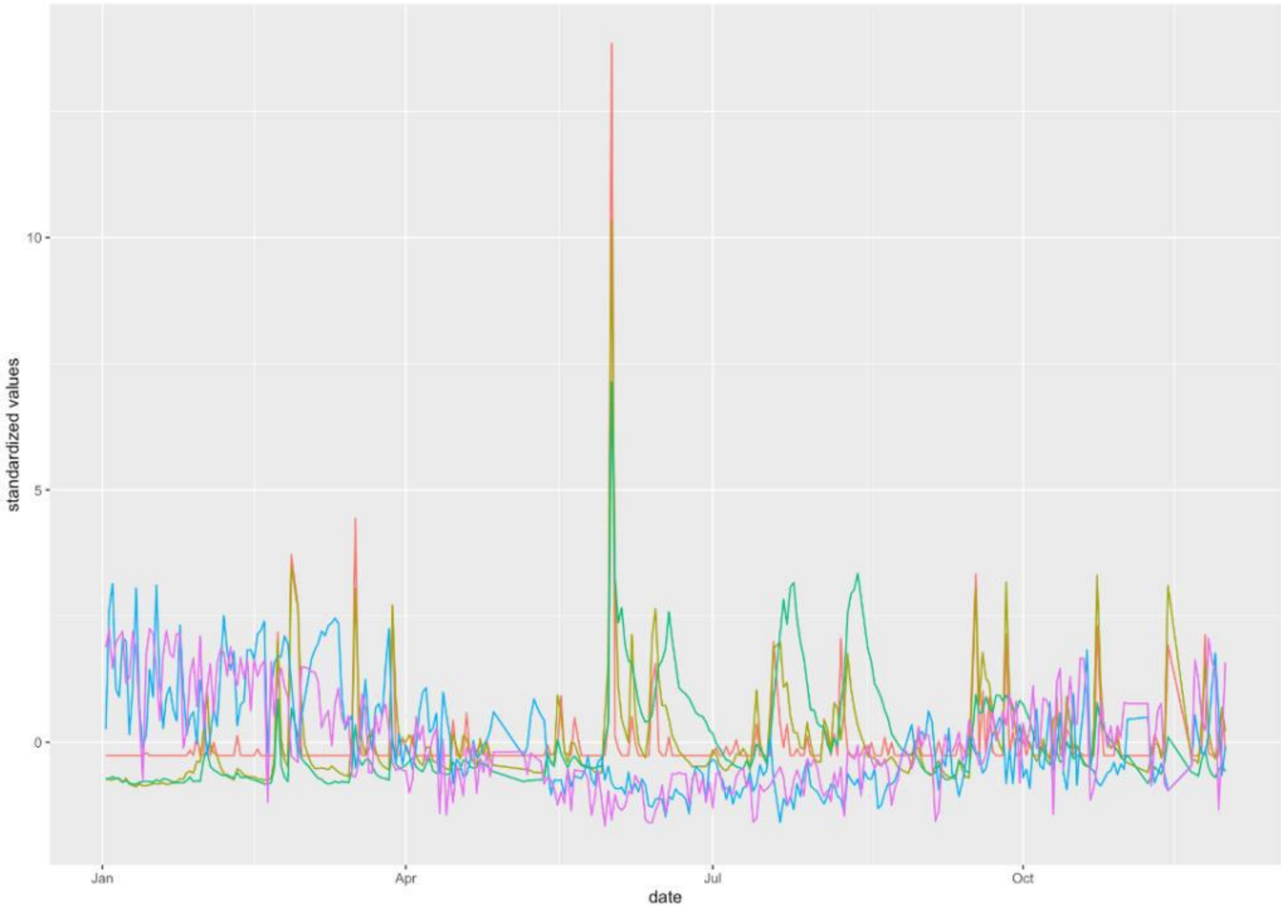

Figure 5: Daily turbidity (NTU; bright green), average rainfall (mm, red), water level (masl; yellow-green), maximum temperature (°C, blue) and total global solar exposure (MJ/m^2, purple) from January 2013 – November 2013 (standardized).

