Macroscale hydrologic modeling of ecologically relevant flow metrics

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[1] Stream hydrology strongly affects the structure of aquatic communities. Changes to air temperature and precipitation driven by increased greenhouse gas concentrations are shifting timing and volume of streamflows potentially affecting these communities. The variable infiltration capacity (VIC) macroscale hydrologic model has been employed at regional scales to describe and forecast hydrologic changes but has been calibrated and applied mainly to large rivers. An important question is how well VIC runoff simulations serve to answer questions about hydrologic changes in smaller streams, which are important habitat for many fish species. To answer this question, we aggregated gridded VIC outputs within the drainage basins of 55 streamflow gages in the Pacific Northwest United States and compared modeled hydrographs and summary metrics to observations. For most streams, several ecologically relevant aspects of the hydrologic regime were accurately modeled, including center of flow timing, mean annual and summer flows and frequency of winter floods. Frequencies of high and low flows in the summer were not well predicted, however. Predictions were worse for sites with strong groundwater influence, and some sites showed errors that may result from limitations in the forcing climate data. Higher resolution (1/16th degree) modeling provided small improvements over lower resolution (1/8th degree). Despite some limitations, the VIC model appears capable of representing several ecologically relevant hydrologic characteristics in streams, making it a useful tool for understanding the effects of hydrology in delimiting species distributions and predicting the potential effects of climate shifts on aquatic organisms.

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1. Introduction

[2] Hydrologic regimes in the western United States have undergone substantial changes over the last half century, including trends toward earlier snowmelt runoff [*Mote*, 2003; *Regonda et al.*, 2005; *Stewart et al.*, 2005], reduced water yields [*Luce and Holden*, 2009], lower summer flows [*Luce and Holden*, 2009; *Rood et al.*, 2008], and increased or altered flood risk [*Hamlet and Lettenmaier*, 2007]. These hydrologic trends are especially strong in the Pacific Northwest [*Hidalgo et al.*, 2009; *Regonda et al.*, 2005; *Stewart et al.*, 2005]. These trends have been related to the effects of a warming climate [*Barnett et al.*, 2008; *Hidalgo et al.*, 2009], particularly an increase in temperature [*Hamlet et al.*, 2005; *Mote*, 2003], although precipitation shifts may also play a role in some regions [*Luce and Holden*, 2009; *Moore et al.*, 2007; *Hamlet et al.*, 2005]. Ongoing increases in atmospheric carbon are expected to continue warming trends and shifts in hydrologic regimes during the 21st century [*IPCC*, 2007; *Adam et al.*, 2009; *Hayhoe et al.*, 2004; *Knowles and Cayan*, 2002; *Stewart et al.*, 2004].

[3] Hydrologic changes have implications not only for humans but for populations of fish and other aquatic organisms that are adapted to specific flow regimes [*Crozier et al.*, 2007; *Fausch et al.*, 2001; *Lytle and Poff*, 2004; *Poff et al.*, 1997]. For example, many trout species depend on relatively stable, low flows during the critical period of fry emergence from redds (nests), as newly emerged fish may suffer high mortality in high flows [*Crisp and Hurley*, 1991; *Heggenes and Traaen*, 1988; *Seegrist and Gard*, 1972; *Tonina et al.*, 2008]. This suggests that fall spawning species will tend to benefit from infrequent winter flooding (as occurs in snowmelt-runoff streams), while spring spawning species will benefit from infrequent flooding in summer [*Fausch et al.*, 2001; *Fausch*, 2008; *Latterell et al.*, 1998; *Seegrist and Gard*, 1972; *Strange et al.*, 1993]. Researchers have also found that overall hydrologic regime (snowmelt-dominated versus rain-dominated) influences spawning timing and life history of Chinook salmon [*Beechie et al.*, 2006]. Flow changes may have important indirect effects as well, such as increasing the rate of stream warming as summer flows decline [*Isaak et al.*, 2010].

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[4] Hydrologic models are commonly used to explore climate-driven shifts in hydrologic regime of importance to ecosystems [*Batin et al.*, 2007; *Crozier et al.*, 2007; *Mantua et al.*, 2009]. One model in particular, the variable infiltration capacity (VIC) model [*Liang et al.*, 1994; *Liang et al.*, 1996], has been widely adopted in the western United States and used to study the effects of droughts [*Luo and Wood*, 2007], changes in snowpack [*Hamlet et al.*, 2005], water resources impacts [*Hamlet et al.*, 2009; *Vano et al.*, 2010a, 2010b], and for various other applications. For simulation of daily flows, the VIC model is typically coupled with a flow routing model to accommodate downstream transport time [*Lohmann et al.*, 1996, 1998] and simulate hydrographs [e.g., *Hamlet and Lettenmaier*, 2007; *Hidalgo et al.*, 2009; *Hurkmans et al.*, 2008; *Maurer et al.*, 2002]. Nearly all such studies have been performed on large rivers (often $>10^4$ km^2 drainage area). However, the ability to simulate flows in small- to mid-sized streams (10^1–10^3 km^2 drainage area) would also be desirable. Smaller streams often have significant amounts of biological data available, figure prominently in many conservations efforts, and usually comprise large fractions of the total length in river networks. However, VIC calibration has also been limited to the scale of large river basins, and it cannot be assumed that outputs from a distributed model calibrated at a broad scale are transportable to the fine scale, even within the calibrated domain [e.g., *Beven*, 1989; *Bloschl and Sivapalan*, 1995]. Therefore, any attempt to apply VIC outputs to the fine scale requires careful validation of the resulting hydrographs and streamflow metrics.

[5] Here we use a simplified routing approach to construct hydrographs from VIC flow data for all streams <2500 km^2 in the Pacific Northwest (PNW) within the United States. We validate the output by comparing attributes of simulated hydrographs to those from observed hydrographs at 55 U. S. Geological Survey (USGS) gaging stations (drainage area 27–2318 km^2), with a focus on aspects of the hydrologic regime hypothesized to affect fish and other freshwater organisms. Secondarily, we examine how differences in model resolution affect predictive accuracy. Most applications of VIC have been at a resolution of 1/8th degree [*Hamlet et al.*, 2005; *Maurer et al.*, 2002], but some recent efforts have adopted a resolution of 1/16th degree [*Elsner et al.*, 2009]. We compare the performance of these two model resolutions in simulating observed hydrologic metrics.

2. Methods

2.1. VIC Modeling

[6] VIC is a fully distributed and largely physically based model that solves the surface energy and water balance. Infiltration, runoff, and base flow processes are based on empirically derived relationships [*Liang et al.*, 1994] and characterize the average conditions over the macroscale grid cell. For historical simulations as performed here, meteorological forcing data for the model are produced using hybrid methods that combine both low-elevation station observations and statistically derived estimates of high-elevation temperature and precipitation [*Daly et al.*, 1994; *Hamlet and Lettenmaier*, 2005; *Maurer et al.*, 2002]. The model can also be driven by output from climate models to forecast flows under future conditions. The physically based energy balance snow model in VIC is shared with the fine-scale distributed hydrology soil vegetation model (DHSVM) [*Wigmosta et al.*, 1994, 2002] and explicitly accounts for canopy processes that strongly affect snow accumulation and melt in the PNW. Snow simulations from VIC were validated over the Western United States by *Mote et al.* [2005]. The 1/8th degree version of the model employed here was calibrated for the PNW by *Matheussen et al.* [2000] using an earlier meteorological forcing data set, with minor recalibration for the 1/16th degree version [*Elsner et al.*, 2009]. Calibration consisted of adjustment of soil parameters, especially three parameters to which the model showed the greatest sensitivity: the infiltration capacity shape factor, the soil moisture threshold separating linear and nonlinear base flow, and the linear base flow storage constant [*Matheussen et al.*, 2000]. The model was run on a daily time step, except for the snowmelt model, which was run on a 3 h time step. More detail on the VIC data set used here can be found in the work of *Elsner et al.* [2009].

