



Complex network theory, streamflow, and hydrometric monitoring system design

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Abstract. Network theory is applied to an array of streamflow gauges located in the Coast Mountains of British Columbia (BC) and Yukon, Canada. The goal of the analysis is to assess whether insights from this branch of mathematical graph theory can be meaningfully applied to hydrometric data, and, more specifically, whether it may help guide decisions concerning stream gauge placement so that the full complexity of the regional hydrology is efficiently captured. The streamflow data, when represented as a complex network, have a global clustering coefficient and average shortest path length consistent with small-world networks, which are a class of stable and efficient networks common in nature, but the observed degree distribution did not clearly indicate a scale-free network. Stability helps ensure that the network is robust to the loss of nodes; in the context of a streamflow network, stability is interpreted as insensitivity to station removal at random. Community structure is also evident in the streamflow network. A network theoretic community detection algorithm identified separate communities, each of which appears to be defined by the combination of its median seasonal flow regime (pluvial, nival, hybrid, or glacial, which in this region in turn mainly reflects basin elevation) and geographic proximity to other communities (reflecting shared or different daily meteorological forcing). Furthermore, betweenness analyses suggest a handful of key stations which serve as bridges between communities and might be highly valued. We propose that an idealized sampling network should sample high-betweenness stations, small-membership communities which are by definition rare or undersampled relative to other communities, and index stations having large numbers of intracommunity

links, while retaining some degree of redundancy to maintain network robustness.

1 Introduction

1.1 Network theory

Network theory is the practical application of graph theory, which is itself the study of the structures formed by a system of pairwise relationships (Elsner et al., 2009). In this paper we will use the terms network theory and graph theory interchangeably. The system in this context consists of a collection of nodes (vertices in graph theory), which are connected to each other by links (edges). Such a general and simple concept has allowed a wide range of systems to be successfully studied with graph theory. Network theory has been applied to a tremendous variety of systems, such as social networks, communication networks (e.g., the Internet), transportation networks (e.g., airports), epidemiology, ecology, climate, and biomolecular networks. Overviews of network theory and its real-world applications are provided by, for example, Strogatz (2001), Tsonis et al. (2006), Newman (2008), da Fontoura Costa et al. (2011), and Sen and Chakrabarti (2013).

1.2 Definitions

There are many diagnostics used to characterize the topology and behaviour of networks, but we will primarily be concerned with three major and widely used properties: the degree distribution, $P(k)$, average clustering coefficient, C , and average path length, L . These specific metrics are particu-

larly useful because they allow the network under consideration to be easily compared to known network types, which have well-known characteristics. Expressions for some of these metrics can be written in more than one way, and certain formulations can be highly geometric in character. For practical applications, these definitions are most commonly phrased as follows (e.g., da Fontoura Costa et al., 2007; Sen and Chakrabarti, 2013). Consider a network containing N nodes. Begin by defining the $N \times N$ adjacency matrix, \mathbf{a}_{ij} , which is 1 if nodes i and j are connected and 0 otherwise; entries along the diagonal are 0 by convention, unless the network contains self-loops, a concept we will not explore here. The degree, k , of a given node is the number of other nodes to which it is connected, that is, the number of links the node possesses. The degree of node i can be expressed in terms of the adjacency matrix as $k_i = \sum \mathbf{a}_{ij} \forall j$. Then, the degree distribution, $P(k)$, is the probability distribution of network degrees across all the nodes, $i = 1, N$, in the network. The other two metrics, C and L , are scalar quantities. The clustering coefficient measures the tendency for nodes to cluster together into so-called cliques. The neighbourhood of a given node is normally defined to be the set of nodes to which it is linked. Thus, we can represent the neighbourhood of the i th node as $j | \mathbf{a}_{ij} = 1$. Then, the local clustering coefficient for that node is the number of links amongst the nodes in its neighbourhood, expressed as a proportion of the maximum number of links possible amongst the neighbouring nodes, that is, the probability that the direct neighbours of a given node are themselves direct neighbours. The clustering coefficient for the i th node can be represented as $C_i = [k_i(k_i - 1)]^{-1} 2E$, where E is the number of links that are actually observed to exist between the k neighbours of node i . We follow standard practice and use the average of all the local clustering coefficients over the network as a bulk measure of the clustering tendency or cliquishness of the network as a whole. Finally, average path length is the average over all nodes of the shortest path, d_{ij} , between every combination of node pairs. Path length is measured as the number of links needed to connect a node pair. Thus, the average path length is given as $L = [N(N - 1)]^{-1} \sum d_{ij} \forall i \neq j$.

The application of these three fundamental graph theoretical measures to real networks has revealed the existence of a diverse range of network topologies (e.g., Tsionis et al., 2006; da Fontoura Costa et al., 2011; Sen and Chakrabarti, 2013). However, many fall within a small number of known architectures. This library of topologies is widely used across the physical and social sciences to characterize, classify, and understand networks.

The simplest network is a regular network, where, by definition, each node has the same number of degrees. A simple example is a 3-D Cartesian grid. In the special case where each node is connected to every other node, the network is said to be fully connected. Regular networks display a wide range of properties because there are many ways to construct them while keeping the degree uniform across all nodes.

In general, however, regular networks are highly clustered, and therefore said to be stable, but have long average path lengths, implying inefficiency. In the context of complex networks, stability means that the removal of any randomly chosen node will have little effect on the network as a whole, while efficiency means that information may easily be propagated across the network because the average path length is small. Another fundamental type is the random network. Random networks are networks whereby pairs of nodes are connected randomly. Random networks have a small clustering coefficient and a small average path length, which means that they tend to be unstable but efficient.

While regular and random networks serve as useful idealizations, they are not often observed in real-world phenomena. Instead, the so-called “small-world” network has been found to describe a number of networks found in nature and engineering. Small-world networks are regarded as a hybrid of random and regular networks because they are highly clustered (like regular graphs) and have short path lengths (like random graphs) (Watts and Strogatz, 1998). They are said to be both stable and efficient. Examples of small-world networks include the climate system (Tsionis and Roebber, 2004), social networks (i.e., the six degrees of separation phenomenon), and the power grid of the western United States. The small-world classification does not necessarily specify the degree distribution.

One subset of small-world networks, known as scale-free, has been particularly successful in describing real systems. The degree distribution for these networks asymptotes to a power law relationship for large k , that is, $P(k) \propto k^{-\gamma}$, meaning nodes with a large number of degrees are present but rare. These networks retain the stability and efficiency of small-world networks. However, their outstanding characteristic is that they contain supernodes, which are rare but important nodes that contain a very high number of degrees. The climate and Internet networks are examples of small-world networks which are also scale-free.

1.3 Application to hydrometric networks

Here, we apply the analytical and interpretive framework of complex network theory to streamflow data, with two goals in mind. The first is simply to broach an interesting and fundamental scientific question: might regional streamflow data be quantitatively represented as a formal network, and, if so, what are the corresponding network theoretic properties, and, in particular, into what fundamental class of network architecture do streamflow data fall? That is, we explore the use of network theory and historical streamflow observations to characterize a regional system of stream gauges. Indeed, the very fact that a collection of stream gauges is typically referred to as a “network” begs for the application of network analysis. We accomplish this task by applying generally accepted approaches of network analysis to daily flow data and then assessing how our outcomes relate to established net-

work topologies. In doing so, minor analytical or interpretive adjustments from prior applications of network theory need to be considered, as discussed in due course below. The overall notion, however, is straightforward in principle: we test the idea that stream gauges constitute nodes in a formal graph theoretic construct as described generically above, and the relationships between the flow time series measured at each such station form the links.

Our second goal is to assess whether these network theoretic results might inform the optimal design of hydrometric monitoring systems. As network theory describes the complex relationships between a system of measurement points – in our case, hydrometric stations – it seems reasonable to conjecture that certain outcomes from this theory might contain insight that could be useful in hydrometric monitoring system design. Because our implementation of network theory is based on historically observed hydrologic time series, this information would take the form of guidance on deciding which existing stations are most important, least important, or important in various different respects. More specifically, the results might be used to guide decisions about the placement or removal of gauges within the region while retaining the maximum amount of information. In other words, our analysis helps address questions such as the following: what is the degree of redundancy in the current network? Are there under-sampled regions? Is the network, in its current state, stable and efficient?

The study is conducted within the geographic context of the Coast Mountains of British Columbia and Yukon. As discussed in more detail below, this region, which spans almost 2000 km along the Pacific coast of Canada and adjacent interior regions, exhibits a distinctive range of streamflow regimes. It receives high annually averaged precipitation, and the extreme vertical relief, exceeding 4000 m over short distances, lends itself to microclimates and complicated hydrologic dynamics which are strongly varied in both space and time. Both the forest and glacial hydrology of the region, for example, are highly complex and remain incompletely understood. Furthermore, using stream gauges to capture such complexity over a large swath of difficult terrain is challenging, especially under the constraint of a finite operating budget and logistical challenges associated with establishing and maintaining gauging stations, so that any additional guiding information regarding sampling system design may be useful.

