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Vancouver, Canada

May 31 – June 3, 2017/ *Mai 31 – Juin 3, 2017*

RESPONSE OF STREAM TEMPERATURE TO PRECIPITATION (A CASE STUDY OF THE CHESTNUT BRANCH, NEW JERSEY, UNITED STATES)

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Abstract: Stream temperature is one of the key factors that determines biotic and abiotic processes in a stream. Stream temperature is affected by many variables. Impacts of global climate change on stream temperature vary widely on a regional basis due to the complexity of variables that impact temperature response in watersheds. Understanding the response of stream temperature to different external variables can provide information valuable to the management and protection of freshwater systems. The aim of this paper was to evaluate the relationship between stream temperature and precipitation for Chestnut Branch, a stream in New Jersey, USA, using a Bayesian learning network (BLN).The BLN was compared with a regression model, a method most commonly used in environmental research to establish relationships among variables and to predict the response of variables of interest. Stream temperature and meteorological data (precipitation, wind speed, dew point, air temperature and solar radiation) were gathered at 15 minutes intervals for the fall, winter, spring and summer seasons in 2013-2014.The results show that stream temperature decreased during precipitation events by 17% on average. There was also a high correlation between below average stream temperature and with the occurrence of precipitation at the sub-daily time scale. The results of the BLN and multiple linear regression model showed similar relationships. The BLN relationship is preferred to the regression analysis since new information from a constantly changing complex system like streams can be updated rather than a new setup which is the case in regression analysis.

1. INTRODUCTION

Stream temperature is one of the primary factors that regulates biotic and abiotic processes in a stream. It influences rates of metabolic processes and life cycles of aquatic organisms (Allen et al., 2006), chemical reactions rates, dissolved oxygen levels (Ducharne, 2008), and recycling of nutrients (Null et al., 2012). High stream temperature may diminish biodiversity at the community level, alter the abundance and distribution of organisms (Caissie, 2006), cause local extinction, and facilitate the intrusion of invasive species (Rahel and Olden, 2008; Hellman et al., 2008; Harley et al., 2006). Jager et al., (1999) and Sharma et al., (2007) have indicated that the distribution of cold water species may become altered due to increased temperature with climate change. Analysis of data covering recent decades has revealed that increases in stream temperatures have already occurred with rising air temperatures (Hari et al., 2006; Kaushal et al., 2010).

A strong correlation between air temperature and stream temperature has been well documented (Kaushal et al., 2010; Mohseni et al., 1998; Mantua et al., 2010). However, stream temperature is affected by many factors (Poole and Berman, 2001; Sinokrot and Stefan, 1993) including meteorological, biological, ecological, and geological characteristics. Examining the effect of each factor can be challenging (Johnson, 2004), and we focus here on meteorological characteristics. Solar radiation has been acknowledged as the primary source of energy for streams (Sinokrot and Stefan 1993), and other literature has suggested that the major factor influencing stream temperature are the same factors that affect air temperature (Mantua et al., 2010; Johnson, 2004; Mohseni and Stefan, 1999).

The time scale used to relate stream temperature with air temperature impacts the strength of the relationship and determines the relative importance of the characteristics that contribute to stream temperature variation. Many studies used regression models to estimate stream temperature based on air temperature at weekly intervals (Mohseni and Stefan, 1998; Mantua et al., 2010). The results of these studies did show high prediction accuracies but also had significant errors. Some studies have been carried to identify factors that cause daily variation in stream temperatures (Daraio et al., (under review); Letcher et al., (2016); Lei et al., (2014)). For monthly data of stream temperatures, linear models were preferred since ‘the evaporative cooling at that timescale is hidden within the averaging of the temperatures' (Cassie, 2006). For weekly time scales, logistic regression models have often been used to study stream temperatures with the acceptable fit (Mohseni and Stefan, 1999). However, when the logistic model was applied to the daily time scale, the performance was poor (Cassie et al., 2001). This poor performance of the model necessitated recent studies of hierarchical models that incorporate time lags and autocorrelation to account for the variation in stream temperatures at the daily time scale (Letcher et al., 2014). The time scale chosen for each study was dependent on the application to which the predicted stream temperatures were to be used. Variation in stream temperatures at finer time scales is of importance when dealing issues such as water quality parameters, such as dissolved oxygen, that can have significant ecological impacts in sensitive systems.