2.2. Assigning Output to Stream Segments

[7] We used VIC model outputs to construct hydrographs for every stream segment in the National Hydrography Database Plus data set (NHD Plus; http://www.horizon-systems.com/nhdplus/) in USGS hydrologic region 17 (Pacific Northwest) with watersheds <2500 km^2. This was an arbitrary cutoff set at a level that included most streams in the region for which freshwater biotic data were available, but which excluded rivers. We assumed that for sites larger than this, a flow modeling approach incorporating channel routing would be more appropriate and desirable than the method employed here. Excluding streams with watersheds >2500 km^2 eliminated 3.4% of segments.

[8] To develop stream hydrographs, we first summed the runoff and base flow values from the VIC output flux files for the 1915–2006 period for each 1/16th degree cell. We then applied a unit hydrograph developed for an application of the VIC model to the Fraser River Basin in Canada [*Schnorbus et al.*, 2010] that imposed modest flow lags to represent the travel time to each cell outlet. The unit hydrograph specified a flow distribution of 0.9 on day 0, 0.075 on day 1, and 0.025 on day 2. We then assigned the resulting hydrographs to NHD Plus catchments based on the cells the catchments fell within (or mostly within) and multiplied by the area of the catchment-cell intersection to produce an estimated daily flow from that portion of the catchment. In the NHD Plus data set, catchments are non-overlapping polygons that define the drainage area above the outlet of each stream segment, exclusive of all upstream catchments. We then conducted a downstream accumulation (summation) of these flows, such that the flow for each stream segment was the sum of all upstream flows, plus its own (Figure 1). This approach was very similar to that used by *Yang et al.* [2010] for routing VIC flows in the Indianapolis region. We repeated this process using the 1/8th degree resolution VIC data. Calculations were performed in ESRI ArcGIS 9.2, Filemaker Pro and R 2.8.

2.3. Calculating Metrics

[9] From these hydrographs, we calculated a set of metrics to summarize aspects of the flow regime hypothesized

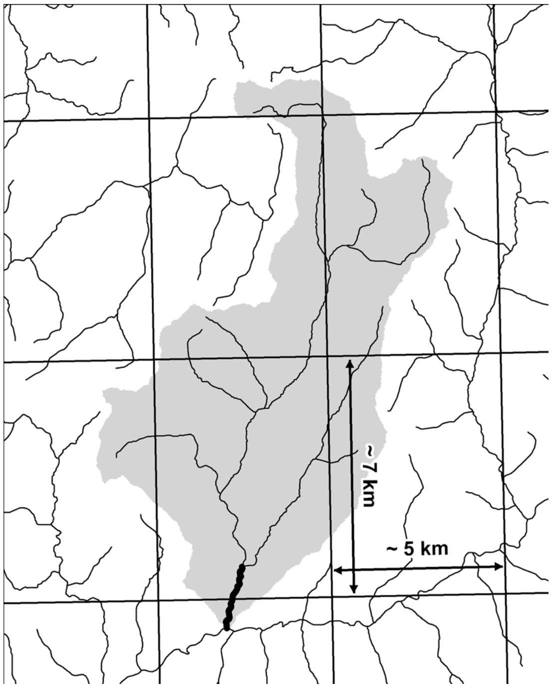

Figure 1. Illustration of the area-weighted sum methodology for 1/16th degree cells. The heavy-weighted stream segment drains all of the area shown in gray. The grid overlay shows 1/16th degree cells. The calculation of flow for that stream segment is obtained by multiplying the unit-sum hydrograph for each upstream cell (outlined in bold) by the drainage area within that cell; these are summed to produce the flow for the segment. Eighth degree cells are composed of four 1/16th degree cells and are approximately 10 km by 14 km (varying by latitude).

to be important determinants of fish distributions. These are listed in Table 1 and described below. All metrics were calculated for the 20 year period between 1 October 1977 and 30 September 1997. We selected this time frame due to the availability of good flow records and numerous contemporaneous fish collection data to which flow metrics could later be matched.

[10] 1. Center of timing of flow (CT). The center of timing of the mass of flow (CT) for an annual water year hydrograph summarizes a great deal of information about the flow regime, including type and timing of precipitation, timing of snowmelt, and length of the summer low-flow season [*Regonda et al.*, 2005]. The statistic can be defined as the centroid or mean of the annual flow mass [*Stewart et al.*, 2005] or the date at which half of the annual flow has been exceeded (i.e., the median) [*Regonda et al.*, 2005]. We used the latter as it is purported to be less sensitive to extreme flow events [*Moore et al.*, 2007], although our tests showed very similar results for both methods.

[11] 2. Overall hydrologic regime (HR). On the basis of CT, we grouped streams into three classes of hydrologic regime: "early" streams with CT < 150 (27 February), which have rainfall and high flows in the winter; "late" streams with CT > 200 (18 April), which have snowfall and few high flows in the winter; and "intermediate" streams with CT between 150 and 200. These classes are analogous to previous classifications of Northwestern streams into rain-dominated, snowmelt-dominated, and transient hydrographs [e.g., *Beechie et al.*, 2006; *Mantua et al.*, 2009].

[12] 3. Frequency of high flows during winter (W95, W99, W1.5, W2). As mentioned above, high winter flows may negatively affect fall-spawning fish. Because it is unclear what threshold of flow is harmful, we calculated four metrics: the number of days in winter that flow was in the top 5% or top 1% of annual flows (W95 and W99, respectively), and the probability that a 1.5 year flow event or a 2 year flow event would occur during the winter (W1.5 and W2, respectively). Winter was defined as December through March.

[13] 4. Frequency of high flows during summer (S95). Similarly, we calculated the frequency of high summer flows, which may be harmful to spring-spawning fish. We calculated only S95 (analogous to W95), as flow events larger than this almost never occur in the summer in much of the region. The start of summer was calculated individually for each stream segment and each year as the first day after 1 June when flows fell below the mean annual value; this ensured that summer started after the subsidence of the snowmelt flood. Summer was assumed to end on 30 September, regardless of the starting date.

[14] 5. Mean annual flow (MA) and mean summer flow (MS). Most fish species are adapted to a certain range of stream sizes, which correlate with mean annual flow. Mean summer flow (calculated for the season as described above) may be even more relevant as it describes the lowest-flow period that may be most limiting to fish and may correlate with maximum water temperature [*Isaak et al.*, 2010].