The work presented here has some practical limitations which should be recognized. As a first-of-its-kind investigation, we elect to maintain simplicity in certain aspects of the analysis. Earth science applications of network theory are growing rapidly, but remain in their relative infancy. The preponderance of these applications appears to focus on global climate dynamics (Tsonis and Roebber, 2004; Yamasaki et al., 2008; Donges et al., 2009; Martin et al., 2013), with some other examples including studies of hurricanes and earthquakes (e.g., Elsner et al., 2009; Fogarty et al., 2009; Abe

and Suzuki, 2004). For a recent review of geoscientific applications of graph theory, see Phillips et al. (2015). Narrowing the view to water resource studies, network theory applications have been even more limited to date, though evidently valuable to the extent that they have been conducted. Examples appear to include analysis of virtual water trade networks, river network analysis, hydrologic connectivity analysis, and exploration of new hydrologic modelling paradigms (Rinaldo et al., 2006; Suweis et al., 2011; Spence and Phillips, 2014; Sivakumar, 2015). To our knowledge, only one other study has performed a quantitative network theoretic analysis of observational streamflow data, an innovative study primarily involving application of a modified clustering coefficient to a large assemblage of streamflow stations spanning the coterminous US (Sivakumar and Woldemeskel, 2014). Furthermore, no prior work has evaluated which of the fundamental network architectures discussed above (small-world, scale-free, and so forth) best describes the dynamics of streamflow; or employed the community detection algorithms associated with network theory, as discussed in more detail below, for studying river discharge; or used any of these techniques for informing the optimal design of streamflow monitoring systems. In light of this, we obviously cannot provide a comprehensive and comparative study of all such possible applications, and we are obligated to somewhat restrict our scope, such as our choice of focusing strictly on daily flows for a particular region.

Similarly, practical hydrometric sampling system design is a function of many considerations, and some of the most powerful of these are in some sense non-scientific. Factors influencing real-world gauge placement include capital and maintenance costs, remoteness, legal authorization for land access, occupational health and safety considerations, availability of hydrodynamically and geomorphologically suitable sites for gauge installation and stable rating curve development, and specific engineering or socioeconomic drivers for station placement. Examples of the latter include the need to monitor a particular river at a particular location to constrain the design of a bridge or highway, set instream flow requirements for a river with special ecological significance, monitor high-flow conditions for a downstream inhabited flood plain, estimate water availability for a particular water supply utility, provide key input information to an environmental assessment process around a proposed natural resource development project, and so forth. That said, there is a long history of using quantitative analysis of environmental data to provide information that might enable improved sampling system design, including correlation, cluster, principal component, information theoretic (entropic), geostatistical, and other types of analysis (e.g., Bras and Rodríguez-Iturbe, 1976; Caselton and Husain, 1980; Flatman and Yfantis, 1984; Burn and Goulter, 1991; Yang and Burn, 1994; Norberg and Rosén, 2006; Fleming, 2007; Pires et al., 2008; Mishra and Coulibaly, 2010; Archfield and Kiang, 2011; Neuman et al., 2012; Putthividhya and Tanaka, 2012; Mishra

and Coulibaly, 2014). A review specifically of streamflow monitoring system design applications of such methods is provided by Mishra and Coulibaly (2009), and for a recent example of continued innovation in this field, see Hannaford et al. (2013). The network theoretic approach implemented here adds to this rich heritage. However, it is far beyond the scope of the present study to compare this method to the data analysis-based techniques for informing the hydrometric monitoring system design listed above; nor do we claim that it is superior (or in fact that any single method should be viewed as such). Perhaps more importantly, we emphasize that like these other techniques, the network theoretic approach appears restricted to providing information about the relative importance of previously operated gauges, giving less direct insight into the optimal placement of new gauges, and not explicitly incorporating important types of non-technical considerations into sampling system design.

With this in mind, our results confirm that network theory can indeed be successfully used to describe inter-gauge hydrologic relationships, and to guide sampling system design in a novel way which seems fruitful and warrants further investigation by the hydrologic community. The results additionally add to the broader literature in network theory by quantitatively identifying the network properties and, in particular, the fundamental network topology associated with the terrestrial hydrologic cycle.

2 Study area and data

In general, streamflow is determined by the interaction of weather and climate with the terrestrial environment. The specific factors which determine the nature of observed daily streamflows (i.e., the hydrograph) in the Coast Mountains are numerous. The region consists primarily of temperate rain forest, but also includes extensive glaciated alpine areas and some drier inland locations. The broad meteorological context involves the progression of a series of North Pacific frontal storms propagating roughly eastward across the region over the November-to-March storm season, occasionally with warmer tropical or sub-tropical moisture feeds associated with atmospheric rivers. Generally drier conditions prevail during the summer. The first-order controls on local terrestrial hydrologic responses to this meteorological forcing are drainage elevation and drainage area, which can be viewed as gross descriptors incorporating or parameterizing a number of complex characteristics and processes (precipitation type, ice cover, forest cover, groundwater, soil moisture, storage, and so forth). Drainages in the Coast Mountains exhibit a wide range in mean basin elevation and drainage area, which in turn creates a variety of hydrograph types. Broadly speaking, however, streamflow hydrographs in the Coast Mountains can be classified by their dominant freshwater source: rainfall, snowmelt, and glacier melt (e.g., Eaton and Moore, 2010).

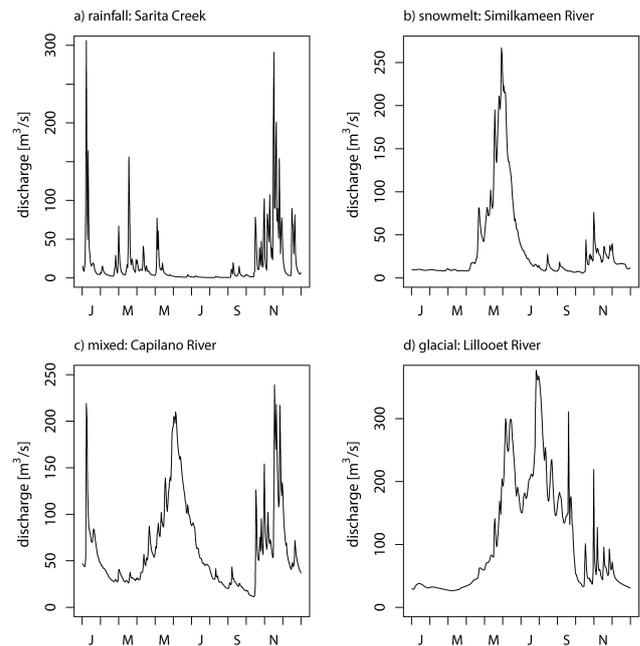


Figure 1. Selected examples illustrating the four main types of annual hydrographs found in the Coast Mountains of British Columbia and Yukon as described by Eaton and Moore (2010).

Systems dominated by rain are typically found on the windward (western) side of the Coast Mountains, and they tend to have small, low-elevation drainage areas which receive precipitation mostly in the form of rain. Peak flows are often observed during autumn and winter, concurrent with peak rainfall, while low flows occur in late summer when rainfall is at an annual minimum (Fig. 1a). Snowfall-dominated systems are found throughout most of the Coast Mountains, but particularly in high-elevation coastal regions and/or inland regions. Peak flows occur in spring through mid-summer when snowpack melt rates are the highest. However, the highest-elevation basins can retain snow late into the summer, thereby prolonging the freshet (Fig. 1b). Some systems in the Coast Mountains exhibit characteristics of both rainfall and snowmelt systems, especially when their drainage basin occupies a large range of elevation. In these cases, the hydrographs show both a spring–summer snowmelt freshet as well as a significant winter rainfall freshet (Fig. 1c). The ratio of rainfall to snowmelt decreases with decreasing temperature, which (broadly speaking) can be achieved by moving inland, northward, or higher in elevation (Eaton and Moore, 2010). The fourth hydrologic regime type found in the Coast Mountains consists of drainages which have water stored as glacial ice. In these systems, the high early summer snowmelt streamflow is followed by ice melt, which effectively extends the high discharge period into late summer or early autumn (Fig. 1d). Only 2% of the drainage area needs to have ice cover in order to add a glacial melt signature (Eaton and Moore, 2010).

Daily discharge data for all of Canada are maintained and archived by the Water Survey of Canada. In this study, only stations with continuous daily discharge records were selected, and geographic range was constrained to stations on rivers originating in the Coast Mountains (Fig. 2). We restricted the station search to select only natural drainages, omitting rivers regulated by dams or other structures. We additionally screened for record completeness, requiring each station to have more than 80 % of the possible daily values. The longest daily record dates back to 1903, but the total number of stations in the database steadily increases with time over the 100+ years. Therefore, to maximize the number of stations in the analysis, the period 2000–2009 was selected because it contained the highest number of active stations. This choice involves a trade-off. A 10-year record is insufficient to analyze climatic effects. For example, El Niño–Southern Oscillation, the Pacific Decadal Oscillation, and the Arctic Oscillation impact the hydrology of the Coast Range in British Columbia (BC) and Yukon, and some of those effects differ between regime types (Fleming et al., 2006, 2007; Whitfield et al., 2010). Likewise, longer-term climatic trends may affect different hydrologic regime types within the region in different ways or, eventually, lead to regime transitions from one type to another (Whitfield et al., 2002; Fleming and Clarke, 2003; Stahl and Moore, 2006; Schnorbus et al., 2014). Thus, distinctions between the lower-frequency hydroclimatic dynamics of different stations seem unlikely to be fully captured by the present analysis. The reward gained in exchange for this sacrifice is maximization of the number of stream gauges incorporated into the analysis. As the density of stream gauges is extremely sparse through much of our study area (e.g., Whitfield and Spence, 2011; Morrison et al., 2012), and analysis of climatic effects is merely one of the many uses of hydrologic monitoring networks (see Sect. 1), our choice is reasonable for our current purposes.

