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To aggregate or not? Capturing the spatio-temporal complexity of the thermal regime

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ABSTRACT

Freshwater stream systems are under immense pressure from various anthropogenic impacts, including climate change. Stream systems are increasingly being altered by changes to the magnitude, timing, frequency, and duration of their thermal regimes, which will have profound impacts on the life-history dynamics of resident biota within their home range. Although temperature regimes have a significant influence on the biology of instream fauna, large spatio-temporal temperature datasets are often reduced to a single metric at discrete locations and used to describe the thermal regime of a system; potentially leading to a significant loss of information crucial to stream management. Models are often used to extrapolate these metrics to unsampled locations, but it is unclear whether predicting actual daily temperatures or an aggregated metric of the temperature regime best describes the complexity of the thermal regime. We fit spatial statistical stream-network models (SSNMs), random forest and non-spatial linear models to stream temperature data from the Upper Condamine River in QLD, Australia and used them to semi-continuously predict metrics describing the magnitude, duration, and frequency of the thermal regime through space and time. We compared both daily and aggregated temperature metrics and found that SSNMs always had more predictive ability than the random forest models, but both models outperformed the non-spatial linear model. For metrics describing thermal magnitude and duration, aggregated predictions were most accurate, while metrics describing the frequency of heating events were better represented by metrics based on daily predictions generated using a SSNM. A more comprehensive representation of the spatio-temporal thermal regime allows researchers to explore new spatio-temporally explicit questions about the thermal regime. It also provides the information needed to generate a suite of ecologically meaningful metrics capturing multiple aspects of the thermal regime, which will increase our scientific understanding of how organisms respond to thermal cues and provide much-needed information for more effective management actions.

1. Introduction

Spatio-temporal variation in water temperature is one of the most important factors influencing the dynamics of freshwater populations and communities (Jackson et al., 2001). Climate change impacts on temperature are predicted to be particularly profound for aquatic ecosystems. Warming air temperatures, increased thermal variability and changing precipitation are likely to result in increased water temperatures, altered stream hydrology, and changes in the frequency, magnitude, and extent of extreme climate events including floods and droughts (Jentsch et al., 2007; Rieman and Isaak, 2010; Cahill et al., 2013). The biological implications of climate change are expected to be significant as physiological tolerances are exceeded, leading to fundamental changes in physiology and behaviour (Ebersole et al., 2003).

Temperature affects aquatic populations both directly and indirectly across local and broad geographic scales. Thermal tolerances of species help describe broad geographic patterns of occurrence, while thermal preferences acting at finer scales are often reflective of conditions that are optimal for growth, feeding and reproduction (Pankhurst and Munday, 2011). Given the current climate and

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expected rate of temperature increase, it is likely that the thermal regimes of streams will shift upwards and increase in variability. Altered thermal regimes are likely to exceed physiological thresholds and reduce the amount of thermally suitable habitat available to many aquatic species, having population and ecosystem wide consequences (Parmesan and Yohe, 2003; Pörtner and Farrell, 2008; Rieman and Isaak, 2010). As well as the direct physiological impact of increased temperature, higher water temperatures reduce oxygen availability which can have a direct impact on individuals. The combination of warmer temperatures and reduced oxygen can indirectly impact organisms through reduced fitness (Ficklin et al., 2013).