[15] 6. Days of summer low flows (S10, S20) and 7Q10. The number of zero-flow days is a straightforward indicator of drought and a frequently calculated flow metric [*Poff and Ward*, 1989; *Richter et al.*, 1997], but the VIC model does not allow zero flow. As an alternative, we calculated the number of days in the summer in which flows were less than 10% of MA and 20% of MA (S10 and S20). We also calculated the 7Q10 statistic, the 7 day low flow with a 10 year return interval.

[16] 7. High pulse count (HP). This is a measure of stream flashiness, which may exercise an important influence on aquatic organisms, especially in urban areas [*Konrad and Booth*, 2005]. We followed *DeGaspari et al.* [2009] in

Table 1. Mean Absolute Percent Error (MAPE) and Bias for Flow Metrics Calculated From 1/16th Degree Resolution VIC Model Versus Observed Data (MAPE16 and Bias16) and 1/8th Degree Resolution VIC Model Versus Observed Data (MAPE8 and Bias8)[a]

Flow Metric	MAPE16	MAPE8	Bias16	Bias8
W2	32%	31%	4%	8%
W1.5	29%	31%	9%	4%
W99	27%	29%	−7%	−3%
W95	22%	26%	−3%	−1%
S95	245%	315%	181%	244%
MA	18%	20%	−12%	−15%
MS	32%	37%	−10%	−17%
S20	83%	89%	−29%	−21%
S10	101%	103%	−94%	−90%
7Q10	57%	59%	−10%	−15%
HP	137%	141%	137%	141%

[a]Metrics are defined in the text.

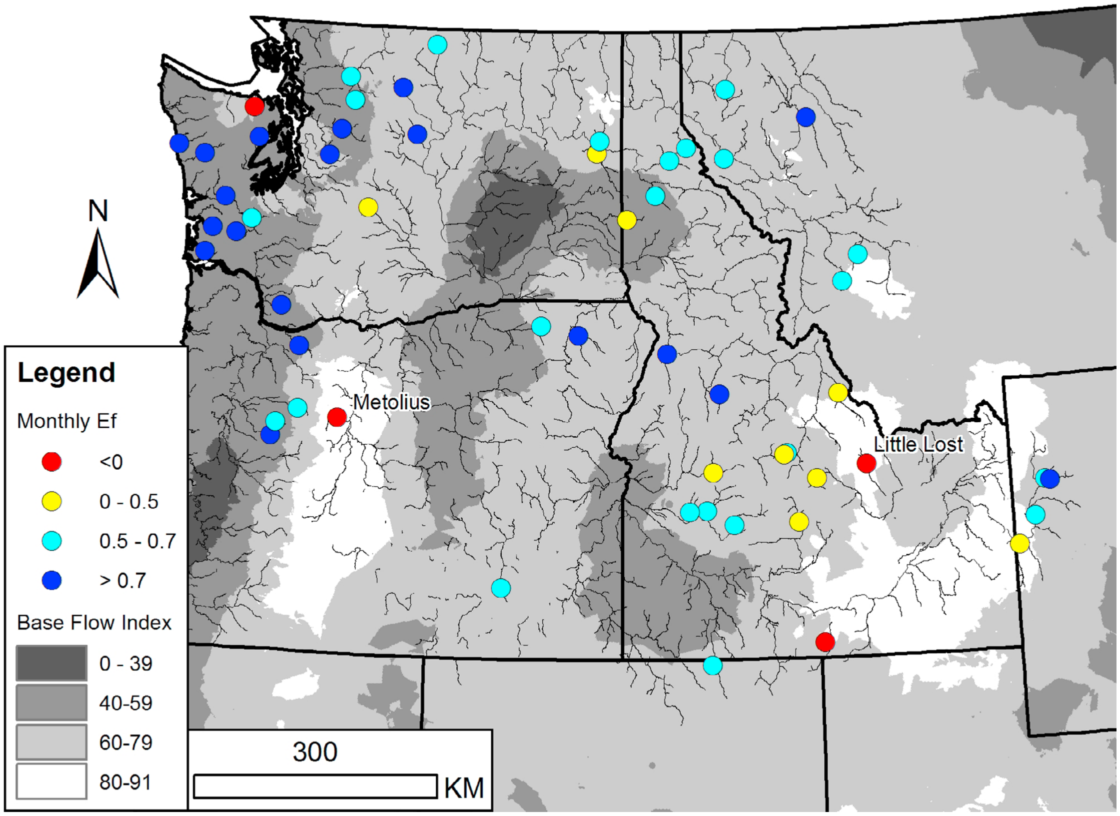

Figure 2. Validation gaging stations, monthly Nash-Sutcliffe efficiencies (E_f), and base flow index (BFI). Circles show gaging stations used for validation, coded by model predictive performance as indicated by monthly E_f. Baseflow index is indicated by gray shading. Large streams and rivers within the study domain are shown as fine black lines. The two labeled sites (Metolius and Little Lost) are described in the text as examples of poor performance in areas of high BFI. Map extent is 110°W–125°W, 41°N–49°N.

defining HP as the frequency of events that exceed the threshold of 2 times mean annual flow.

2.4. Model Validation

[17] We identified 55 USGS gaging stations in the Pacific Northwest to serve as validation sites (Table A1, Figure 2). Fifty of these were part of the Hydro-Climatic Data Network (HCDN) [*Slack et al.*, 1993], a set of gaging stations on streams with minimal anthropogenic flow alteration. We excluded large stations (those draining >2500 km^2) and those partly draining Canadian land, because they lacked NHD coverage. We supplemented these with five other gaging stations that met these criteria but were excluded from the HCDN list because of minor station relocations or shorter flow records (but which had flow records for the 1978–1997 period of interest). We compared flow metrics calculated from the observed daily hydrographs with those calculated from the VIC flow data (both 1/16th degree and 1/8th degree resolutions) for the appropriate stream segments at each station. We summarized differences between predicted and observed values as mean absolute percent error (MAPE) and prediction bias. In addition, we calculated the Nash-Sutcliffe efficiency index (E_f) [*Nash and Sutcliffe*, 1970] for modeled versus observed hydrographs at a daily, weekly, and monthly time steps for the 20 year period to assess the overall goodness of fit of the hydrologic models.

[18] Because analysis of initial results showed poor modeling of low flows, we conducted an additional test to determine whether these results represented systematic biases (which could be improved via calibration) or random errors. We calculated the E_f and the Pearson correlation coefficient (r) for the annual 7 day low-flow values for 1/16th degree output versus observed values. The E_f statistic measures degree of agreement between predicted and observed values, whereas r measures degree of correlation between the values. If errors were due to systematic biases, r would tend to be high even when E_f was low.