A total of 127 stations met the selection criteria. The distribution of stations primarily reflects the population distribution, meaning that the greatest density of stations is found near the dense urban centres of southwestern British Columbia. Drainage elevation statistics were computed by constructing a digital elevation model (DEM) for each gauged basin. Gridded tiles from three DEM products were used: the 25 m British Columbia Terrain Resource Information Management (TRIM), the 30 m USGS National Elevation Database, and the 30 m Yukon DEM. Mean elevation was calculated as the average of all cells for each gauge basin using the ESRI ArcGIS Arc/Info and Spatial Analyst/GRID software. Mean drainage elevation ranges from 127 to 2252 m, with an average of 1186 m, while drainage areas range from 2.9 to 50 900 km², with a median value of 318 km².

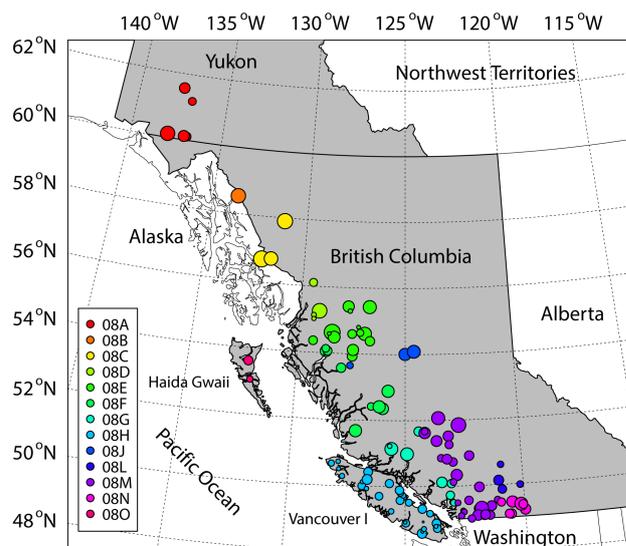


Figure 2. Map of the Canadian west coast showing the 127 Water Survey of Canada (WSC) streamflow gauging stations used in this study. The stations are coloured according to the first three characters in the WSC naming convention (example – 08M), which defines the stations according to subdivisions of the major drainage basins. The size of each circle scales with the logarithm of the drainage area. The streamflow database was subsetted for stations draining the Coast Mountains.

3 Network topology

3.1 Link definition

In some applications of network theory, the decision of whether to assign a link to a pair of nodes is straightforward. For example, in a social network, friendships define the links between people. In the case of the Internet, websites can be unambiguously connected by hyperlinks. In other applications, there might not be a straightforward binary relationship between nodes, meaning it becomes necessary to consider empirical relationships. A simple and common method is to assign links to node pairs which share a linear (Pearson) correlation coefficient, r_p , which exceeds some threshold, r_t . Such an approach has been extensively used in studies of the global climate system (e.g., Tsonis and Roebber, 2004; Donges et al., 2009; Yamasaki et al., 2008), as well as in finance and genetics (see references in Tsonis et al., 2011). Numerous other methods for defining links have been developed (e.g., Abe and Suzuki, 2004; Elsner et al., 2009; Fogarty et al., 2009), but they are, to some degree, specific to the data set and scientific objective.

If links are defined by a threshold correlation coefficient, then the question of which threshold to choose naturally arises. A few specific methods have been explored in prior studies. Here, we use $r_t = 0.7$ because it is intuitively and statistically meaningful: a link between two stations is identified only if the streamflow time series from one explains

about 50 % or more of the variance in the other. Note that this value is generally similar to the ranges considered by Sivakumar and Woldemeskel (2014) in their analysis of streamflow data, and by various climate studies using correlation-based network link definitions (e.g., Tsonis and Swanson, 2008).

When calculating the correlation matrix, a pairwise-complete method was chosen to avoid the errors that could otherwise be introduced by interpolating over missing data. The correlation matrix is then thresholded at r_t to form an adjacency matrix, \mathbf{a}_{ij} . As noted in the introductory section, this is a matrix consisting of logical elements that define which node pairs are linked. The network analysis was carried out using the `igraph` package (Csardi and Nepusz, 2006) in the GNU R computing environment (R Core Team, 2014).

3.2 Inferred network type

The network formed by the 127 streamflow records distributed across the Coast Mountains has a total of 1247 pairwise links between the stations. The average number of degrees per node is 19.6, the minimum is 0 (station numbers 08AA009, 08EE0025, 08FF006, and 08MH029), and the maximum is 43 (08EE020). The connections are illustrated in Fig. 3. Several spatial patterns are immediately evident. First, the stations on Vancouver Island and the stations within southwestern British Columbia are highly interconnected. Second, the stations on the mainland of British Columbia and southern Yukon are highly connected. Finally, the three stations on Haida Gwaii and the two northernmost stations in the Yukon are largely or completely unconnected to larger groups.

As discussed in the introduction, we can place the streamflow network in context with the known network topologies by computing three network properties, the degree distribution ($P(k)$), the clustering coefficient (C), and the average path length (L). We begin by computing the degree distribution for the streamflow network and comparing it to the expected distribution for regular, random, and scale-free networks having the same number of nodes and links (Fig. 4). The streamflow network degree distribution is characterized by a weak peak centred at about 19 degrees (corresponding to the mean), which is flanked by symmetric, broad, and noisy wings. The noise arises from the relatively low number of nodes in the network compared to some other applications, such as the Internet. From Fig. 4, it is immediately clear that the streamflow network is not a regular network because, by definition, each node in a regular network has the same number of links, i.e., $P(k) = \delta_k$, where δ_k is the Kronecker delta function located at a single value of k . Furthermore, the streamflow network degree distribution is not consistent with the expected degree distribution for a scale-free network because scale-free networks have an asymmetric degree distribution which asymptotes to $P(k) \propto k^{-\gamma}$ at sufficiently large values of k , where γ ranges from 2.1 to 4 for a wide array of observed networks (Barabási and Albert, 1999). The stream-

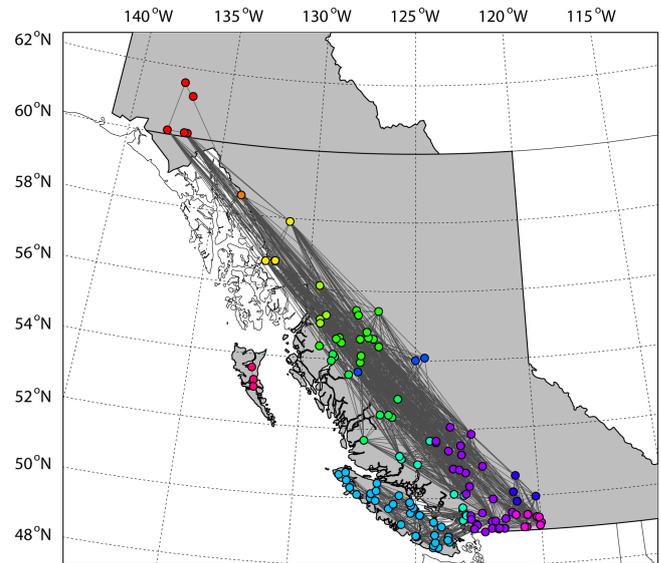


Figure 3. Georeferenced representation of the streamflow network. A line is drawn between each pair of stations if their linear correlation coefficient exceeds 0.7. The station colours are based on the WSC designated subregion as in Fig. 2.

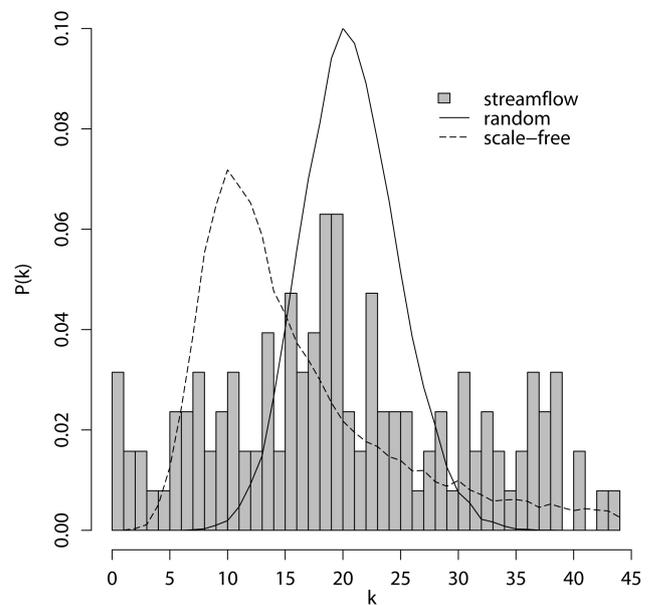


Figure 4. Discrete representation of the degree distribution for the streamflow network (grey bars). Also shown are ensemble means of the equivalent degree distributions for a random network (solid line) and for a scale-free network with $P(k) \propto k^{-2}$ (dashed line), each having the same number of vertices and edges as the streamflow network. Not shown is the degree distribution for a regular network, which is simply a Kronecker delta function at some value of k .

flow network degree distribution, on the other hand, bears some resemblance to the degree distribution for a random network, which is a binomial distribution. The random network has a narrower peak and lower tails in comparison.