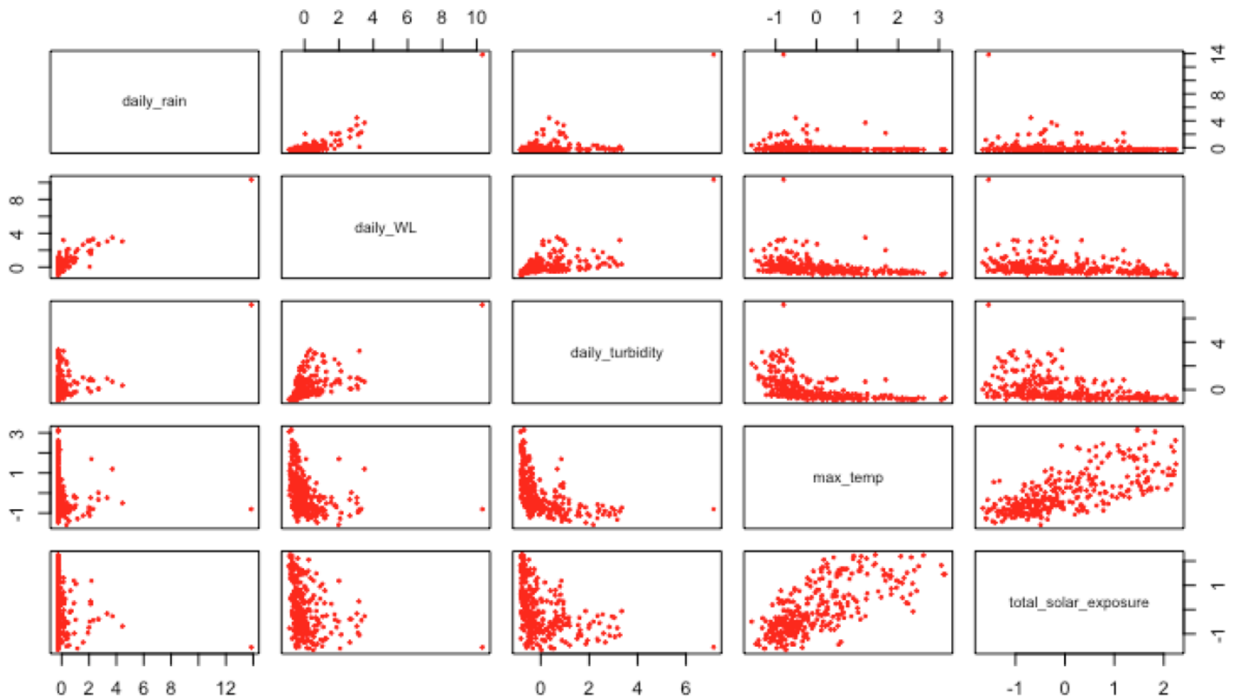

Figure 6: Scatterplot for all variables in our model training set. From Janurary 2013 – November 2013 (standardized). WL, water level; max_temp, maximum daily air temperature.

3.2 Predictive models

The best predictive model, based on the AICc, was a dynamic regression model. Dynamic Harmonic Regression, TBAT and lagged predictor models were also evaluated based on the AICc, however, none of these models performed as well as the dynamic regression models. Rainfall, water level and errors distributed as an ARIMA(3,1,4) process were the best predictors for daily turbidity (Table 1).

Table 1: Dynamic regression model's diagnostics and specifications, where daily turbidity was predicted using covariates. The models were created over a training set that consists of daily values from January 2013 – November 2013. ACF, autocorrelation function.

Variables (1=rainfall, 2=water level, 3=temperature, 4=solar exposure)	ARIMA errors	AICc	Residuals (white-noise)	Residuals (all non-significant ACF)	Ljung-Box Test
1	ARIMA(1,1,4)	155.96	×	×	√
1,3	ARIMA(1,0,3)	156.67	×	√	√
1,4	ARIMA(1,1,4)	157.98	×	×	√
1,2,4	ARIMA(1,1,3)	138.18	×	×	×
1,2	ARIMA(3,1,4)	122.39	×	√	√
1,2,3	ARIMA(1,0,3)	123.48	×	√	√
1,2,3,4	ARIMA(1,0,3)	125.58	×	√	√

For all models, the residual series looked approximately like white noise despite there being a few visually noticeable spikes associated with high turbidity values (see Appendix for a figure showing the diagnostics). For the best model, the errors approximately followed a white-noise process with no significant autocorrelations up to lag 25. The model also appeared to be a good fit for our data according to the Ljung-Box test carried out at the 5% level of significance. Point forecasts and their confidence intervals, constructed using the selected model, were therefore valid. The model also indicated how rainfall and water level related to turbidity in Galada Tamboore from 2013-2014, both having positive relationships with turbidity (Table 2).