[19] We used a form of residual analysis to explore patterns in model predictive success by linearly regressing flow metrics and other potential predictors against monthly E_f. We hypothesized that three factors might influence E_f: (1) stream size (indicated by MA), as smaller streams might show greater bias, or larger streams might be poorly predicted due to lack of formal routing; (2) runoff timing (indicated by CT), as rainfall-dominated or snowfall-dominated regimes might prove easier to predict; and (3) degree of groundwater connectivity, indicated by base flow index (BFI) [*Wolock*, 2003], as VIC does not explicitly model movement of water into and out of deep subsurface reservoirs. The BFI measure, which ranges in value from 0 to 100, is an independent estimate of groundwater connectivity not derived from the VIC modeling. Because two sites had

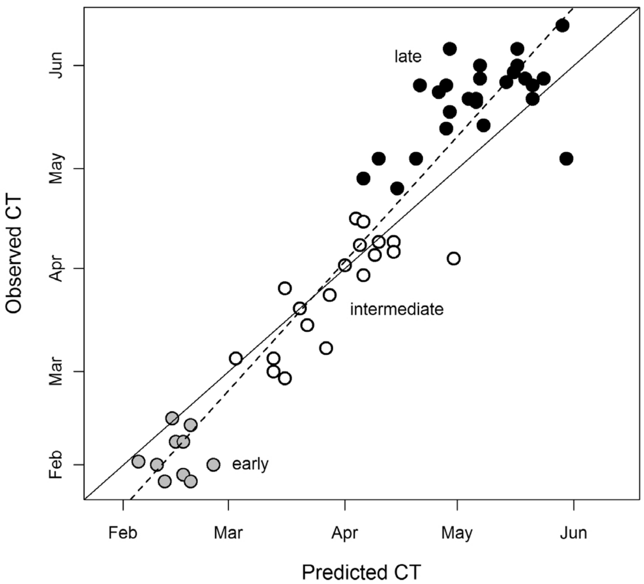

Figure 3. Predicted versus observed timing of the center of flow mass. Hydrologic regime is indicated by symbol color: gray for early timing, white for intermediate timing, black for late timing. The 1:1 line is shown as a solid line, and the best fit linear regression line is shown as a dashed line.

large negative monthly E_f values that severely skewed the distribution of the response variable, we converted all negative values to zero for the residual analysis, which preserved the overall pattern of the responses while preventing these outliers from exerting excessive influence.

3. Results

[20] Modeling results described here refer to outputs of the 1/16th degree VIC modeling compared to observed values unless otherwise noted. For overall goodness of fit, we focus on monthly E_f because it captures most of the essential seasonal components of the hydrograph. For 19 sites (35%, Table A1 and Figure 2), $E_f > 0.7$, which is often cited as a threshold for a good model fit [e.g., *Boone et al.*, 2004]. For an additional 23 sites (42%) $0.5 < E_f < 0.7$, a range that can be considered acceptable fit [*Boone et al.*, 2004]. For the remaining 23% of sites fit was fair to poor ($E_f < 0.5$), with four sites scoring negative E_f values, reflecting significant bias in the models [*McCuen et al.*, 2006]. The median E_f score for all sites was 0.63 (we report the median instead of the mean because the distribution of scores is heavily skewed, as negative E_f scores are unbounded while positive scores are bounded by 1). The median weekly E_f was 0.54 and the median daily E_f was 0.43.

[21] Predictions of CT had a median error of 12 days, with a negative bias for snowmelt sites (i.e., snowmelt was predicted to occur earlier than was observed) and a positive bias for rainfall sites (Figure 3). There was a consistent linear relationship between predicted and observed CT; a regression of predicted on observed yielded a coefficient of determination (r^2) of 0.90. This linear regression can be used to bias-correct the predictions, reducing median CT error to 9 days. Only 4 of the 55 sites were misclassified in terms of hydrologic regime. Three of these were predicted to be intermediate but observed to be early, while one was predicted to be early but observed to be intermediate.

[22] The probabilities and frequencies of high winter flows were predicted with low bias and good accuracy (Table 1, Figure 4a). Predictions of more frequent events (W95) were more accurate than those of less frequent events (W2). In contrast, S95 was poorly predicted and heavily biased (Table 1, Figure 4b), largely due to a tendency to predict high summer flows in many streams where they were not observed.

[23] Mean annual flow was predicted with good accuracy and a slight negative bias (Table 1, Figure 4c), while mean summer flow was predicted with moderate accuracy and a slight positive bias (Table 1). Low summer flows were poorly predicted with a strong negative bias, especially for the S10 metric, for which MAPE exceeded 100% (Table 1 and Figure 4d). In many cases, this resulted from a failure to predict observed low flows; for example, at seven sites observed S10 was >10 days but predicted S10 was 0. Results for 7Q10 were better (Table 1), but still showed high error rates (MAPE of 57%). High pulse count was poorly predicted, with high error and high bias (Table 1), resulting from a general over-prediction of events. We noted that the model frequently predicted a strong flow response to a precipitation event that elicited a relatively small observed response.

[24] Additional analysis of the low-flow errors showed that median E_f (across all sites) for minimum annual 7 day low flows was −4.39, indicating very poor fit. However, median r for predicted versus observed 7 day low flows was 0.75, indicating that much of the prediction error can be removed by a simple linear transformation. This suggested that the temporal pattern of ups and downs (i.e., the rank structure) was reasonably well modeled, but that the magnitude of fluctuations and the mean low flow were not well specified. On the whole, larger streams had better rank structure, with the three largest streams recording the three highest correlations of predicted versus observed low flows ($r > 0.90$), while smaller streams had more variable performance. There were no obvious correlates to explain the worst performing sites, which varied greatly in geographic location, stream size, and flow timing.

[25] In most cases, there was little difference between predictions from the 1/8th degree resolution VIC output and the higher resolution 1/16th degree output (Table 1). Predictions of flow metrics from the 1/16th degree model tended to be more accurate, with one exception (W2), but the differences were small. Where the 1/16th degree data produced better predictions, it was often due to a better ability to capture the timing and magnitude of the spring flood peak.

[26] The residual analysis revealed a noisy but significant negative quadratic relationship between CT and monthly E_f ($p < 0.01$ for both CT and CT^2, $r^2 = 0.16$), with higher average E_f scores at low and high CT than at intermediate CT. BFI showed an even stronger relationship with monthly E_f ($p = .0001$, $r^2 = 0.23$), such that sites with high BFI tended to have low E_f. Results were somewhat confounded by a strong correlation ($r = 0.81$) between CT and BFI, which made it difficult to separate these relationships. Nearly all streams with low CT also had low BFI, suggesting the