Therefore two possibilities remain – small-world (but not scale-free) or random. The difference between these cases lies in the clustering coefficient and average path length. A network is considered small-world if $C \gg C_{\text{random}}$ and $L \gtrsim L_{\text{random}}$ (Watts and Strogatz, 1998). The streamflow network has a global clustering coefficient of $C = 0.69$ and an average path length of $L = 3.03$, whereas the equivalent random graph has a clustering coefficient of $C_{\text{random}} = 0.15$, and a path length $L_{\text{random}} = 1.88$. Therefore the streamflow network satisfies the conditions for a small-world network. Thus, the streamflow network is an example of a small-world network that does not exhibit scale-free behaviour. This is uncommon but not unprecedented. Examples of small-world networks that do not have power law distributions are discussed in Amaral et al. (2000).

As noted in the introduction, small-world networks are characterized by stability and efficiency. A stable network is one that retains its integrity even if nodes are removed because of the high degree of clustering. In other words, the removal of a node at random will likely not fragment the network. In the context of the streamflow network, this means that if a randomly selected station is removed then it should be possible to recover most of its information through the interdependence of the stations. Network efficiency is sometimes thought of as the ease with which information propagates across the network. A network with a small average path length is highly efficient because two arbitrary nodes are likely to be separated by only a few links.

3.3 Sensitivity tests

While assigning links to stations sharing a correlation coefficient in excess of 0.7 assures that the links are statistically and intuitively meaningful, one might question whether the specific threshold value has any impact on the structure of the network. An excessively low threshold, below perhaps 0.4 or so, causes identification of links where, in general, none exists in any statistically or (potentially) physically meaningful way. In the limit of $r_t \rightarrow 0$, the network becomes fully connected with what are largely spurious links, which is not interesting or useful. At the other extreme, an excessively high threshold would lead to identification of links only between extremely closely related stations, leaving many unconnected nodes, which again is not very meaningful. For example, at $r_t = 0.9$, 30% of the nodes in the streamflow network are completely isolated. Similar behaviour was observed in the network-based analysis of climate by Tsonis and Roebber (2004), who note a large fraction of disconnected nodes when $r_t = 0.9$, which serves to distort the network.

However, there is still a range of reasonable threshold values which deserve some attention. To assess whether global

network properties of the streamflow network are sensitive to the choice of threshold, we evaluated the network for two additional values of the selected threshold, $r_t = 0.6$ and $r_t = 0.8$. This is similar to the range considered by Sivakumar and Woldemeskel (2014) in their sensitivity analysis, and for similar reasons. We then calculated the degree distribution, clustering coefficient, and average shortest path length for each of these alternative threshold values, and compared the results to what would be expected for several idealized network architectures.

The streamflow network degree distribution undergoes a few obvious changes when r_t is varied (Fig. 5). For example, both the average and maximum degree decrease with increasing r_t . However, there is little evidence of a fundamental change in network topology, as the streamflow network still does not appear to strictly fit the degree distributions expected for regular, random, or scale-free networks as discussed above. Some asymmetry in the streamflow network degree distribution begins to appear at $r_t = 0.8$, but as noted earlier, the network becomes increasingly fragmented and less meaningful at very high r_t . The streamflow network degree distribution bears some similarity to a random network degree distribution at $r_t = 0.6$; however, as we will show, the clustering coefficient and average path length indicate that the streamflow network is not a random network. The clustering coefficient has only a weak dependence on the threshold correlation, decreasing from 0.74 to 0.64 as r_t increases from 0.6 to 0.8 (Fig. 6a). More importantly, it is always much larger than the expected value for an equivalent idealized random network. Similarly, the average path length increases from 2.8 to 3.2 over the range of $0.6 \leq r_t \leq 0.8$ (Fig. 6b), but it remains only slightly higher than what would be expected for the equivalent random network. In summary, then, our inference that these streamflow data are consistent with a small-world network topology appears insensitive to reasonable perturbations of the correlation threshold used for link definition.

A change in global network properties as a function of correlation threshold was observed by Tsonis and Roebber (2004) in their analysis of climate. They argue, however, that there is no fundamental change in the network structure because the clustering coefficient always remains higher than what would be expected for a random network. The same conclusion can be drawn for the streamflow network because the clustering coefficient and average path lengths satisfy the criteria for small-world networks for reasonable values of r_t , as discussed above. The implication, then, is that the choice may not be critically important to overall network characterization.

Additionally, we explored the impacts of using Spearman rank correlation in place of Pearson linear correlation, and of deseasonalized anomaly time series in place of the observed hydrographs. Both affected certain details – for example, the network contains fewer links at a given threshold correlation coefficient when the seasonal cycle is removed

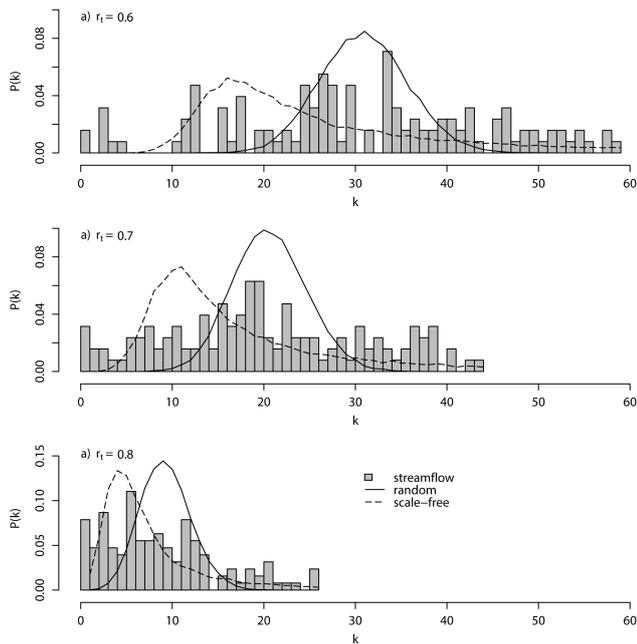


Figure 5. Degree distribution, $P(k)$, for three values of the correlation coefficient threshold, r_t , for the streamflow network (grey bars). Also shown are the ensemble means of the expected degree distributions for a random network (solid line) and a scale-free network with $P(k) \propto k^{-2}$ for large k (dashed line). The random and scale-free networks were configured to have the same number of vertices and edges as the streamflow network.

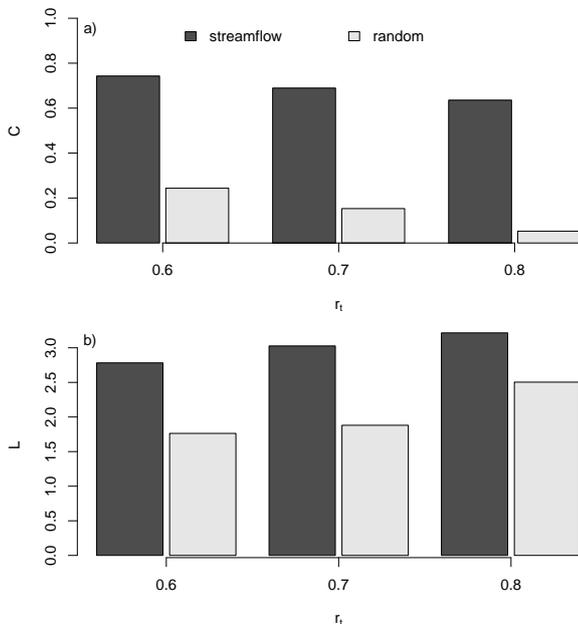


Figure 6. Network clustering coefficient, C , and average shortest path length, L , for the streamflow network and the equivalent random networks for three values of the correlation coefficient threshold, r_t .

from the data because much of the variance in streamflow is associated with seasonality. Use of Spearman correlation has a tendency to increase the number of links between stations because rank correlation allows for more complex (yet monotonic) relationships. However, these choices do not affect the global network structure as diagnosed by the clustering coefficient or average path length. Note also that when making the decision to use absolute or anomalous values, we may additionally refer back to one of the major impetuses for this paper, which is to use network theory to assess how well the current array of streamflow gauges samples the hydrology of the Coast Mountains and to explore how network theoretic insights might help guide future decisions on streamflow monitoring system design. That is, the emphasis lies on actual river flows, as might be required for water supply, ecology, civil engineering, or other potential applications. These actual discharge values are influenced to a considerable degree by seasonal forcing, and therefore require direct sampling by a hydrometric monitoring system. Additionally, sharing a common seasonal flow regime, especially within our study region (where seasonal regimes exhibit great basin-to-basin heterogeneity as discussed in detail above), is a fundamentally meaningful and operationally important physical link between two stations. That is, we would in general wish the network analysis, and a streamflow monitoring system, to directly capture such connections. Further discussion on the use of anomalous values of geophysical data and network analysis can be found in Tsonis and Roebber (2004).

4 Community structure

Many networks consist of distinct groups of highly interconnected nodes, which are often referred to as communities. This is particularly true of small-world networks observed in nature (Girvan and Newman, 2002), and also of the streamflow network, as we will show.