Solar exposure and air temperature were not included as covariates in the best model. A forecast evaluation of the models that included solar exposure and temperature produced a higher RMSE than the best model without these covariates. The solar exposure and temperature covariates seemed to underestimate daily turbidity, thus appearing to offset the forecasts (see Appendix). Furthermore, the models containing these two covariates had residual diagnostics that were less than ideal. This is perhaps because the variables are above water measurements; thus, potentially consisting of a component that does not directly affect turbidity in addition to a component that adds noise to the model. However, both covariates *were* included in the second and third best models according to the AICc (Table 1), indicating they (or their in-stream equivalents of light and water temperature) may still have some value and use in acting as covariates for turbidity in streams.

Table 2: Coefficients of the covariates in the best dynamic regression model, specifically daily turbidity regressed on daily rainfall and daily water level and errors that follow an ARIMA(3,1,4) process. The model was created over a training set that consisted of daily values from January 2013 – November 2013. AR, autoregressive component; MA, moving average component.

Coefficients	Estimates	Standard Error
Daily water level	0.20	0.03
Daily rainfall	0.18	0.02
AR(1)	0.68	0.14
AR(2)	0.46	0.13
AR(3)	-0.36	0.13
MA(1)	-0.70	0.13
MA(2)	-0.42	0.12
MA(3)	0.48	0.12
MA(4)	-0.33	0.06

The point forecasts, and their respective confidence intervals for the next 46 days (after 30 November 2013) indicated that the accuracy of the best model reduced as we moved further into the forecast period (Figure 8). This is somewhat to be expected, however, given that the first forecast is in part used to determine the second forecast (so on and so forth). The first 7-14 forecasts appeared to be reasonably accurate. The RMSE of the model was low at 0.28 NTU, the lowest of all tentative models.