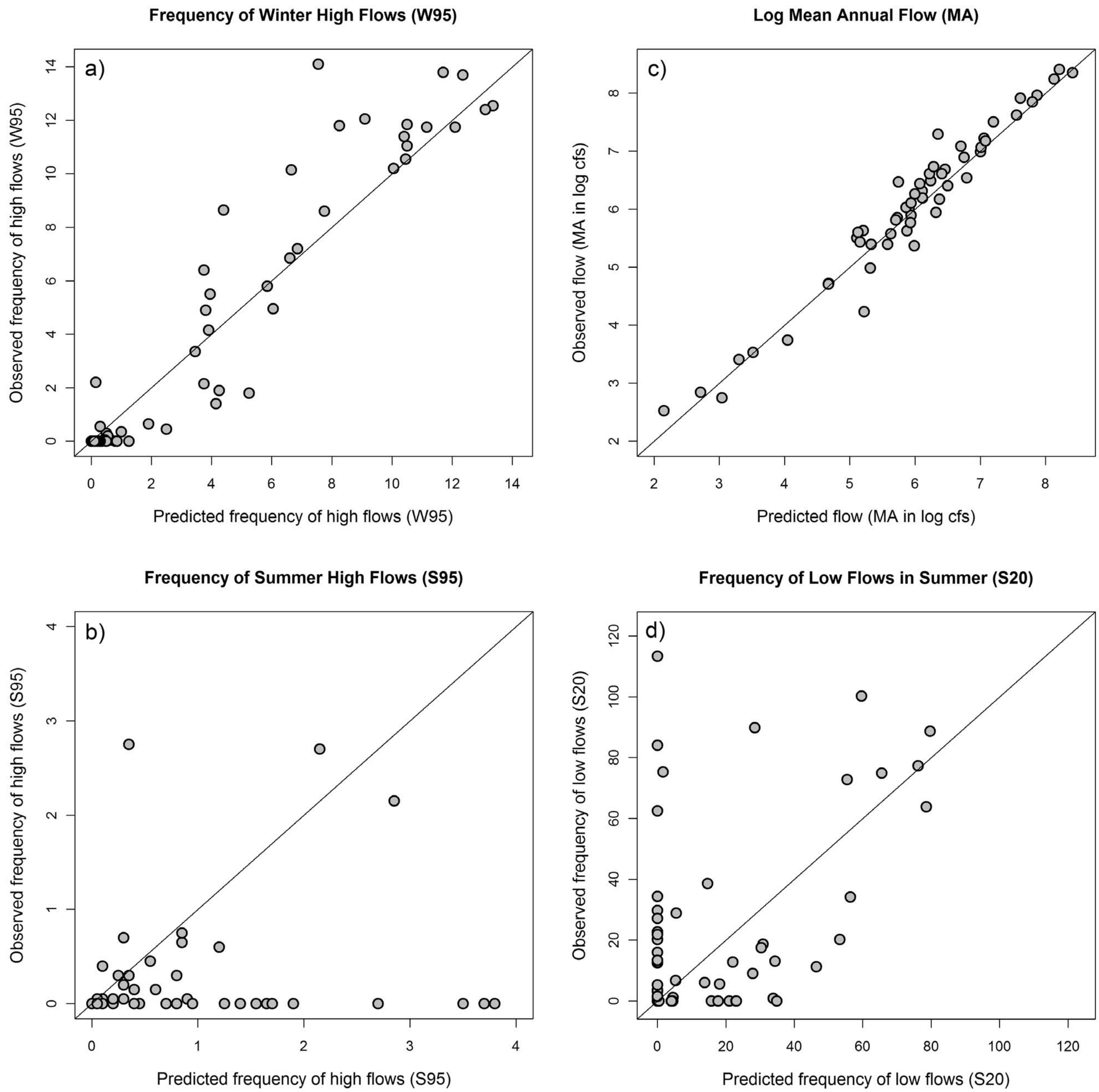

Figure 4. Predicted versus observed metrics for (a) W95, (b) S95, (c) MA (log scale), and (d) S20. The 1:1 line is shown as a solid line.

possibility that the apparently good performance of streams with low CT could be a function of low BFI. However, streams with high CT performed well in spite of the fact that many had high BFI, suggesting a pattern of good predictions for snowmelt-dominated systems. There was a weak but significant relationship between MA and E_f (p = 0.01, r^2 = 0.10) such that sites with higher mean annual flows tended to be slightly better predicted than sites with low flows.

4. Discussion

[27] Our simplified routing approach for applying VIC data to small streams produced hydrographs that were often a good fit to observed data, with median E_f values that compared favorably to those reported in other VIC studies [e.g., *Hurkmans et al.*, 2008]. More importantly, a number of flow metrics derived from the modeled hydrographs accurately represented attributes of the observed hydrographs. Mean flows, winter high flows, CT, and hydrologic regime were usually accurately predicted, although summer high and low-flow metrics were not. Residual analysis revealed that the strongest correlate of model predictive ability was BFI. This was consistent with the expectation that sites with large groundwater effects (contributions or losses) would not be well predicted. In the Metolius River, for example, substantial ”interbasin’ groundwater inflows

Table A1. U.S. Gaging Stations Used in Model Validation, With Drainage Area, Flow, Monthly E_f, and Daily E_f[a]

Station	Name	Drainage Area (km^2)	Mean Annual Flow (cfs)	Mean Annual Flow/Area (mm yr^{-1})	Monthly Ef	Daily E_f
14091500	Metolius River, OR*	818	1469	1603	−7.79	−10.05
13118700	Little Lost River, ID*	1140	69	54	−5.19	−10.65
12048000	Dungeness River, WA	404	382	844	−0.36	−0.12
13083000	Trapper Creek, ID*	139	16	101	−0.23	−3.03
13305000	Lemhi River, ID	2318	264	102	0.25	−0.67
12488500	American River, WA	204	221	964	0.28	0.18
13235000	S. Fork Payette, ID	1181	840	635	0.31	0.19
13120500	Big Lost River, ID	1165	320	245	0.33	−0.11
12424000	Hangman Creek, WA	1785	215	108	0.35	0.18
13023000	Greys River, WY	1160	645	496	0.36	0.32
13345000	Palouse River near Potlatch, ID	821	247	268	0.39	0.27
13139510	Big Wood River, ID	1658	490	264	0.4	0.13
13297330	Thompson Creek, ID*	75	17	204	0.45	0.12
12413000	N. Fork Coeur d'Alene at Enaville, ID	2318	1816	700	0.51	0.33
13297355	Squaw Creek, ID*	185	34	165	0.52	0.29
12411000	N. Fork Coeur d'Alene above Shoshone, ID	868	660	679	0.54	0.37
13161500	Bruneau River @ Rowland, NV	989	111	100	0.55	0.35
12332000	Middle Fork Rock Creek, MT	319	113	316	0.57	0.33
14020000	Umatilla River, OR	339	229	603	0.57	0.43
12390700	Prospect Creek, MT	471	221	418	0.58	0.3
10396000	Donner und Blitzen River, OR	518	146	252	0.59	0.37
12027500	Chehalis River near Grand Mound, WA	2318	2739	1055	0.59	0.45
12447390	Andrews Creek, WA	57	30	472	0.59	0.41
13186000	S. Fork Boise River, ID	1645	744	404	0.59	−0.11
13011500	Pacific Creek, WY	438	271	553	0.61	0.54
12431000	Little Spokane River, WA	1722	278	144	0.62	−0.48
12186000	Sauk River, WA	394	1089	2470	0.63	0.46
12414900	St. Maries River, ID	712	348	436	0.63	0.17
12302055	Fisher River, MT	2170	479	197	0.64	0.49
13200000	Mores Creek, ID	1033	280	242	0.64	0.64
13185000	Boise River, ID	2150	1193	496	0.65	0.57
14178000	N. Santiam River, OR	559	987	1575	0.66	0.64
14185900	Quartzville Creek, OR	257	628	2183	0.66	0.55
13018300	Cache Creek, WY	27	12	406	0.67	0.38
12189500	Sauk River near Sauk, WA	1849	4242	2048	0.68	0.18
12330000	Boulder Creek, MT	185	42	205	0.68	0.65
12020000	Chehalis River near Doty, WA	293	553	1686	0.71	0.52
13316500	L. Salmon River, ID	1492	743	445	0.73	0.65
13011900	Buffalo Fork, WY	837	525	560	0.74	0.65
12054000	Duckabush River, WA	172	409	2121	0.75	0.64
+12134500	Skykomish River, WA	1386	3798	2448	0.75	0.68
14137000	Sandy River, OR	681	1309	1716	0.75	0.71
14222500	E. Fork Lewis River, WA	324	693	1913	0.76	0.55
14185000	S. Santiam River, OR	451	801	1588	0.79	0.75
12010000	Naselle River, WA	142	416	2619	0.8	0.74
12370000	Swan River, MT	1738	1174	603	0.82	0.7
13313000	Johnson Creek, ID	552	336	544	0.82	0.72
12451000	Stehekin River, WA	831	1370	1472	0.83	0.48
12013500	Willapa River near Willapa, WA	337	604	1602	0.84	0.68
12040500	Queets River near Clearwater, WA	1153	4496	3483	0.84	0.73
12452800	Entiat River, WA	526	364	617	0.84	0.75
12144500	Snoqualmie River, WA	971	2560	2354	0.86	0.77
13331500	Minam River near Minam, OR	622	449	645	0.89	0.81
12035000	Satsop River, WA	774	2048	2361	0.91	0.77
12039500	Quinault River, WA	684	2877	3757	0.92	0.61