Consider Fig. 7, an alternative representation of the streamflow network in which the stream gauge station positions are not georeferenced. Instead, the nodes were arranged by an algorithm which determines the positions in such a way as to clearly present the network structure (Kamada and Kawai, 1989). This particular representation suggests that there are two dominant groups in the streamflow network: Vancouver Island and everything else.

In this section we will formally analyze the streamflow network for community structure and show that the delineation made above is an oversimplification, but still accurate in the most general sense. We then explore what causes community structure in the streamflow network, and also what the community structure can tell us. It is important to note that the following does not require assumptions regarding network topology. The corresponding results are, therefore, in some sense independent of the foregoing conclusions.

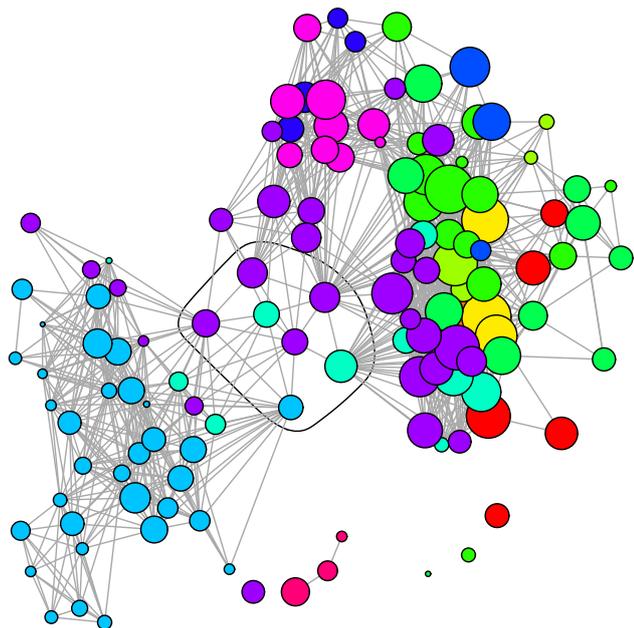


Figure 7. Graph representation of the streamflow network. The vertices were arranged by the algorithm of Kamada and Kawai (1989). The colours represent the WSC designated subregion as in Fig. 2. The stations inside the black circle are a subset of the stations having a high value of betweenness.

4.1 Algorithms and sensitivity testing

Many algorithms have been developed to find community structures in graphs (see Fortunato, 2010, for an extensive review). The number of algorithms is due to, in part, the fact that there is no strict definition of a community (Fortunato, 2010). Furthermore, the task of community detection is, in general, computationally intensive, and the proliferation of network theoretic algorithms for community detection has been partly driven by the development of fast approximate methods, which are necessary for large networks.

Given the rather imprecise definition of a community, we cannot expect that there will be a single correct algorithm which can find the one true answer. Thus the task of choosing an algorithm comes down to practical considerations. For example, run times can vary considerably between the algorithms because the computational costs of some scale linearly with the number of nodes or edges, while others scale exponentially (Danon et al., 2005). Our own testing even suggests that the underlying network topology can affect the run time for an algorithm even when the number of edges and vertices are held constant.

Although we cannot assess whether an algorithm can find the single true answer (if such a thing exists), we can compare the algorithms to see if they find the same answer. We therefore applied eight such algorithms to the hydrologic data: walk trap, fast greedy, leading eigenvector, edge be-

tweenness, multi-level, label propagation, info map, and optimal. A review of these various algorithms is beyond the scope of our article. Interested readers may refer to Fortunato (2010) for further background, and a description of the algorithm we ultimately selected is provided below. The streamflow network community structure identified by the various algorithms was then compared using the normalized mutual information (NMI) index, a measure of the similarity of clusters (Danon et al., 2005). This index is normalized on the interval of 0–1, and high values indicate that two algorithms produce similar community structures. In the case of the streamflow monitoring network, the NMI index varies between 0.81 and 1.00 for the eight different algorithms tested (Table 1). This indicates that the results are not particularly sensitive to the community detection algorithm.

In addition to finding similar community structures, the algorithms return a similar, but not identical, number of communities (between 8 and 10). In general, all of the algorithms find three large communities, and five to seven smaller ones. The three largest communities contain between 84 and 94 % of the total number of stations. All of the algorithms find a handful of communities which contain only one member (station nos. 08AA009, 08EE025, 08FF006, and 08MH029). This is a trivial result (in a strictly graph theoretic sense) because these particular stations have no links to the network. The edge betweenness algorithm (discussed below) also identified a community composed of a single station which, unlike the cases just mentioned, had links to other stations (08AA008, two links).

If we consider the reasonable consistency in the number of communities found by each algorithm, the tendency for most stations to fall within three large communities, and the high NMI scores, it is apparent that choice of algorithm is not of critical importance. We therefore proceed by using the edge betweenness algorithm to isolate the communities because it is well documented, and because its NMI index ranges from 0.86 to 0.94, indicating a good agreement with the other algorithms.

The edge betweenness algorithm works as follows. The algorithm identifies communities by finding bottlenecks (or bridges) between highly clustered regions of the graph. These bridges are found by exploiting a property known as edge betweenness (Girvan and Newman, 2002; Newman and Girvan, 2004). Edge betweenness is the number of shortest paths between all combinations of node pairs which pass through a particular edge. It is an extension of the concept of node betweenness, which is itself a useful property that will be used and discussed in Sect. 4.3.

More specifically, the algorithm works by first calculating edge betweenness scores for every edge in the network. The edge with the highest score is removed, which in some sense splits the network, and the edge betweenness for the resulting network is calculated again. The algorithm is reminiscent of hierarchical divisive (top-down) clustering methods in statistical analysis and data mining, partitioning larger-

Table 1. Comparison of community detection algorithms with the normalized mutual information (NMI) index (Danon et al., 2005).

| Algorithm | WT | FG | LE | EB | ML | LP | IM | O |
|-----------|------|------|------|------|------|------|------|------|
| WT | 1.00 | – | – | – | – | – | – | – |
| FG | 0.97 | 1.00 | – | – | – | – | – | – |
| LE | 0.97 | 0.95 | 1.00 | – | – | – | – | – |
| EB | 0.94 | 0.91 | 0.94 | 1.00 | – | – | – | – |
| ML | 0.87 | 0.89 | 0.87 | 0.88 | 1.00 | – | – | – |
| LP | 0.92 | 0.91 | 0.90 | 0.86 | 0.83 | 1.00 | – | – |
| IM | 0.87 | 0.90 | 0.88 | 0.91 | 0.86 | 0.81 | 1.00 | – |
| O | 0.87 | 0.89 | 0.87 | 0.88 | 1.00 | 0.83 | 0.86 | 1.00 |

WT: walk trap; FG: fast greedy; LE: leading eigenvector; EB: edge betweenness; ML: multi-level; LP: label propagation; IM: info map; and O: optimal.

scale communities into progressively smaller ones in a dendritic fashion. At each step, a measure of the optimal community structure called modularity is calculated (Newman and Girvan, 2004). Roughly speaking, high-modularity networks are densely linked within communities but sparsely linked between communities. In practice, the iteration is terminated when modularity reaches a maximum.

4.2 Community structure in the streamflow network

Application of the edge betweenness algorithm to the streamflow network sorts the stations into 10 communities. Communities 3, 4, and 8 are the largest, and together they contain 90 % of the stations. Five communities consist of a single station. A summary of the community membership, along with a basic description of a typical station in each community is given in Table 2, while a table of the complete community membership is given in Table A1.

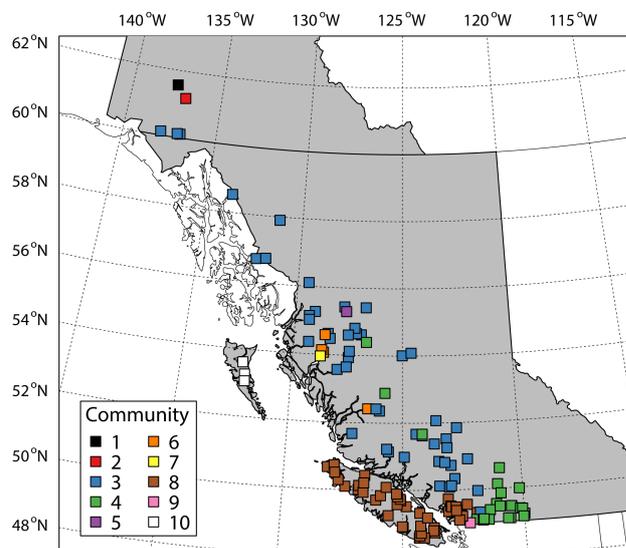
The geographic distribution of the communities is mapped in Fig. 8. The most striking result is that the spatial extent of the communities is variable; some communities are localized, while others are dispersed widely over the domain. For example, community 3 consists of mainland stations located throughout the Coast Mountains, while community 4 consists primarily of stations in the southeasternmost Coast Mountains except for a few stations further north. Community 8 consists entirely of stations on the southwesternmost British Columbia mainland and on Vancouver Island. Most communities do not map in a straightforward way onto the geographic regions defined by the WSC station designation prefix (Fig. 2).