In particular, little work has been carried out in establishing the relationship between stream temperature and meteorological variables (van Vliet et al., 2013) at a sub-daily time step. Additionally, most environmental research has used linear regression analysis to establish relationships between variables of interest. These range from linear regression models to multilayer perceptron (Maldonado et al., 2015). In this paper, we established an explicit relationship for stream temperature with air temperature, solar radiation, wind speed, dew point, and precipitation using a Bayesian network analysis and compared results to a simple linear regression model using data from a small headwater stream in southern New Jersey, USA.

2. MATERIALS AND METHODS

2.1 STUDY SITE

The Chestnut Branch, a perennial first-order stream, is a headwater tributary of Mantua Creek, which flows into the Delaware River. Its basin is approximately 2 km^2 in size with 1155mm annual rainfall on the average, and contains the campus of Rowan University, in the town of Glassboro, New Jersey. Over the past decade, this area has seen a substantial increase in development that has increased runoff and reduced water quality. The mean annual flow at its outlet and base flow were estimated at 0.062 m^3/s and 0.057 m^3/s respectively (unpublished data).

Table 1: Basin characteristics and description of site locations

Site	L (m)	A (ha)	CN	Description of site
1	0	64.4	77	Outlet of the basin, highly shaded reach with intermittent tributaries that flow during rainfall events.
2	303	3.29	77	Confluence of surface inflow from Rowan Pond, which is shaded most of the day and groundwater fed with a baseflow of approximately 25% of flow in Chestnut Branch.
3	376*	7.17	92	Drainage conduit that runs under a parking lot and drains a constructed wetland/detention area that primarily collects runoff from student residences on campus. Baseflow in this conduit was estimated to be < 0.001 m^3s^{-1} with enough flow for the logger to be fully submerged.
4	417	9.35	93	Shaded area about midway between sites 2 and 5.
5	540	1.92	93	Incised shaded section of the stream about midway between sites 4 and 6.

6	675	8.34	81	Midway point of a relatively broad meandering section of the stream with sparse riparian cover. The stream is incised in this area
7	794	2.28	92	Downstream site 8 in a sparsely shaded, slow flowing, relatively deep reach that receives runoff directly from a large area of impervious surface.
8	852	79.1	81	Downstream of shaded riparian area with multiple storm drainage inlets fed from off campus areas of Glassboro.
9	1090	7.93	77	Downstream of Abbott's Pond, which is surface water fed and not well shaded.
10	1246	18.75	78	Upstream most open section of Chestnut Branch.

*L-length in meters of the location of the site upstream from the stream outlet at site 1; A-area in hectares of drainage area for the basin delineated at the location of the logger. CN- Composite Curve Number for each basin, indicating an urbanized watershed with a significant amount of impervious area. * - not on the main stem of Chestnut Branch.*

2.2 DATA

Stream temperature (°C) was recorded at ten sites in a 1.3 km reach of the headwaters of Chestnut Branch using Onset® HOBO® Water Temperature Pro v2 Data Loggers. Site selection was based on riparian characteristics to encompass the variation in riparian and watershed conditions along the stream. Stream temperatures were recorded at 15-minute intervals. A description of each site and some basin characteristics is provided in Table 1. Meteorological data were also collected at 15-minute intervals on the roof of a building close to the branch on the Rowan University campus using an Onset® HOBO® weather 122 station. The meteorological data included precipitation (inches), solar radiation (Wm^{-2}), air temperature (°C), wind speed (ms^{-1}) and dew point temperature (°C). Precipitation was recorded using a tipping-bucket rain gauge. Missing data in this study were augmented by data obtained from the NOAA website (2013). For times where data were available, this was tested against the data available from the NOAA website to be sure it was a good fit before being employed in the study. Streamflow (m^3/s) was recorded in the basin from fall 2013 to spring 2014 (Daraio et al., under review).

2.3 METHOD

Data were analysed using a continuous Bayesian Learning Network (BLN), which are graphical, probabilistic models (Pearl 2014, Kurowicka and Cooke 2006) that can use data to describe (i.e. learn) dependencies between variables with fewer assumptions than traditional linear regression models. The graphical nature of the network makes the dependence configuration clear. The ability of a BLN to learn dependencies between various variables makes it a more robust method with which to analyse the complex interactions affecting stream temperature. Additionally, BLNs are able to capture non-linear dependencies of variables.