It is commonly accepted that the spatio-temporal variability of both physical and biological components within ecological systems is important for ecosystem integrity (Gomi et al., 2002; Thorp et al., 2006). Historically, limitations on the spatial and temporal density of stream temperature datasets may have limited our ability to capture the full spatio-temporal complexity of the thermal regime. However, advancements in in-stream sensor technology, along with reduced prices, have increased the number and rate at which data loggers have been deployed across large catchments globally. For example, the NorWeST database in the Pacific North-Western USA has over 15,000 unique locations collecting temperature readings across over 25,000 km^2 of fish bearing streams (Isaak et al., 2011). Such technological developments have led to the proliferation of data available to stream ecologists. Unfortunately, these 'big data' are often aggregated over time and reduced to a single temperature metric (e.g. weekly, monthly, seasonal means or maximums or instantaneous maxima or minima) at discrete locations. When semi-continuous data are reduced to aggregated metrics, information about specific aspects of the thermal regime (e.g. magnitude, frequency, duration, timing, or variability) may be lost, which are important for management decisions as key drivers of ecological processes (Mohseni et al., 1998; Moore et al., 2013). Aggregated metrics are likely an oversimplification of the underlying thermal processes occurring in stream ecosystems and potentially lack biological and ecological significance (Arismendi et al., 2013; Butryn et al., 2013). Various methods have been used to predict stream temperature from measured locations to unsampled locations including spatial stream-network models (SSNMs) (Isaak et al., 2010; Ruesch et al., 2012; A. Steel, personal communication), non-spatial regression-based models (Mohseni et al., 1998) and machine learning methods (Chenard and Caissie, 2008), but it is unclear whether a loss of information occurs when data are aggregated through time and single metrics are subsequently extrapolated through space. An alternate approach would be to use the full spatio-temporal dataset to make daily predictions at unsampled locations throughout a network. These daily predictions could then be used to generate a semi-continuous coverage of ecologically and biologically relevant temperature metrics throughout the network. However, to our knowledge this approach has not been implemented in stream systems. Given that anthropogenic stressors related to land-use and climate change are likely to synergistically alter the temporal regime in important headwater habitats (Piggott et al., 2012), there is an urgent need to make full use of the 'big data' being collected by new sensor technologies.

Our goal was to compare a suite of methods used to generate stream temperature metrics to determine whether spatially and temporally dense stream temperature data can be used to better describe the magnitude, frequency, and duration of the thermal regime throughout a stream network. We used SSNMs, random forest and non-spatial linear models to predict five temperature metrics throughout the Upper Condamine River catchment, Queensland (QLD), Australia. Temperature metrics at unsampled locations were generated using two different approaches; first, we fit models to maximum daily temperature at sampled locations and predicted maximum daily temperature at unsampled locations. These daily predictions were then used to generate metrics at unsampled locations (i.e. daily metrics). Then, models were fit to metrics generated from daily maximum temperature measurements at sampled locations and used to predict metrics, rather than daily temperatures at unsampled locations (i.e. aggregated metrics) (Fig. 1). The three models and two metric-based generation approaches were compared to determine whether (1) models based on daily or aggregated metrics had greater predictive ability; (2) the predictive ability of the metric-generation approach differed depending on the type of stream temperature metric (magnitude, frequency, or duration); and (3) one model type had more predictive ability than the others, depending on the metric type and metric-generation approach.

2. Methods

2.1. Study area

The Condamine River catchment in southern QLD spans an area of approximately 29,150 km^2. The study area is located in the upper Condamine River and Spring Creek tributaries, QLD, Australia, with the elevation ranging between 507 m at Killarney up to 900 m above

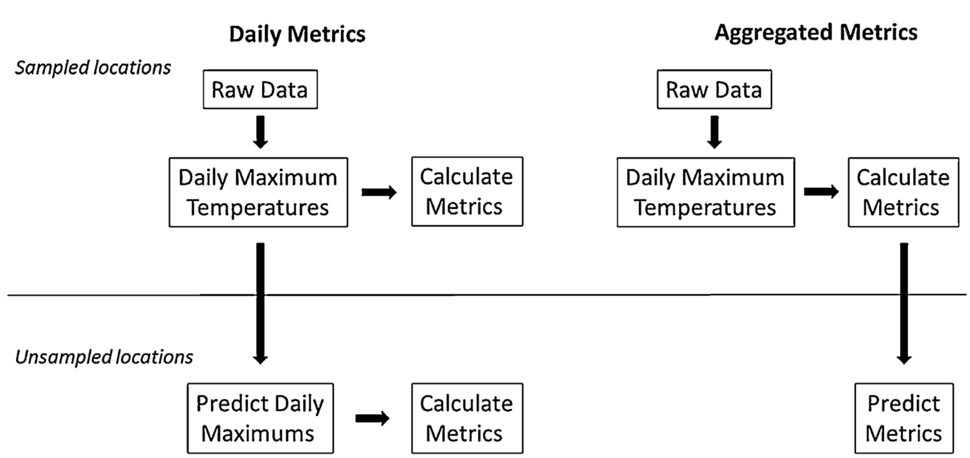

Fig. 1. Conceptual flowchart visualising the process of calculating daily (left) and aggregated (right) temperature metrics. Daily metrics were generated from daily maximum stream-temperature observations and predictions, at sampled and unsampled locations respectively. In contrast, aggregated metrics were generated using maximum stream-temperature observations at sampled locations and then the temperature metric was predicted at unsampled locations.