If the streamflow communities are not solely defined by the geographic distribution of their members, then what forms them? The answer must lie in the hydrographs, since the network was defined by their covariance. To investigate this, a representative hydrograph was computed for each community by first forming a median annual hydroclimatology for each station using the same 10-year time series that defined the network. The climatological median discharge for each station was then normalized by drainage area to form the unit area discharge. Finally, the median unit area hydro-

Table 2. Summary of the community analysis. The communities were found using the edge betweenness algorithm (Girvan and Newman, 2002; Newman and Girvan, 2004).

| Community number | Number of members | Geographic description |
|------------------|-------------------|---|
| 1 | 1 (< 1 %) | Yukon, high elevation ^a |
| 2 | 1 (< 1 %) | Yukon, high elevation |
| 3 | 49 (39 %) | Wide geographic range, high elevation |
| 4 | 22 (17 %) | Southern BC, mid-elevation ^b |
| 5 | 1 (< 1 %) | Central BC, mid-elevation, small drainage |
| 6 | 5 (4 %) | Central BC, mid-elevation |
| 7 | 1 (< 1 %) | Central BC, low elevation ^c , small drainage |
| 8 | 43 (34 %) | Southwestern BC and Vancouver Island, low elevation |
| 9 | 1 (< 1 %) | Southwestern BC, near sea level |
| 10 | 3 (2 %) | Haida Gwaii, low elevation |

^a > 1200 m, ^b ≈ 1000 m, ^c < 800 m.

**Figure 8.** Streamflow station map coloured according to community membership. The communities were identified with the edge betweenness algorithm (Girvan and Newman, 2002; Newman and Girvan, 2004).

graphs were averaged by community to form a representative annual hydrograph.

The representative annual hydrographs are shown in Fig. 9. By construction there are 10 community hydrographs, which might initially be unexpected in light of the four canonical annual hydrologic regimes commonly found in the Coast Mountains (Fig. 1). This essentially implies that two rivers can each have the same type of hydrograph – that is, the same hydrologic regime – even though their individual flow series do not correlate strongly. In other words, there is not a 1 : 1 correspondence between streamflow community and seasonal flow; the community detection algorithm does not simply constitute a graph theoretic approach to hy-

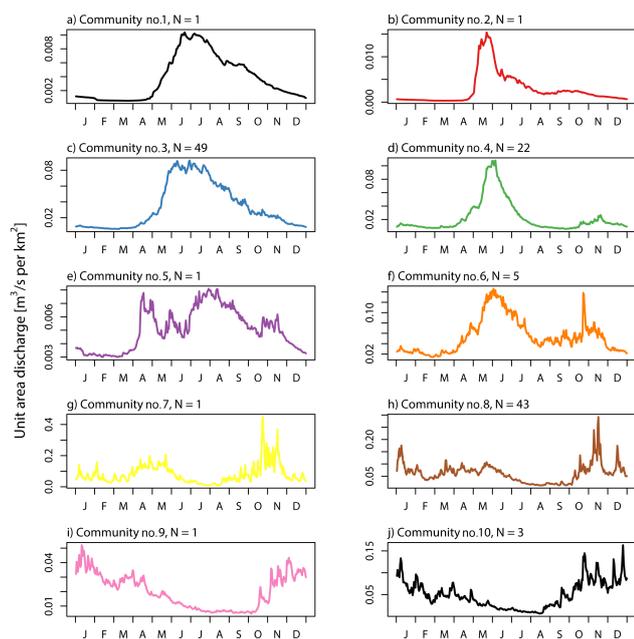


Figure 9. Representative unit area hydrographs for each of the 10 communities. The hydrographs were created by averaging the 10-year median climatology for all stations within the community. The line colours are consistent with the map in Fig. 8, except for the community 10, which is plotted here in black. N gives the number of hydrometric stations within each community.

drologic regime typing. Conversely, all four of the canonical hydrographs are represented by at least one community.

How can two stations of the same hydrologic type be poorly correlated? The average annual cycle and its overall physical controls are only one aspect of a river's dynamical properties. As an example, consider two small pluvial basins, one on an island of Haida Gwaii on the northern BC coast, and the other 800 km away on Vancouver Island on the southern BC coast. Although peak flow for both stations occurs in winter, when rainfall is highest, the rainfall is episodic because it is caused by frontal systems embedded in low pressure cyclones. Even if the same weather system impacts both stations, the travel time between stations will create a phase lag which is large enough compared to the falling limb to create a weak zero-lag correlation. More importantly, in many cases a specific storm will affect one region but not another 800 km away. Indeed, precipitation teleconnections to El Niño–Southern Oscillation and the Pacific Decadal Oscillation differ fundamentally between the southern and northern BC coasts (Fleming and Whitfield, 2010). It seems clear that such disconnected meteorological forcing is why communities 8 and 10 are distinct in spite of having very similar median annual hydrographs.

A similar argument can be made for nival stations, although the mechanisms might be different. Day-to-day, basin-to-basin variability in the snowpack and/or melt rates

(set by temperature or rain-on-snow events) can affect peak flow timing or the length of the falling limb, and therefore impact the correlation between two stations. Although the dominant forcing causing snowmelt is seasonal, the spatial scale of specific forcing anomalies (i.e., weather) could easily create spatial variability on scales smaller than the distance separating two different nival basins.

It is also interesting to explore how these network theoretic communities might reflect different catchment properties. For example, both the day-to-day streamflow dynamics and the overall seasonal hydrologic regime exhibited by data from a particular hydrometric station are determined to a significant extent by the elevation of the upstream basin area since in the Coast Mountains elevation determines in large part whether the basin receives daily precipitation as rain, snow, or some mixture of the two, and also what time of year the corresponding runoff occurs. Thus it might be possible to understand the community structure, at least in part, in terms of basin elevation. Consider Fig. 10, which summarizes the distribution of mean drainage elevations for the stations within each community. The figure shows that the communities are, to some degree, stratified by elevation. Communities 1 through 4 represent stations which sample high-elevation basins (loosely defined here as > 1200 m), communities 5 and 6 represent middle-elevation stations (≈ 1000 m), while 7 through 10 represent low-elevation stations (< 800 m). Cross referencing this with the map in Fig. 8, we see that community 3 contains the high elevation stations which span most of the Coast Mountains, community 4 mostly contains the high elevation stations in the southeastern Coast Mountains, and community 8 contains low-elevation stations from southwestern BC and Vancouver Island.

We can also test whether the communities are influenced by the drainage area upstream of the stream gauge. Drainage area impacts hydrological time series because it might indicate the potential for storage mechanisms (lakes, groundwater, etc.), which would in turn dampen impulsive precipitation events and “redde” the spectrum of a theoretical hydrograph. This means all large basins might have similar hydrographs (all else being held equal) and therefore fall within the same community. The drainage areas, sorted by community, are shown in Fig. 11. From this figure it appears that drainage area does not delineate communities to the same extent that elevation does. However, it might play a higher-order role and reveal, for example, why communities 3 and 4, which are both large groups of high-elevation stations with significant but not complete geographical overlap, do not form a single community. Community 3 has a median drainage area of 1750 km^2 , while community 4 has a median drainage area of 565 km^2 , which might explain their differing representative annual hydrographs (Fig. 9). That said, the range of drainage areas in each community is large compared to the difference in median values, meaning that the difference is weak on statistical grounds.

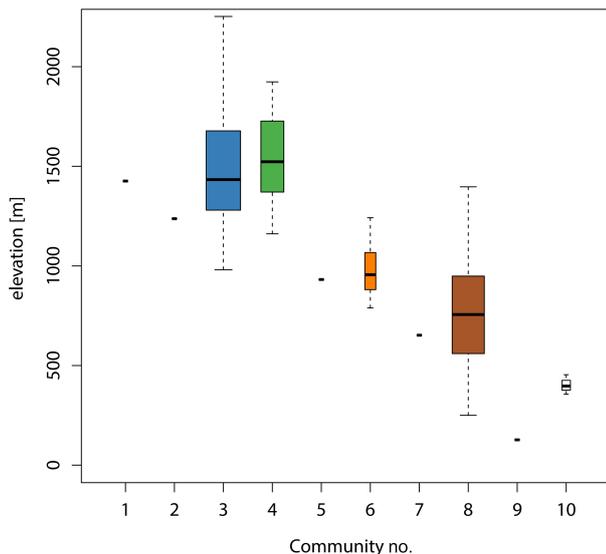


Figure 10. Boxplots of mean basin elevation grouped by community. The colours are consistent with the map in Fig. 8.

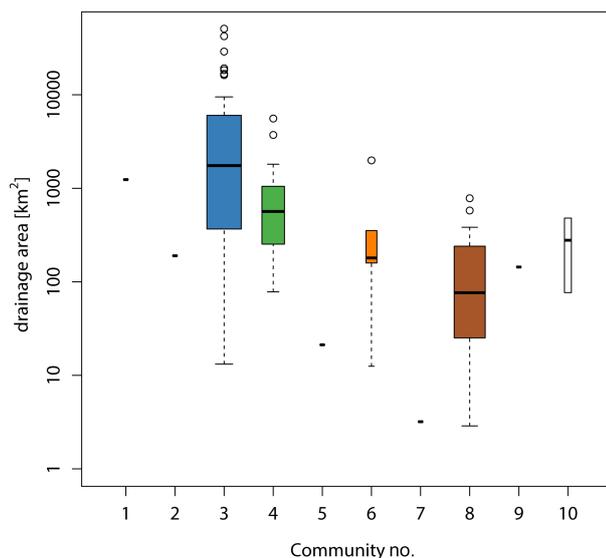


Figure 11. Boxplots of upstream basin drainage area grouped by community. The colours are consistent with the map in Fig. 8.