The central notion of a BLN is to portray, through conditional probabilities, the cause and effects between variables in a system (Fenton & Neil, 2012; Astrom, 2015). The BLN represents the dependency relationships as arcs between variables, represented as nodes (Figure 1). The arcs connecting the nodes are directional and point from parent nodes to child nodes. A directional link starts at the parent node and indicates a direct influence on the child node (a conditional probabilistic relationship). Consider X and Y as two continuous random variables with joint probability density function (pdf), $f(x,y)$ and marginal pdf of X, $f_X(x)$ then the conditional probability function for Y given X=x is given by:

$$[1]\ f_{Y|X}(y|x) = \frac{f(x,y)}{f_X(x)}; f_X(x) > 0$$

All variables are assumed to follow a normal distribution. This assumption can pose a limitation to the BLN learning of the actual structure that exist between variables since the available data may not follow a normal distribution or may have an unknown distribution.

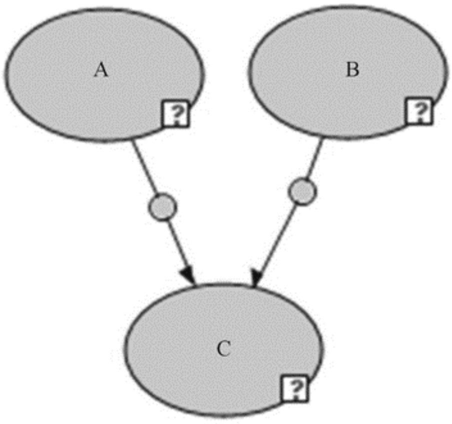

Figure 1: Layout of a Bayesian network (A and B – parent nodes; C- child node whose parents are A and B)

The lack of a link between two variables indicates conditional independence between them. The degree of the dependency relationship between a child and its parent node(s) is summarised in a conditional probability table (CPT). The CPT specifies the conditional likelihood of the child node being in a particular state, given the states of all its parents: P (child|Pa1, Pa2,…, PaN). Should a node have no parents, the table reduces it to an unconditional one, P (child).

Since the nature of the relationship between these variables is not explicitly known, the BLN algorithms first try to learn the graphical structure (hence the name of structure learning algorithms) and further infer the parameters of the local distribution functions based on the learned structure. This process is perhaps the most challenging task when dealing with BLNs. The structure learning method used for this study is the Grow-Shrink Markov Blanket algorithm. This algorithm was chosen over other techniques because it has been shown to perform better than the PC and Hill-climbing algorithms (Hanea et al., 2015). Details of this method can be found in Margaritis (2003). In addition to the learned structure, a multiple structure setup system was also implemented where variables were omitted and added in a stepwise manner so as to identify the correlation between them.

Parameter learning of a network structure is a familiar problem in statistics. The literature on BN often follows the pattern where a prior distribution, usually a non-informative uniform distribution, is presumed over the parameters of the local probability distribution functions before the data are used (Margaritis, 2003). The parameters of the Bayesian Network determined in this study were estimated using the multinomial method (see Margaritis, 2003 for details). Parameter learning and the structure learning method were implemented with the Bayes Server program, and the learned structure was reconstructed in Netica (http://www.norsys.com) to perform a sensitivity analysis. This analysis allowed for the identification of variables that had the greatest influence on stream temperature. The sensitivity analysis was conducted by systematically varying the values of individual variables to determine how they affected stream temperature.

The results obtained using the BLN were then compared with that of a multiple linear regression model.

$$[2]\ T_s = a + b_1 R_s + b_2 P + b_3 V_w + b_4 T_a + b_5 T_d$$

where R_s = solar radiation (Wm^{-2}), P = precipitation (mm), V_w=wind speed (ms^{-1}), T_a = air temperature (^oC), Td = dew point temperature (^oC), a is the intercept, and $b_{1,\dots,5}$ are regression parameters.

3. RESULTS AND DISCUSSION

The Bayesian network indicates that stream temperature is directly impacted by precipitation, air temperature, solar radiation and wind speed (Figure 2). For each node (variable), the mean and variance are indicated on the graph. Dew point has a relationship with precipitation and air temperature. Air temperature is impacted by precipitation, wind and solar radiation. Solar radiation is related to precipitation, while wind speed is affected by solar radiation and precipitation. Physical sense can be made of some of these relationships. For instance, there may be a negative correlation between solar radiation and precipitation because it is not likely that the sun will be shining when it is raining. However, it is not possible from the network diagram alone to draw any conclusions about causal relations.