[a]Stations with an asterisk indicate those that are not part of the HCDN data set.

[*Gannet et al.*, 2001] caused predicted flow to be underestimated. Conversely, the Little Lost River is a losing stream that flows over fractured basalt, and VIC greatly overestimated summer flows in this system.

[28] The relationship with BFI is more striking when gage sites are divided into high, medium, and low categories. Sites with BFI less than 60 have a mean monthly E_f of 0.72; those with BFI of 60–80 have a mean monthly E_f of 0.58; and those with BFI above 80 have a mean E_f of −2.52. If we exclude the anomalous Metolius and Little Lost Rivers, we find that monthly E_f tends to be high (mean 0.70, standard error 0.15) for the 25 streams >500 cfs mean annual flow but ranges from poor to very good for the 28 smaller streams (mean monthly E_f 0.52, standard error 0.28). This is consistent with the hypothesis that VIC predictions may exhibit fine-scale biases in some cases, but these become less important at broader scales. This could arise due to unmodeled within-cell variability, limitations of calibration, or

errors in interpolating weather station data that might be large for individual cells but lower when averaged across many cells. The generally good performance for larger stream sites suggests that the lack of a network flow routing algorithm did not impose a major performance penalty.

[29] The estimates of CT were biased early for snowmelt sites and late for rainfall sites. A potential explanation for this is underestimation of winter precipitation. That is, if winter rain is underestimated then CT will be overestimated, whereas if winter snow is underestimated the snowpack will be predicted to melt earlier [*Luce and Holden*, 2009] and CT will be underestimated. These biases could result from limitations of the meteorological forcing data, which are extrapolated from weather stations located mainly at low and mid elevations [*Hamlet et al.*, 2005]. Alternatively, the bias could arise from other errors, such as failure to account for heterogeneity in snowmelt rates [*Luce et al.*, 1998] or streamflow recession rates [*Tague and Grant*, 2009]. If such errors resulted in underestimation of CT at high-elevation sites, improper calibration (performed at large river sites far downstream) might have effectively balanced this by adjusting parameters that resulted in overestimation of CT at low-elevation sites.

[30] Although low flows were not accurately predicted by VIC, our analyses suggested that these errors may derive from systematic biases rather than a failure to match climatic signals. That is, model predictions tend to be systematically higher or lower than observed values, but interannual variability in flows is still captured with reasonable fidelity in the historical data (as indicated by the correlation between predicted and observed minimum annual 7 day low flow). This means that low-flow predictions in their raw form should probably not be used for spatial comparisons among sites, but may be useful for long-term trend analyses at single sites. For example, it might be perfectly reasonable to use VIC to predict trends in low-flow responses to climate change at a specified site (assuming accurate driving data). However, before doing so we suggest evaluating model performance at nearby gaging stations and giving careful consideration to the nature and potential causes of model error in that region. Biases could also be reduced through postprocessing via statistical procedures such as linear regression or quantile mapping [*Snover et al.*, 2003]. Alternatively, the VIC model could be calibrated on a region-by-region basis via adjustments in soil or vegetation parameters.

[31] Performance of VIC modeling using a 1/8th degree resolution was almost as good as 1/16th degree resolution, for the metrics we examined. This is promising because 1/16th degree VIC modeling is not only much more computationally intensive (by a factor of 4) but also has only been performed in limited regions to date, whereas 1/8th degree modeling has been conducted across the Western United States [*Hamlet et al.*, 2005]. We caution, however, that our validation sites were on streams large enough to drain at least several 1/8th degree cells. For headwater streams small enough to drain only one or two 1/16th degree cells, the finer-resolution data could provide more accurate predictions, especially in areas of high relief.

[32] Our results indicate that it is possible to use VIC to accurately predict several ecologically relevant hydrologic metrics for entire stream networks. Previous efforts toward this goal relied on statistical approaches to classify streams by flow regime and then built regression equations to predict flow metrics from landscape characteristics within each classification. This can be effective [e.g., *Sanborn and Bledsoe*, 2006] but the resulting prediction sets are static and not readily modified to account for hydrologic changes induced by warming. In contrast, the VIC model can be forced with data from general circulation models to explore the effects of altered temperature and precipitation patterns on critical processes such as snow dynamics, evapotranspiration rates and soil moisture. Thus, it provides a rational basis for predicting changes to snowmelt timing, winter high-flow frequencies, and other aspects of the hydrologic regime that may be critical determinants of aquatic species distributions and population dynamics.

Appendix A

[33] The gaging stations used in model validation are listed in Table A1.

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References

Adam, J. C., A. F. Hamlet, and D. P. Lettenmaier (2009), Implications of global climate change for snowmelt hydrology in the 21th century, *Hydrol. Processes*, *23*, 962–972.

Barnett, T. P., et al. (2008), Human-induced changes in the hydrology of the western United States, *Science*, *319*, 1080–1083.

Batin, J., M. W. Wiley, M. H. Ruckelshaus, R. N. Palmer, E. Korb, K. K. Bartz, and H. Imaki (2007), Projected impacts of climate change on salmon habitat restoration, *Proc. Nat. Acad. Sci. USA*, *104*, 6720–6725.

Beven, K. (1989), Changing ideas in hydrology – The case of physically-based models, *J. Hydrol.*, *105*, 157–172.

Beechie, T., E. Buhle, M. Ruckelshaus, A. Fullerton, and L. Holsinger (2006), Hydrologic regime and the conservation of salmon life history diversity, *Biol. Conserv.*, *130*, 560–572.

Bloschl, G., and M. Sivapalan (1995). Scale issues in hydrological modeling: A review, *Hydrol. Processes*, *9*, 251–290.