Alternatively, the division between communities 3 and 4 might also be driven by the increased likelihood for stations in community 3, which extends further north than community 4, of having more permanent ice coverage or a thicker snowpack. Unfortunately this cannot be tested quantitatively because ice cover data were not readily available for about half of the stations in this analysis. However, mid-to-late summer differences in median hydrograph form are consistent with this interpretation, with community 3 exhibiting a more seasonally extensive melt freshet than community 4 (Fig. 9).

4.3 Additional network metrics – betweenness

The edge betweenness community detection algorithm placed 90% of the stations into three communities, while the remaining 10% fell within single-member and small-membership communities. Small-membership communities have daily streamflow dynamics that are uncommon because they represent undersampled and/or rare hydrometeorological regimes, which we will argue makes them important if the goal of a hydrometric network is to sample the inherent hydrometeorological diversity of the Coast Mountains. As we will show here, there are also several additional important stations which were not directly identified by the community analysis.

A closer inspection of the streamflow network representation in Fig. 7 reveals a handful of stations which are positioned in-between the large communities. These stations belong to large communities, but unlike most stations they tend to possess intercommunity connections. Such stations act as bridges between communities, and thus they can be regarded as hybrid stations representing the transition between station groups having different day-to-day hydrometeorological dynamics and even annual regime types.

The local network property that sets them apart is called betweenness, a concept we broached briefly in our discussion of community detection algorithms. Formally, the betweenness of a node is the number of geodesic paths passing through it, where a geodesic path is the shortest path between a node pair. In fact, the concept of edge betweenness, which was used to identify the community structure, is an extension of the concept of node betweenness. A high betweenness node would host a great amount of geodesics in the same way that a bridge hosts a great amount of traffic in a transportation network. As for the community-finding process, no assumptions are required regarding network topology.

The bar plot in Fig. 12 shows that node betweenness is unevenly distributed across the streamflow stations such that a small number of stations have very high scores, while most stations have low scores. The high scores are of interest here, so for the purpose of discussion we select stations having a (somewhat arbitrarily chosen) normalized betweenness score of 0.06 or higher. There are seven stations fitting this criterion: 08GA071, 08GA075, 08HB074, 08MF065, 08MF068, 08MG001, and 08MH147. These seven stations are encircled in Fig. 7.

The seven stations together connect communities 3, 4, and 8, the three largest communities in the streamflow network. Community 3 occupies a large part of the Coast Mountains but, interestingly, the high-betweenness stations within it are all located in southern BC. These particular stations contain links to stations in communities 4 (southern-central BC) and 8 (Vancouver Island and southwestern BC). Intuitively, we expect the hydrograph of a high-betweenness station to bear some resemblance to the multiple communities it joins. This appears to be borne out in practice: the clima-

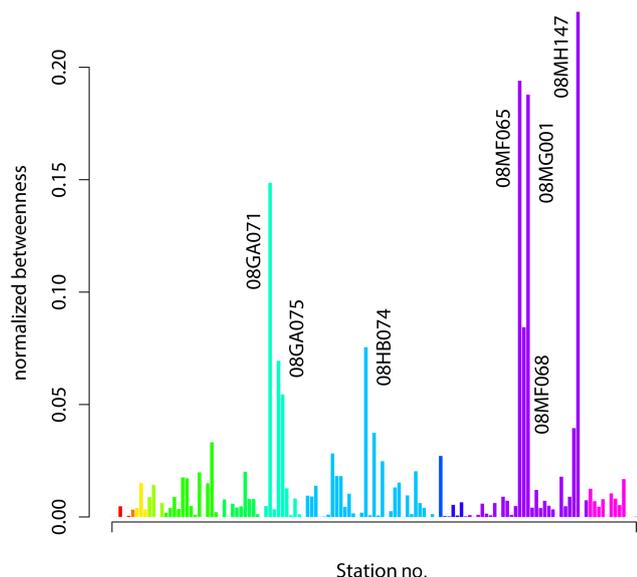


Figure 12. Bar plot of the betweenness scores for every station, with several high-betweenness stations highlighted. The station colours are based on the WSC designated subregion shown in Fig. 2.

tological hydrographs for each of these seven stations resembles the mixed rain–snow regime (e.g., Fig. 1c).

In terms of network theory, high-betweenness stations are important to network stability given their role as bridges between communities. For this reason we argue that they are essential members of the network, but not in the same way as the stations forming the small-membership communities. The loss of just a few high-betweenness stations would fragment the network into isolated communities. Information flow, or in our context, transferability of discharge measurements across locations, would be restricted in their absence.

5 Implications for the streamflow monitoring network

The various network diagnostics and tools have provided micro-level (i.e., individual stations) and macro-level (community structure and network architecture) descriptions of the streamflow network. The question now becomes: how can we use these results to inform and guide streamflow network design? We begin by first summarizing what the network analysis told us about the data from the current monitoring system. As discussed above, the architecture of the streamflow network is consistent with the small-world class of networks. Small-world networks are considered stable, meaning that the removal of a node at random is unlikely to fragment the network. In terms of the streamflow monitoring system, this implies there may be a sufficient amount of redundant information, or a relatively large number of station pairs with high correlation coefficients. A randomly selected station will likely have 19.6 connections (the network-wide node degree average). As such, the loss of any one station

selected at random will probably not result in the loss of a significant amount of information or a fragmented network. However, if a high-betweenness station is lost, then the likelihood of fragmenting the network is increased. Moreover, the loss of a station which belongs to a single-membership community is essentially the loss of unique and therefore unrecoverable information because there is no means to reconstruct its streamflow.

The edge betweenness community detection algorithm identified 10 communities within the streamflow network, but 90 % of the stations fell within just 3 communities. A community, defined on the basis of network theoretic analysis, shares specific elements which can be tied back to two general physical hydrologic characteristics: mean annual hydrograph form reflecting similar precipitation phasing in this transitional rain–snow region, in turn largely a function of basin elevation or secondarily latitude and continentality, and geographic proximity reflecting shared day-to-day local-to-synoptic scale meteorological forcing. Therefore, the number of communities reflects the hydrometeorological diversity of the Coast Mountains, and the number of stations per community sets the extent to which each distinct hydrologic “family” is sampled. The stations within each community having the highest number of intracommunity links can be thought of as index or reference stations (explicitly summarized for the three largest communities in Table 3; selecting an index station is obviously less necessary or useful for smaller communities). Such stations have streamflow time series that are representative of the other members of their respective communities. Because the distribution of intracommunity degrees was somewhat evenly distributed across the stations, no single station can clearly be identified as the sole index for each of the large communities, and presumably any of those short-listed in Table 3 would suffice for its respective community.

The community-detection and node-betweenness algorithms identified two types of “outlier” stations. The first type consists of those stations belonging to small-membership communities. These stations represent rare or undersampled hydrometeorological regimes. Such communities may exhibit a median annual hydrograph similar to other communities, but they appear to be sufficiently distant in space that they do not, in general, share the same meteorological forcing with those other communities. Thus, the streamflow time series from one such community cannot be accurately indexed by, or easily reconstructed from, the streamflow time series from another.

The second type of outlier station consists of those with high betweenness scores. These stations contain intercommunity links, which serve to bridge disparate communities. The hydrographs of these stations can be regarded as hybrids of the communities they connect. These might be viewed as do-it-all stations, which provide information about several communities of hydrometeorological variation, though incompletely. The loss of such stations would fragment the

Table 3. The most highly connected (in an intracommunity sense) stations in each of the three largest communities and the number of intracommunity links (k_{com}). These stations could serve as index stations for their respective community.

| Community no. | Station no. | k_{com} |
|---------------|-------------|------------------|
| 3 | 08EE020 | 43 |
| | 08DB001 | 42 |
| | 08DA005 | 40 |
| | 08ED001 | 38 |
| | 08JA015 | 38 |
| 4 | 08NL038 | 20 |
| | 08LG008 | 19 |
| | 08LG048 | 19 |
| | 08NL007 | 19 |
| | 08NL069 | 19 |
| 8 | 08HA072 | 27 |
| | 08HA070 | 25 |
| | 08HB002 | 25 |
| | 08HC002 | 25 |
| | 08HB086 | 24 |

network, in principle making it more difficult to recover information.

There is a substantial amount of redundancy (many pairs of stations with a high correlation coefficient) within the three large communities identified in this paper. Stations having a low betweenness score, a high number of degrees, and membership to a large community might be regarded as redundant and thus, perhaps, candidates for decommissioning under, for example, budgetary pressure. However, the network theoretic perspective suggests that this type of redundancy could alternatively be considered a strength of the hydrometric monitoring system, insofar as it implies that the stream gauges, in their present arrangement, form a stable network which is resilient to the unintended loss of a node (as might occur operationally due to equipment failure, for example). Much of the high interconnectedness within each of the three large communities may simply be driven by seasonal snow and ice melt from mid- to high-elevation basins, or, in the case of the pluvial drainages of Vancouver Island and the low-elevation regions of southwestern BC, a dense array of gauges sampling a sufficiently small region.