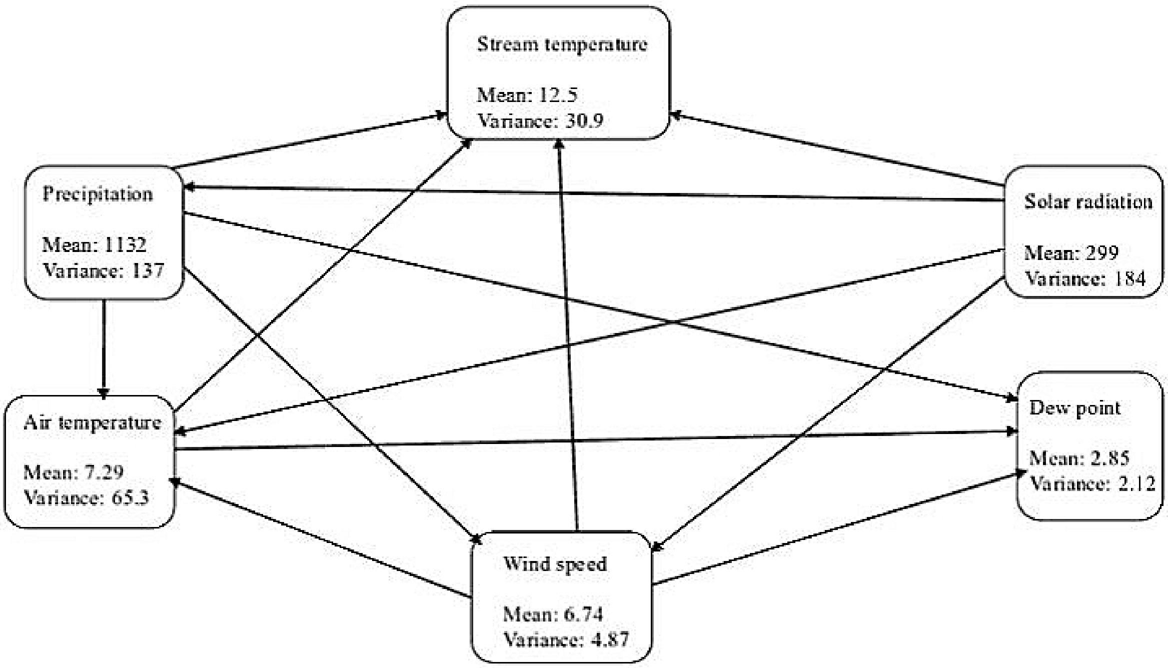

Figure 2: Bayesian network of the variables of interest

Time series of stream temperature indicates a reduction of stream temperature with the occurrence of precipitation (Figure 3). The results show that the stream temperature was reduced between 5 and 19% when precipitation occurred during the spring and summer seasons. These observed changes can be more clearly identified as time scales get finer and less visible as the time scale increases. It is very probable that this level of variation cannot be easily observed on large timescales as autocorrelation between variables will most likely be averaged out. This observation seems to be in agreement with the statement made by Cassie (2006) that autocorrelation of stream temperature averages out on large timescales. While other factors such as reduced solar radiation can contribute to variation in stream temperature, the effect of precipitation on this change seems like it may be causal at sub-daily time scales.