Boone, A., et al. (2004), The Rhone-aggregation land surface scheme intercomparison project: An overview, *J. Clim.*, *17*, 187–208.

Crisp, D. T., and M. A. Hurley (1991), Stream channel experiments on downstream movement of recently emerged trout, *Salmo trutta* L and salmon, *S. salar* L. 1. Effect of 4 different water velocity treatments on dispersal rate, *J. Fish Biol.*, *39*, 347–361.

Crozier, L., R. W. Zabel, and A. H. Hamlet (2007), Predicting differential effects of climate change at the population level with life-cycle models of spring Chinook salmon, *Global Change Biol.*, *14*, 236–249.

Daly, C., R. P. Neilson, and D. L. Phillips (1994), A statistical topographic model for mapping climatological precipitation over mountainous terrain, *J. Appl. Meteorol.*, *33*, 140–158.

DeGaspari, C. L., H. B. Berge, K. R. Whiting, J. J. Burkey, J. L. Cassin and R. R. Fuerstenberg (2009), Linking hydrologic alteration to biological impairment in urbanizing streams of the Puget Lowland, Washington, USA, *J. Am. Water Resour. As.*, *45*, 512–533.

Elsner, M. M., L. Cuo, N. Voisin, J. S. Deems, A. F. Hamlet, J. A. Vano, K. E. B. Mickelson, S. Lee, and D. P. Lettenmaier (2009), Implications of 21st Century Climate Change for the Hydrology of Washington State, in *The Washington Climate Change Impacts Assessment: Evaluating Washington's Future in a Changing Climate*, edited by J. S. Littell, M. M. Elsner, L. C. W. Binder, and A. K. Snover, pp. 69–106, University of Washington Climate Impacts Group, Seattle, WA.

Fausch, K. D. (2008), A paradox of trout invasions in North America, *Biol. Invasions*, *10*, 685–701.

Fausch, K. D., Y. Taniguchi, S. Nakano, G. D. Grossman, and C. R. Townsend (2001), Flood disturbance regimes influence rainbow trout invasion success among five holarctic regions, *Ecol. Appl.*, *11*, 1438–1455.

Gannet, M. W., K. E. Lite, D. S. Morgan, and C. A. Collins (2001), Ground-water hydrology of the upper Deschutes Basin, Oregon: U.S. Geological Survey Water-Resources Investigations Report 00-4162, 78 pp, U.S. Geological Survey, Portlant, OR.

Hamlet, A. F., and D. P. Lettenmaier (2005), Production of temporally consistent gridded precipitation and temperature fields for the continental United States, *J. Hydrometeorol.*, *6*, 330–336.

Hamlet, A. F., and D. P. Lettenmaier (2007), Effects of 20th century warming and climate variability on flood risk in the western U.S., *Water Resour. Res.*, *43*, W06427, doi:10.1029/2006WR005099.

Hamlet, A. F., P. W. Mote, M. P. Clark, and D. P. Lettenmaier (2005), Effects of temperature and precipitation variability on snowpack trends in the western United States, *J. Clim.*, *18*, 4545–4561.

Hamlet, A. F., S. Lee, K. E. B. Mickelson, and M. M. Elsner (2009), Effects of projected climate change on energy supply and demand in the Pacific Northwest and Washington State, in *The Washington Climate Change Impacts Assessment: Evaluating Washington's Future in a Changing Climate*, edited by J. S. Littell, M. M. Elsner, L. C. W. Binder, and A.K. Snover, pp. 165–190, University of Washington Climate Impacts Group, Seattle, WA.

Hayhoe, K., et al. (2004), Emissions pathways, climate change, and impacts on California, *Proc. Natl. Acad. Sci. USA*, *101*, 12,422–12,427.

Heggenes, J., and T. Traaen (1988), Downstream migration and critical water velocities in stream channels for fry of 4 salmonid species, *J. Fish Biol.*, *32*, 717–727.

Hidalgo, H. G., et al. (2009), Detection and attribution of streamflow timing changes to climate change in the western United States, *J. Clim.*, *22*, 3838–3855.

Hurkmans, R., H. De Moel, J. Aerts, and P. A. Troch (2008), Water balance versus land surface model in the simulation of Rhine river discharges, *Water Resour. Res.*, *44*, W01418, doi:10.1029/2007WR006168.

IPCC (2007), *Climate Change 2007: Working Group 2: Impacts, Adaptation and Vulnerability*, Intergovernmental Panel on Climate Change, Geneva, Switzerland.

Isaak, D. J., C. H. Luce, B. E. Rieman, D. E. Nagel, E. E. Peterson, D. L. Horan, S. Parkes, and G. L. Chandler (2010), Effects of climate change and wildfire on stream temperatures and salmonid thermal habitat in a mountain river network, *Ecol. Appl.*, *20*(5), 1350–1371.

Knowles, N., and D. R. Cayan (2002), Potential effects of global warming on the Sacramento/San Joaquin watershed and the San Francisco estuary, *Geophys. Res. Lett.*, *29*(18), 1891, doi:10.1029/2001GL014339.

Konrad, C. P., and D. B. Booth (2005), Hydrologic changes in urban streams and their ecological significance, *Am. Fish S. S.*, *47*, 157–177.

Latterell, J. J., K. D. Fausch, C. Gowan, and S. C. Riley (1998), Relationship of trout recruitment to snowmelt runoff flows and adult trout abundance in six Colorado mountain streams, *Rivers*, *6*, 240–250.

Liang, X., D. P. Lettenmaier, E. F. Wood, and S. J. Burges (1994), A simple hydrologically based model of land-surface water and energy fluxes for general-circulation models, *J. Geophys. Res.*, *99*, 14,415–14,428, doi:10.1029/94JD00483.

Liang, X., E. F. Wood, and D. P. Lettenmaier (1996), Surface soil moisture parameterization of the VIC-2L model: Evaluation and modification, *Global Planet. Change*, *13*, 195–206.

Lohmann, D., R. NolteHolube, and E. Raschke (1996), A large-scale horizontal routing model to be coupled to land surface parametrization schemes, *Tellus 48A*, 708–721.

Lohmann, D., E. Raschke, B. Nijssen, and D. P. Lettenmaier (1998), Regional scale hydrology: I. Formulation of the VIC-2L model coupled to a routing model, *Hydrolog. Sci. J.*, *43*, 131–141.

Luce, C. H., and Z. A. Holden (2009), Declining annual streamflow distributions in the Pacific Northwest United States, 1948–2006, *Geophys. Res. Lett.*, *36*, L16401, doi:10.1029/2009GL039407.

Luce, C. H., D. G. Tarboton, and K. R. Cooley (1998), The influence of the spatial distribution of snow on basin-averaged snowmelt, *Hydrol. Process.*, *12*(10–11), 1671–1683.

Luo, L. F., and E. F. Wood (2007), Monitoring and predicting the 2007 U.S. drought, *Geophys. Res. Lett.*, *34*, L22702, doi:10.1029/2007GL031673.

Lytle, D. A., and N. L. Poff (2004), Adaptation to natural flow regimes, *Trends Ecol. Evol.*, *19*, 94–100.