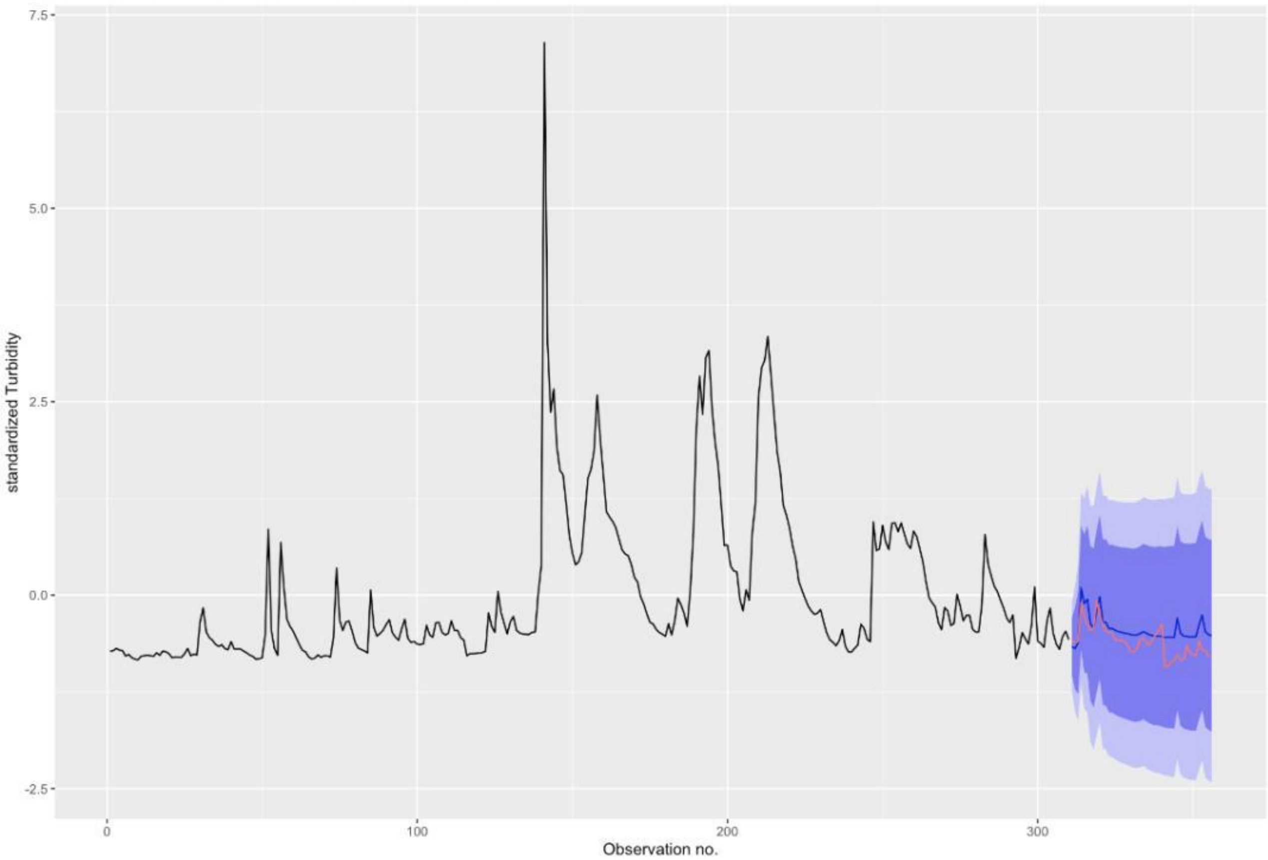

Figure 7: Forecasted daily turbidity (in blue) and actual daily turbidity (in orange) and associated 80% (light purple shading) and 95% (dark purple shading) confidence intervals for the next 46 days following on from 30th November 2013, using daily rainfall and daily water level as predictor variables from January 2013 – November 2013 (standardized).

In terms of cross-validation, the best model also appeared to perform well across all 28 folds (Figure 9). However, where there were large spikes in turbidity, the model captured these spikes a few timepoints later than they occurred in reality. Otherwise, i.e. for lower, more-stable turbidity values, the model seemed to be performing well.