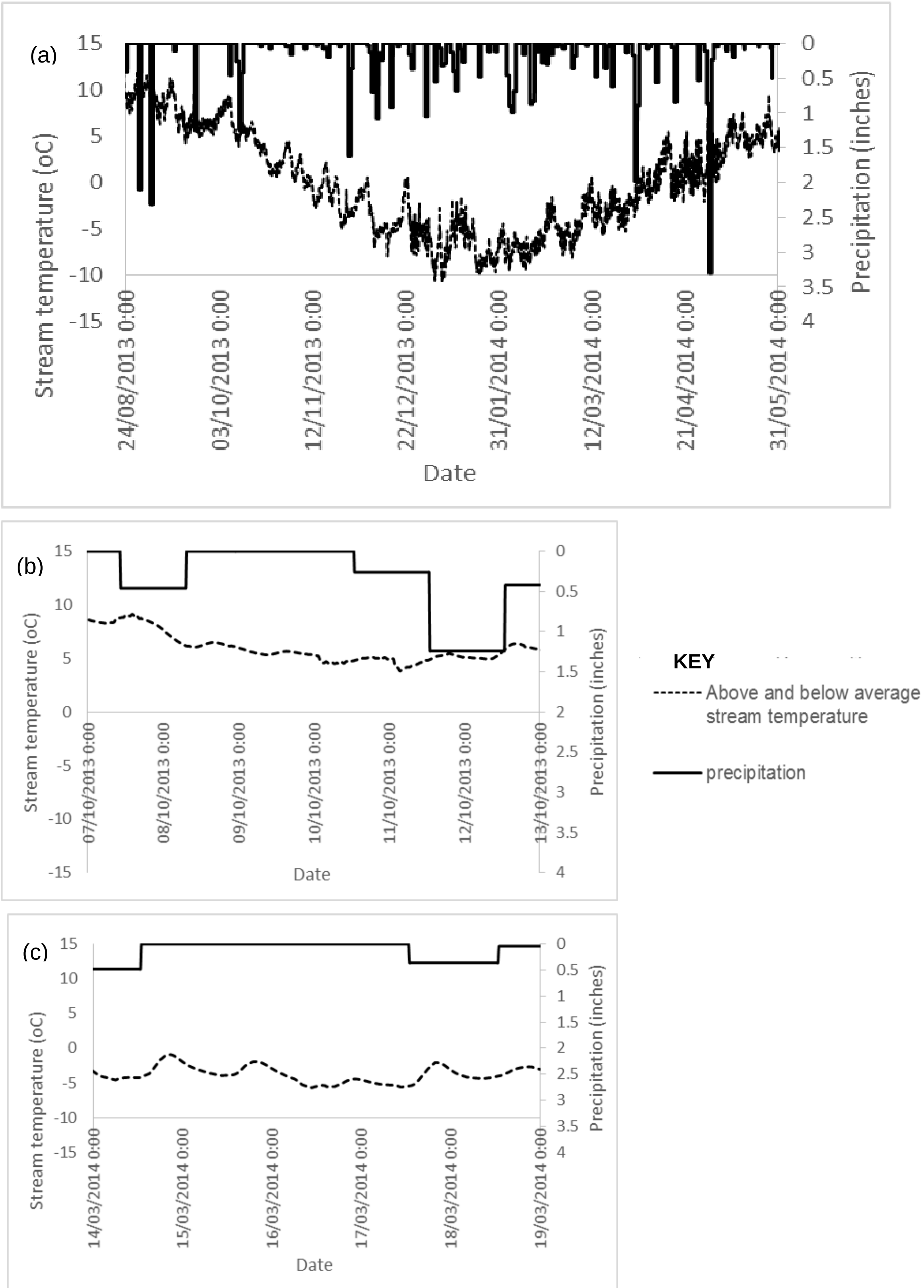

Figure 3: (a) From Fall 2013-Summer 2014; (b) and (c) 6 day periods

The correlation between stream temperature and precipitation in the BLN was found to be 0.60, and the stream temperature correlation with air temperature was 0.61 from the multiple structure setup. It was observed, from the results of the multiple structure configuration of the BLN that the correlation between variables increased as the time scale got finer. This most likely implies that the effect of precipitation on stream temperature is short lived in this small basin. This finding may, however, be different for different basins since characteristics in basin vary widely. It can be inferred from these results that there is a high correlation between above average temperatures and air temperature, that is, above average stream temperatures were more likely to occur in conjunction with high air temperatures. However, below average stream temperature occurred with a higher probability when there was the occurrence of precipitation.

This observed decrease in stream temperature as more precipitation occurs in the watershed is consistent with the "pushing" of groundwater into the stream when it rains. In Chestnut Branch, Daraio et al. (under review) attributed cooler stream temperature to groundwater influx at several sites. The results of this analysis indicated that precipitation likely increased groundwater flux into the stream during precipitation events. Newly infiltrated water probably increases the hydraulic gradient and forces groundwater through the hyporheic zone and/or adjacent land into the stream.

From Figure 4 it can be seen that variation in stream temperature is most influenced, in decreasing order, by air temperature, precipitation, wind speed and dew point. The bars represent the range of variation observed in stream temperature when the values of the states of each variable were varied over the possible range obtained from the data. Stream temperature will vary between average and above average when the air temperature is high, precipitation is low, and wind speed was also low. For the variation of stream temperature between average and below average, the opposite of this happens.