Mantua, N., I. Tohver, and A. F. Hamlet (2009), Impacts of Climate Change on Key Aspects of Freshwater Salmon Habitat in Washington State, in *The Washington Climate Change Impacts Assessment: Evaluating Washington's Future in a Changing Climate*, edited by J. S. Littell, M. M. Elsner, L. C. W. Binder, and A.K. Snover, University of Washington Climate Impacts Group, Seattle, WA.

Matheussen, B., R. L. Kirschbaum, I. A. Goodman, G. M. O'Donnell, and D. P. Lettenmaier (2000), Effects of land cover change on streamflow in the interior Columbia River Basin (USA and Canada), *Hydrol. Processes*, *14*, 867–885.

Maurer, E. P., A. W. Wood, J. C. Adam, D. P. Lettenmaier, and B. Nijssen (2002), A long-term hydrologically based data set of land surface fluxes and states for the conterminous United States, *J. Clim.*, *15*(22), 3237–3251.

McCuen, R. H., Z. Knight, and A. G. Cutter (2006), Evaluation of the Nash-Sutcliffe efficiency index, *J. Hydrol. Eng.*, *11*, 597–602.

Moore, J. N., J. T. Harper, and M. C. Greenwood (2007), Significance of trends toward earlier snowmelt runoff, Columbia and Missouri Basin headwaters, western United States, *Geophys. Res. Lett.*, *34*, L16402, doi:10.1029/2007GL031022.

Mote, P. W. (2003), Trends in snow water equivalent in the Pacific Northwest and their climatic causes, *Geophys. Res. Lett.*, *30*(12), 1601, doi:10.1029/2003GL017258.

Mote, P. W., A. F. Hamlet, M. P. Clark, and D. P. Lettenmaier (2005), Declining mountain snowpack in western north America, *Bull. Am. Meteorol. Soc.*, *86*, 39–49.

Nash, J. E., and J. V. Sutcliffe (1970), River flow forecasting through conceptual models: Part 1. A discussion of principles., *J. Hydrol.*, *10*, 282–290.

Poff, N. L., and J. V. Ward (1989), Implications of streamflow variability and predictability for lotic community structure- a regional analysis of streamflow patterns, *Can. J. Fish. Aquat. Sci.*, *46*, 1805–1818.

Poff, N. L., J. D. Allan, M. B. Bain, J. R. Karr, K. L. Prestegaard, B. D. Richter, R. E. Sparks, and J. C. Stromberg (1997), The natural flow regime, *Bioscience*, *47*, 769–784.

Regonda, S. K., B. Rajagopalan, M. Clark, and J. Pitlick (2005), Seasonal cycle shifts in hydroclimatology over the western United States, *J. Clim.*, *18*, 372–384.

Richter, B. D., J. V. Baumgartner, R. Wigington, and D. P. Braun (1997), How much water does a river need?, *Freshwat. Biol.*, *37*, 231–249.

Rood, S. B., J. Pan, K. M. Gill, C. G. Franks, G. M. Samuelson, and A. Shepherd (2008), Declining summer flows of Rocky Mountain rivers: Changing seasonal hydrology and probable impacts on floodplain forests, *J. Hydrol.*, *349*, 397–410.

Sanborn, S. C., and B. P. Bledsoe (2006), Predicting streamflow regime metrics for ungauged streams in Colorado, Washington, and Oregon, *J. Hydrol.*, *325*, 241–261.

Schnorbus, M., K. Bennett, and A. Werner (2010), Quantifying the Water Resource Impacts of Mountain Pine Beetle and Associated Salvage Harvest Operations Across a Range of Watershed Scales: Hydrologic Modelling of the Fraser River Basin (Information Report BC-X-423), Natural Resources Canada, Canadian Forestry Service, Pacific Forestry Centre, Victoria, BC.

Seegrist, D. W., and R. Gard (1972), Effects of floods on trout in Sagehen Creek, California, *Trans. Am. Fish. Soc.*, *101*, 478–482.

Slack, J. R., A. M. Lumb, and J. M. Landwehr (1993), Hydro-Climatic Data Network (HCDN): Streamflow data set, 1874–1988. Water Resourc. Invest. Rep. 93-4076, USGS, Reston, VA.

Snover, A. K., A. F. Hamlet, and D. P. Lettenmaier (2003), Climate change scenarios for water planning studies, *B. Am. Meterol. Soc.*, *84*(11), 1513–1518.

Stewart, I. T., D. R. Cayan, and M. D. Dettinger (2004), Changes in snowmelt runoff timing in western North America under a "business as usual" climate change scenario, *Clim. Change*, *62*, 217–232.

Stewart, I. T., D. R. Cayan, and M. D. Dettinger (2005), Changes toward earlier streamflow timing across western North America, *J. Clim.*, *18*, 1136–1155.

Strange, E. M., P. B. Moyle, and T. C. Foin (1993), Interactions between stochastic and deterministic processes in stream fish community assembly, *Environ. Biol. Fishes*, *36*, 1–15.

Tague, C., and G. E. Grant (2009), Groundwater dynamics mediate low-flow response to global warming in snow-dominated alpine regions, *Water Resour. Res.*, *45*, W07421, doi:10.1029/2008WR007179.

Tonina, D., C. H. Luce, B. Rieman, J. M. Buffington, P. Goodwin, S. R. Clayton, S. M. Ali, J. J. Barry, and C. Berenbrock (2008), Hydrological response to timber harvest in northern Idaho: Implications for channel scour and persistence of salmonids, *Hydrol. Processes*, *22*, 3223–3235.

Vano, J. A., M. Scott, N. Voisin, C. O. Stöckle, A. F. Hamlet, K. E. B. Mickelson, M. M. Elsner, and D. P. Lettenmaier (2010a), Climate change impacts on water management and irrigated agriculture in the Yakima River basin, Washington, USA, *Clim. Change*, doi:10.1007/s10584-010-9856-z, in press.

Vano, J. A., N. Voisin, L. Cuo, A. F. Hamlet, M. M. Elsner, R. N. Palmer, A. Polebitski, and D. P. Lettenmaier (2010b), Climate change impacts on water management in the Puget Sound Region, Washington, USA, *Clim. Change*, doi:10.1007/s10584-010-9846-1, in press.

Wigmosta, M. S., L. W. Vail, and D. P. Lettenmaier (1994), A distributed hydrology-vegetation model for complex terrain, *Water Resour. Res.*, *30*, 1665–1679, doi:10.1029/94WR00436.

Wigmosta, M. S., L. W. Vail, and D. P. Lettenmaier (2002), The distributed hydrology soil vegetation model, in *Mathematical Models of Small Watershed Hydrology and Applications*, edited by V. P. Singh and D. K. Frevert, pp. 7–42, Water Resource Publications, Littleton, CO.

Wolock, D. M. (2003), *Base-Flow Index Grid for the Conterminous United States*. U.S. Geological Survey open-file report 03-263, USGS, Lawrence, KS.

Yang, G., L. C. Bowling, K. A. Cherkauer, B. C. Pijanowski, and D. Niyogi (2010), Hydroclimatic response of watersheds to urban intensity – an observational and modeling based analysis for the White River Basin, Indiana, *J. Hydrometeorol.*, *11*, 122–138.

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