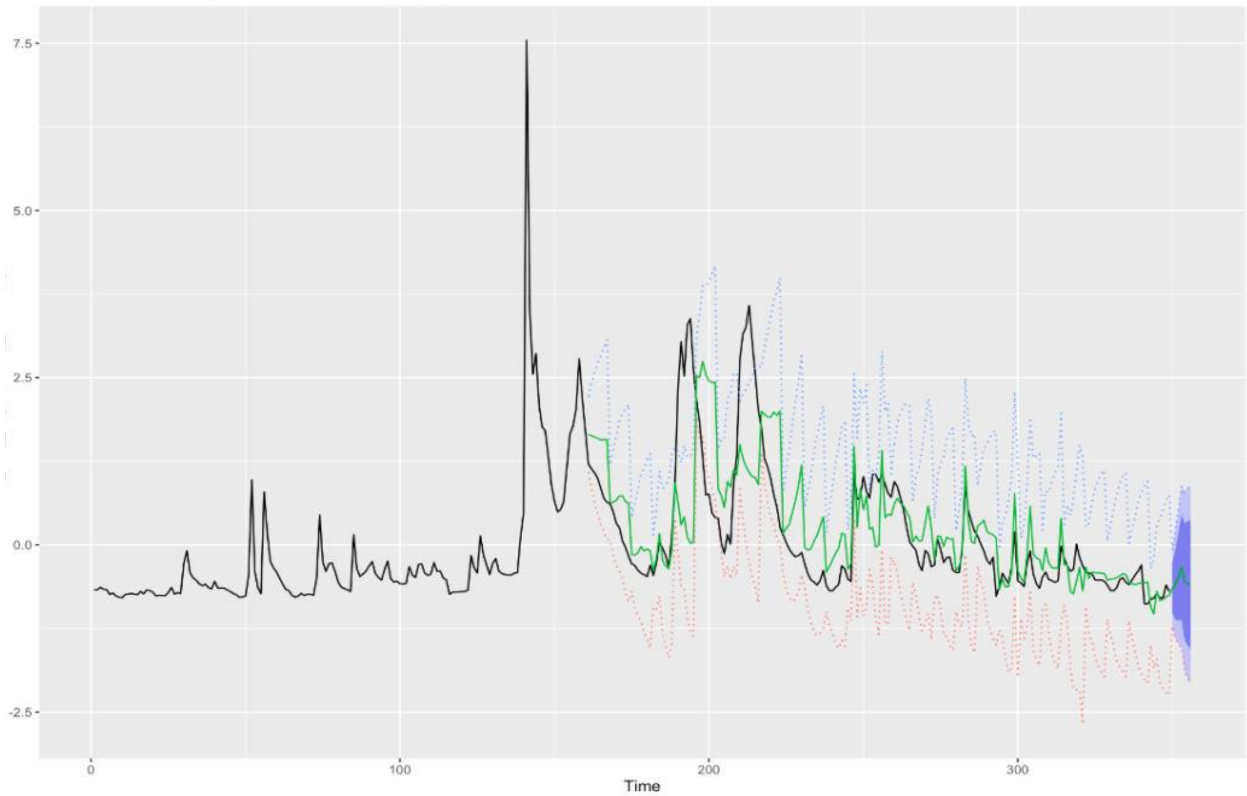

Figure 8: Time series cross validation results when the selected model is used to forecast seven periods ahead over 28 folds. Initial training set ranged from 2013-01-02 to 2013-06-20 and was used to predict turbidity from 2013-06-21 to 2013-06-27 in the first fold. Black line, original turbidity data (NTU); green line, forecasts; blue dotted line; upper 80% confidence interval; red dotted line; lower 80% confidence interval. Light purple shading, 80% confidence interval; dark purple shading, 95% confidence interval.

The average RMSE value of the cross-validation process was 0.30 NTU (see Appendix), similar to the RMSE of the model when fitted on the original training set. Ultimately, the model should be able to predict turbidity values that although they may seem like outliers on first glance, are legitimate spikes in turbidity. The selected model achieves this, given that large turbidity spikes are successfully predicted in the first few folds of the cross-validation process. Large spikes that are predicted inaccurately still have confidence intervals that manage to capture the actual value. Hence, over a 7-period forecast horizon, our model predicts daily turbidity reasonably well when daily rainfall and water level are used as predictors and the errors follow an ARIMA(3,1,4) process. However, there is some lag evident in some of the predicted peaks in turbidity, which may be at least partly explained by the lag time due to runoff and groundwater infiltration process that can cause delays between when peaks in rainfall occur and when peaks in instream turbidity are seen.

4. Discussion

Analysing high-frequency turbidity data from Merri Creek offers support to the extension of work conducted by the City of Whittlesea that aims to provide contemporaneous data that would be publicly available to Melbourne Water, other Councils, tertiary institutions, NGOs and the general public. It could set a new benchmark in the management of waterways and improve the sharing of data, collaboration and community engagement, especially by utilising low-cost sensors that measure properties related to turbidity. Conventional turbidity sensors are currently too expensive to provide enough coverage within waterways for their full potential in quickly identifying and quantifying pollution hot spots and hot moments. Poor water conditions can lead to algal blooms, anoxic water conditions and erosion which can all directly and indirectly affect the health of biota, such as the platypus, fish and macroinvertebrates living within waterways. Sensors may also provide vital data in relation to climate change related extreme events such a flooding, drought, heat waves and bush fires.

In this project, we initially set out to analyse high-frequency turbidity data recorded at Galada Tamboore by studying its relationship with high-frequency underwater light and temperature data, recorded by HOBO sensors on site. However, the ability to perform such an analysis was constrained by the presence of anomalies and missing data within the turbidity time series. To overcome this, our efforts were redirected to predicting turbidity by creating a model based on publicly available data of known good quality using variables as similar as possible to those measured by the sensors: mean turbidity and the covariates maximum air temperature and total global solar exposure, all measured on a daily timestep, along with total daily rainfall and mean daily water level given their availability and the likely relationships that these latter two covariates have with in-stream turbidity.