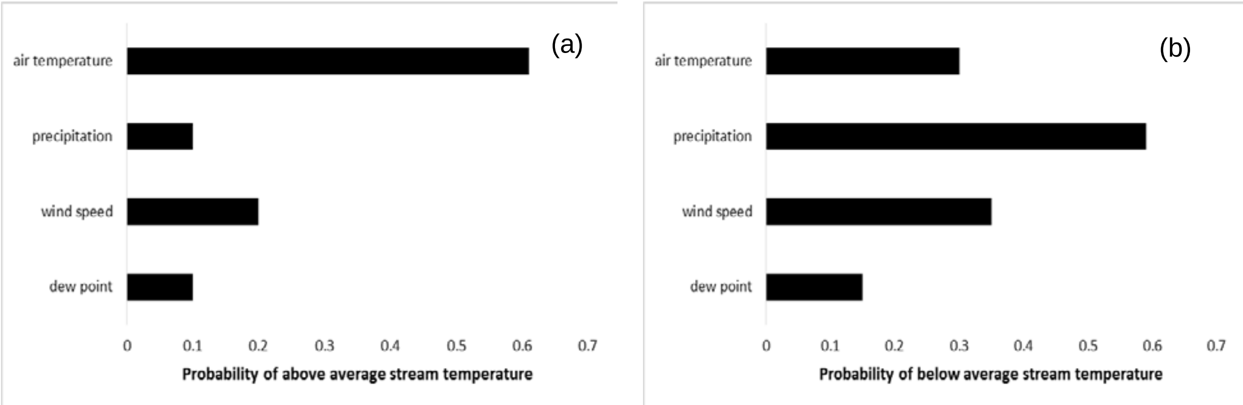

Figure 4: Sensitivity of (a) above average and (b) below average stream temperature to changes in individual nodes of the BN.

The multiple regression analysis of the data resulted in the following:

$$T_s = 9.71 + 0.0R_s + 0.59P - 1.93V_w + 0.61T_a - 0.23T_d$$

Both methods indicate that there is a strong relationship between stream temperature and precipitation. However, the multiple linear regression requires a priori knowledge to assess more complex relationships that the BLN can identify without prior assumptions. Results from the BLN could serve as a guide to additional regression analysis. However, this would be superfluous since the Bayesian network analysis already provides this information.

The correlation between stream temperature and solar radiation was found to be weak, which is consistent with the study carried out by Mohseni and Stefan (1999). The relationship and parameters obtained from the BLN and the multiple linear regression model provided high coefficients for air temperature in its contribution to the variation in stream temperature. Solar radiation, one of the independent factors, had little or no effect on stream temperature change. This effect could be attributed to the fact that the stream temperature responds in a similar manner to air temperature to meteorological drivers (Johnson, 2004). However, the most direct relation between the two will be at night when cooling of stream temperature will be affected by the temperature gradient with the air. Stream temperature is also affected by its watershed's characteristics, riparian conditions and land use. It is more likely that variation in stream temperature is caused by the same factors that affect air temperature. Other factors that could account for the reduced impact of solar radiation on the stream temperature are shading and tree cover (Daraio et al., under review).

4. CONCLUSION

Relationships between stream temperature, air temperature, solar radiation, wind speed, dew point, and precipitation were determined using sub-daily data at a 15-minute interval using a Bayesian Learning Network. The results indicated a strong relationship between air temperatures and stream temperature. However, this is most probably not a causal relationship. Moreover, results showed a high correlation between below average stream temperature and with the occurrence of precipitation at the sub-daily time scale. Understanding the response of stream temperature to different external variables at the sub-daily time scale can provide relevant information for the management and protection of freshwater systems. Potential best management practices for such streams may include temperature monitoring and setting up cooling ponds, although the choice of the method adopted will be site specific. Information obtained from analyses such as this one can be used as a guide in the potential mitigation and adaptation actions.

The BLN results were compared with results from a multiple linear regression analysis. Relationships were found to be similar. However, a BLN has the advantage of estimating the posterior density function of the response variable with available evidence and no assumptions about previous relationships between variables, other than the assumption that all observed data follow a normal distribution. Further, once prior information is available, a BN has the capability to be updated in light of new evidence. For a complex system like streams, this is important since the environment is constantly undergoing changes; unlike regression analysis that requires a new setup when new information becomes available. Therefore, the BN learning process enables us to build on insights already gained.

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