Given the insights gained by analyzing the current network, what might the optimal sampling network look like? As discussed in the introduction, this depends on many practical considerations which are far beyond the scope of this study and, perhaps, any statistical data analysis-based method for hydrometric monitoring system design. Some of these considerations include budget constraints, station accessibility, or special applications (such as fisheries studies, climate variability and change detection, or the need to monitor a particular river for a particular purpose, such as

an assessment for microhydropower generation potential or the design of bridge crossings, for example). In the absence of these considerations, or in addition to them, a sampling program would ideally capture all of the possible types of streamflow dynamics in the region. In the context of network theory, this amounts to maximizing the number of communities sampled because the number of communities reflects hydrometeorological diversity. The number of members in each community should be large enough to provide some redundancy as a safeguard to ensure minimal information is lost if a station fails or is decommissioned; that said, redundancy might also be viewed as an argument in favour of station closure, as noted above. In any event, the small number of stations having high betweenness, and the stations which are members of a small community, constitute two types of particularly high-value stations which should not be removed from the streamflow monitoring system under cost-cutting, for example. Additionally, stations with a high number of intracommunity links might be identified as index or reference stations for their respective communities, and should be viewed as high-value stations.

6 Conclusions

In this paper, we have analyzed the hydrology of the Coast Mountains by applying network analysis tools to a collection of streamflow gauges. Our motivation was to characterize the existing network and place it in context with idealized and observed networks, with an eye to informing streamflow network design.

Daily streamflow data in this region proved amenable to network theoretic analysis. In particular, it was found to display properties consistent with the small-world class of networks, a common type observed in many disciplines. A small-world network implies stability, and that its structure is resilient to the loss of nodes. Interestingly, the results also suggest that the streamflow network in this region is not of the scale-free type. There is precedent for small-world, non-scale-free networks, but they appear uncommon.

Community-detection algorithms separated the network into three main groups, each containing dozens of stations, plus a handful of smaller groups. We then show that these 10 individual communities appear to be defined by both (i) their typical annual hydrograph forms, which in turn correspond to various considerations such as basin elevation, and (ii) their geographical proximity, which in turn corresponds to shared or different meteorological forcing. That is, (i) and (ii) together form distinct classes of daily-to-seasonal hydrological dynamics which are identified by the community-finding algorithm. The number of communities reflects the diversity of such hydrologic dynamical classes, and the number of stations per community sets the extent to which each regime is sampled.

The network theoretic outcomes provide a different way of viewing spatiotemporal hydrologic patterns and, in particular, a novel perspective on the old question of optimal hydrometric monitoring system design. We argue that the idealized sampling strategy should span the full range of dynamical classes described above, and additionally that it should retain some redundancy in the event of station failure, which may be facilitated by the small-world topology identified for this network. Furthermore, we identified a number of stations which warrant special attention because they characterize rare, undersampled, or information-rich hydrometeorological dynamics. Specifically, we propose that from a monitoring system design perspective, the most important stations are (1) those which have a large number of intracommunity links and thus serve as indices for their respective communities, (2) those with high betweenness values, and which thus serve as do-it-all stations embedding information about multiple communities, and (3) those which are members of single-membership or small-membership communities, as their hydrometeorological dynamics are poorly sampled by the existing monitoring system and cannot be readily reconstructed from other hydrometric stations.

The network analysis as applied in this paper required us to choose a number of parameters. For example, it was necessary to fix the threshold correlation coefficient to define the pairwise relationships between streamflow gauges. We reiterate that our analysis showed that the network architecture, a global property, is not sensitive to the threshold coefficient within a realistic range of values. However, we do expect that changing the coefficient will likely impact the details of community membership and the individual high-value stations identified by community detection and betweenness. This is obviously due to the fact that some pairwise relationships will simply change as the threshold correlation coefficient is varied. Care should be taken to understand which stations share correlation coefficients near the threshold before using a community or betweenness analysis to guide practical decisions on whether to alter the streamflow monitoring system.

In addition to hydrometric monitoring system design, this work will hopefully inspire further applications of network theory to regional hydrology. As such, and given the relative newness of network theoretic applications within water resources science as discussed in the introduction, one could envision any number of (potentially) useful extensions or refinements. A few are listed as follows. Repeating the analysis with deseasonalized discharge time series might be interesting because it would remove the seasonally driven component of serial correlation, and therefore more clearly reveal regional climate or weather effects, but might be less useful for hydrometric network design as it would not speak directly to actual streamflow values. The analysis could also be repeated with time periods of different lengths, or with climate-conditioned networks formed by selecting data from particular seasons or years (e.g., winter only, or El Niño years). Application of the methods in different regions could prove

interesting, as the results were found to reflect (in part) hydrologic regime types which, generally speaking, would be different elsewhere. Another option is to apply these methods to derived streamflow metrics, such as annual time series of peak flow, freshet start date, or minimum 7-day mean discharge, though it remains to be seen whether the attendant reduction in the number of samples (by a factor of 365, essentially) might be debilitating to the network analysis algorithms. Our application of network theoretic community detection algorithms to streamflow data could be seen as a new approach to watershed typing, and the success of this procedure provides some confirmation of the possibility, raised by Sivakumar et al. (2015), that network theory could in principle prove instructive to catchment classification, a direction clearly warranting closer investigation. Any number of alternatives to the use of correlation coefficients for link definition might be entertained, ranging from lagged linear cross-correlations, to the p values associated with linear or rank correlation coefficients, various information theoretic (Shannon entropy-based) measures like transinformation, the Nash–Sutcliffe efficiency (or some other goodness-of-fit measure) with which the streamflow time series at one node in a pair can be modelled on the basis of that at the other node using (say) linear regression or an artificial neural network, whether the Akaike information criterion associated with such a model does or does not indicate an acceptable combination of predictive skill and parsimony, and so forth. Indeed, essentially any quantitative measure of the relationship between two time series would, in principle, be a candidate for assigning links; we simply chose one of the most common and intuitive here. Another question to consider is how the sampling system design guidance provided by the network theoretic perspective compares with that from other quantitative techniques, though our suspicion is that the “best” approach would ultimately be to use all the tools available to inform such network design choices, particularly given that, as mentioned above, a wide variety of considerations come into play when actually designing a real-world hydrometric network. Finally, most network analysis algorithms and tools have analogies for weighted networks, which are a type of network that explicitly allows for a variable strength between nodes. Reformulating the streamflow network as a weighted network may circumvent some of the limitations introduced when links are binary – i.e., either present or absent.

Appendix A: Streamflow community membership

The edge betweenness community finding algorithm identified 10 communities within the streamflow network. In Table A1 we provide a complete list of the members in each community.

Table A1. Membership table of the communities in the streamflow network as determined by the edge betweenness algorithm.

| Community | Water Survey of Canada station number | | | | | | |
|-----------|---------------------------------------|---------|---------|---------|---------|---------|---------|
| 1 | 08AA008 | | | | | | |
| 2 | 08AA009 | | | | | | |
| 3 | 08AB001 | 08AC001 | 08AC002 | 08BB005 | 08CE001 | 08CF003 | 08CG001 |
| | 08DA005 | 08DB001 | 08DB013 | 08DB014 | 08EB004 | 08EC013 | 08ED001 |
| | 08ED002 | 08EE004 | 08EE008 | 08EE012 | 08EE020 | 08EF001 | 08EF005 |
| | 08EG012 | 08FA002 | 08FB006 | 08FB007 | 08FE003 | 08GA071 | 08GA072 |
| | 08GD004 | 08GD008 | 08GE002 | 08GE003 | 08JA015 | 08JB002 | 08JB003 |
| | 08MA001 | 08MA002 | 08MA003 | 08MB005 | 08MB006 | 08MB007 | 08ME023 |
| | 08ME025 | 08ME027 | 08ME028 | 08MF065 | 08MG005 | 08MG013 | 08MG026 |
| 4 | 08EE013 | 08FC003 | 08LG008 | 08LG016 | 08LG048 | 08LG056 | 08MA006 |
| | 08MF062 | 08MF068 | 08MH001 | 08MH016 | 08MH056 | 08MH103 | 08NL004 |
| | 08NL007 | 08NL024 | 08NL038 | 08NL050 | 08NL069 | 08NL070 | 08NL071 |
| | 08NL076 | | | | | | |
| 5 | 08EE025 | | | | | | |
| 6 | 08EG017 | 08FB004 | 08FF001 | 08FF002 | 08FF003 | | |
| 7 | 08FF006 | | | | | | |
| 8 | 08GA061 | 08GA075 | 08GA077 | 08GA079 | 08HA001 | 08HA003 | 08HA010 |
| | 08HA016 | 08HA068 | 08HA069 | 08HA070 | 08HA072 | 08HB002 | 08HB014 |
| | 08HB024 | 08HB025 | 08HB032 | 08HB048 | 08HB074 | 08HB075 | 08HB086 |
| | 08HB089 | 08HC002 | 08HC006 | 08HD011 | 08HD015 | 08HE006 | 08HE007 |
| | 08HE008 | 08HE009 | 08HE010 | 08HF004 | 08HF005 | 08HF006 | 08HF012 |
| | 08HF013 | 08MG001 | 08MH006 | 08MH076 | 08MH141 | 08MH147 | 08MH155 |
| | 08MH166 | | | | | | |
| 9 | 08MH029 | | | | | | |
| 10 | 08OA002 | 08OA003 | 08OB002 | | | | |

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