Various combinations of covariates were used to create a set of tentative models form which the model with the lowest RMSE, AICc and the most suited residual diagnostics was selected. Contrary to our expectations, when daily total global solar exposure and daily maximum temperature were used as predictors, our forecasts appeared to overestimate turbidity (perhaps because we were only able to find above-water measurements as opposed to the preferred underwater measurements). The model where daily rainfall and daily water level were used as predictors provided the most accurate forecasts. This accuracy was maintained when running a time-series cross validation process over 28 folds, predicting turbidity 7-days ahead in each fold. The model is expected to capture sudden spikes in turbidity associated with high rainfall and water level.

The data used in creating such a model was publicly available, but not all covariates were available for Galada Tamboore for the 2020-2021 timespan. As such, we were only able to create a model using data from 2013-2014. The mathematical relationship between the variables is nonetheless expected to hold through time, and thus has potential to predict turbidity values using current and future rainfall and water level data for Galada Tamboore.

5. Recommendations and future directions

Solar exposure and air temperature data did show some potential in predicting turbidity, indicating that low-cost light and temperature sensors may still hold promise as potential surrogate indicators for in-stream turbidity. Correspondence of light data with continuous turbidity data may help to reveal stronger relationships between underwater light levels and turbid and/or pollutant-rich discharges into and through stream networks. Thus, with further refinement, the use of low-cost light sensors could be a valuable addition to monitoring programs, to alert of a pollution event as it is happening. This could enable better detection of intermittent pollution events and may assist in being able to trace pollution events back to their source.

The project has also provided useful insights on sensor deployment. When and where sensors are deployed (in the stream network and in the stream itself, e.g., water depth) may influence the data collected from them and hence the inference that can be drawn. Combined use with other sensors, cameras or sampling regimes and configurations may also provide greater insight on spatial and temporal variation in water quality. We also note that if deployed for long periods, sensors will require some regular maintenance e.g., to brush off biofouling every few weeks or more frequently, depending on conditions at each site.

We see benefit in continuing to monitor turbidity along with light and temperature data so that models can be refined, and anomalies can be better detected. Each turbidity value forecast by the model developed herein has an associated confidence interval that can then be used to evaluate sensor-produced values. An unreasonable difference between the model-predicted turbidity value and the sensor-produced turbidity value can signal the need for further evaluation of the latter (given the aforementioned issues in the data collected to date). A value may be deemed an anomaly if it falls outside of the predicted turbidity's confidence interval. On being able to distinguish between bad and good quality data in this manner, we would be able to evaluate the raw turbidity data for Galada Tamboore (2021) by flagging unidentified and unknown anomalies, and eventually studying the relationship between valid turbidity data and underwater light and temperature data. We hypothesize that the inclusion of such underwater light and temperature data within the selected forecasting model could enhance the accuracy of the forecasting model.

Furthermore, a simple clustering algorithm constructed on the final dataset, in addition to the deviations between predicted and actual turbidity values, could be used to group together and categorize time periods by the size of the deviations. A classifier trained on the available data could then allocate future turbidity data to each category. Density Based Spatial Clustering for Applications with Noise (DBSCAN) (Chesnokov, 2019) would be a suitable method to use for the clustering, while K-Nearest Neighbour, Decision Tree and Random Forest classifiers could be used to classify future observations that are recorded by the sensor. Such algorithms can account for the spatial distances between observations (Guo et al., 2003), and thus prove useful in distinguishing valid turbidity values from anomalies. For example, if we have an unusual spike in turbidity, it could be a potentially valid value if similar spikes are observed in the covariate data. However, if an unusual spike in turbidity is observed without any associated covariate spikes, the value is more likely to be an anomaly. A distance-based classifier operating on a multi-dimensional space should be able to distinguish the real and anomalous values by accounting for all available covariate information on a single time period's datapoint. Working on anomaly detection in the turbidity data is thus a potential avenue for future research that may help to enhance the benefits that can be derived from the use of sensor-based monitoring in Merri Creek and other waterways in the region.

6. Acknowledgements

Merri Creek flows through the Country of the Wurundjeri people of the Eastern Kulin Nation. We acknowledge the Traditional Owners and ongoing Custodians of these unceded lands and waters, and the significance of Merri Creek to the Wurundjeri people. We respectfully acknowledge their Elders, past, present and emerging.

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8. Appendix

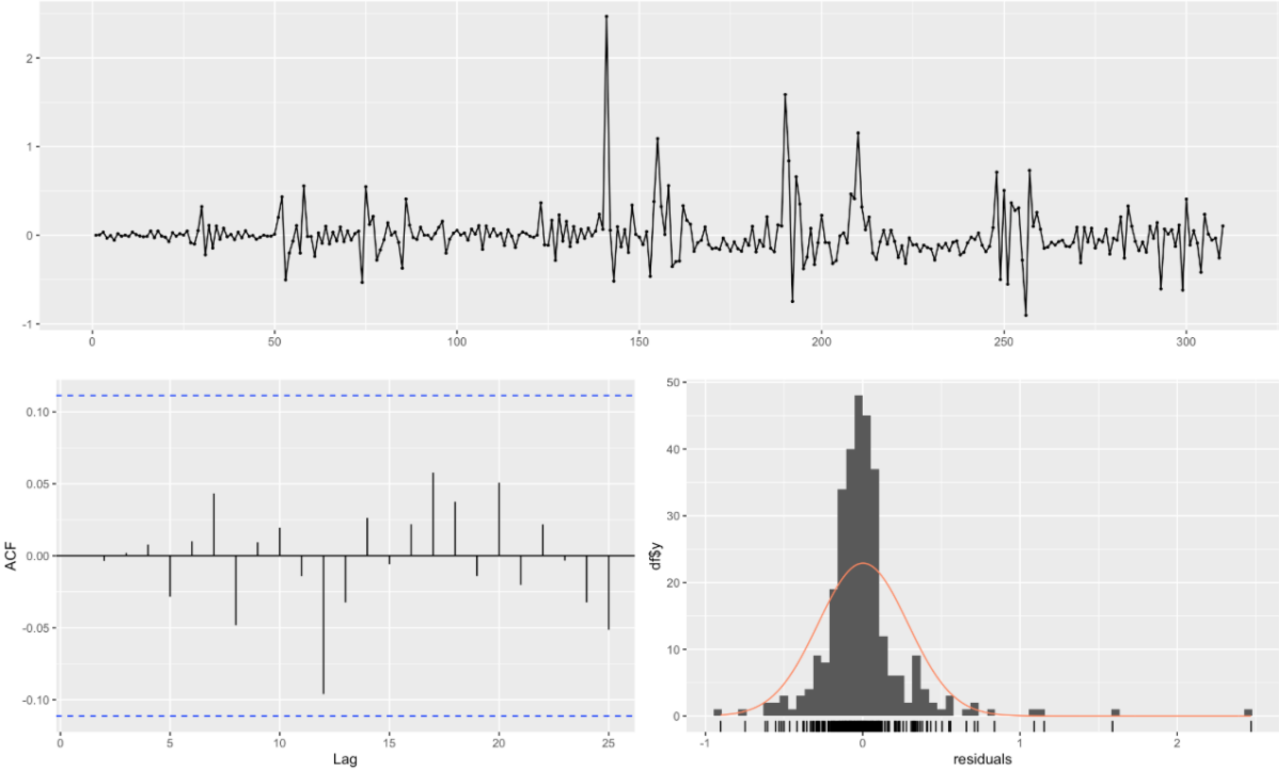

Figure 9: Residual diagnostics for the selected model, where daily turbidity is regressed on daily rainfall and daily water level from January 2013 – November 2013.

Figure 10: Forecast for a tentative model, where daily turbidity is regressed on daily rainfall, daily water level, daily total global exposure and daily maximum temperature from January 2013 – November 2013. Turbidity forecasts (in blue) and actual daily turbidity (in orange) with associated 80% (light purple shading) and 95% (dark purple shading) confidence intervals.

Table 3: Root mean squared error (RMSE) values for all 28 folds, using the selected model. The average RMSE for the cross-validation process is 0.30.

Folds	RMSE	Folds (continued)	RMSE (continued)
1	0.29	15	0.31
2	0.28	16	0.31
3	0.28	17	0.30
4	0.27	18	0.30
5	0.27	19	0.30
6	0.31	20	0.30
7	0.30	21	0.30
8	0.32	22	0.30
9	0.33	23	0.31
10	0.30	24	0.30
11	0.30	25	0.29
12	0.30	26	0.29
13	0.29	27	0.29
14	0.30	28	0.29