

Climate change or climate cycles? Snowpack trends in the Olympic and Cascade Mountains, Washington, USA

Dwight Barry · Shea McDonald

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Abstract Climate change could significantly influence seasonal streamflow and water availability in the snowpack-fed watersheds of Washington, USA. Descriptions of snowpack decline often use linear ordinary least squares (OLS) models to quantify this change. However, the region's precipitation is known to be related to climate cycles. If snowpack decline is more closely related to these cycles, an OLS model cannot account for this effect, and thus both descriptions of trends and estimates of decline could be inaccurate. We used intervention analysis to determine whether snow water equivalent (SWE) in 25 long-term snow courses within the Olympic and Cascade

Mountains are more accurately described by OLS (to represent gradual change), stationary (to represent no change), or step-stationary (to represent climate cycling) models. We used Bayesian information-theoretic methods to determine these models' relative likelihood, and we found 90 models that could plausibly describe the statistical structure of the 25 snow courses' time series. Posterior model probabilities of the 29 "most plausible" models ranged from 0.33 to 0.91 (mean=0.58, $s=0.15$). The majority of these time series (55 %) were best represented as step-stationary models with a single breakpoint at 1976/77, coinciding with a major shift in the Pacific Decadal Oscillation. However, estimates of SWE decline differed by as much as 35 % between statistically plausible models of a single time series. This ambiguity is a critical problem for water management policy. Approaches such as intervention analysis should become part of the basic analytical toolkit for snowpack or other climatic time series data.

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D. Barry (✉) · S. McDonald
Western Washington University,
Huxley College of the Environment-Peninsulas,
1502 E. Lauridsen Blvd.,
Port Angeles, WA 98362, USA
e-mail: dbarry@aya.yale.edu

S. McDonald
Olympic National Park,
500 E. Park Ave.,
Port Angeles, WA 98362, USA

Present Address:

D. Barry
Measurement and Analytics, Group Health,
320 Westlake Ave.,
Seattle, WA 98109, USA

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Introduction

Many studies indicate declining trends in winter snowpack throughout the western USA, and this decline is commonly attributed to anthropogenic climate change

(e.g., Mote et al. 2005; Pierce et al. 2008). Because snowpack is an essential “reservoir” of late summer streamflow, climate change could significantly influence seasonal streamflow and water availability in the snowpack-fed watersheds of the Pacific Northwest (Adam et al. 2009; Casola et al. 2009; Elsner et al. 2010).

Numerous climate change description and forecasting efforts in the region use trend estimates based on long-term Natural Resources Conservation Service (NRCS) snowpack data from the 1 April reporting date; snow water equivalent (SWE; a measure of the water content of the snowpack) at this time is known to be highly correlated with subsequent summer streamflow (Mote et al. 2005; Elsner et al. 2010). These trends are often presented as linear ordinary least squares (OLS) models across the entire time series (e.g., Gottfried et al. 2002; Mote 2006; Mote et al. 2008; Pelto 2008). The presentation of a declining linear trend in snowpack on 1 April thus implies the gradual influence of human-induced climate change. Some of these studies have been cited hundreds of times (e.g., Mote et al. 2005 has been cited more than 200 times to date according to the Science Citation Index), and estimates of percent snowpack decline based on some of these studies have been mentioned in everything from news articles to policy recommendations (e.g., Nickels 2007).

However, precipitation in the Pacific Northwest is known to be closely related to climate cycles (CIG 2012), particularly the El Niño-Southern Oscillation and the Pacific Decadal Oscillation (PDO). If such cycles cause pulse or press changes in the statistical structure of the time series, a single OLS trend line would be statistically (and practically) inappropriate; instead, a step-stationary model would be a more accurate descriptor of snowpack trends. In other words, while an OLS model might indicate climate *change*, a model that incorporates step changes might represent climate *cycles*.

Determining the relative likelihood of these different potential states within the structure of long-term snow course data could provide improved insight into the processes driving observed trends. Furthermore, different models have different implications for the use of these data sets and reporting of results; again, time series that contain a “stationary-between-breakpoints” type of statistical structure *cannot* reasonably be modeled with an OLS trend—and resulting OLS-

based model estimates could be biased toward overestimation of SWE change, with implications that could spread into other studies as well as management or policy decisions.

There are many different tools for modeling time series data, such as econometric tools like intervention analysis, that have been called for in the analysis of climatic data for some time (Granger and Engle 1987; also see Matthews et al. 2011) but have only very rarely been used for climate analysis (e.g., Frank et al. 2005; Pederson et al. 2006; Wilson et al. 2007)—and not at all for the estimation of snowpack trends. Intervention analysis, an extension of autoregressive integrated moving average methods, was originally developed to assess the effect of known interventions (e.g., an environmental disturbance or new policy implementation) on the statistical structure of a time series (Box and Tiao 1975). This approach has been extended in recent years to answer the problem of trying to detect the presence of unknown interventions in a time series, which can suggest structural changes in the underlying statistical model (Chang et al. 1988; Tsay 1988; Zeileis et al. 2003, 2008).

We have applied this type of intervention analysis to long-term 1 April SWE data from the Olympic and Cascade Mountains of western Washington to determine whether there are structural changes in these time series, and if so, when in time the detected breakpoints occurred. Such results could be helpful in determining proper models for describing past trends as well as forecasting future ones. This analysis can also show the usefulness of this statistical approach when evaluating any long-term dataset for purposes of description or modeling of trends. Finally, the results have real implications for public and political discussions regarding the impact of climate change on essential water resources in the Pacific Northwest.

Methods

Field data

There are 95 official NRCS snow courses in Washington; 25 of these are located in the western side of the state (i.e., the Olympic or Cascade Mountains) that have been sampled annually for the 1 April reporting date for at least 40 years and have a period of record that extends at least up until the mid-2000s or later

(Fig. 1). At each snow course, snow depth, SWE, and snow density data have been collected using a Federal snow sampling tube at several points along a transect, and the data points averaged to determine the course's reporting values. For the 1 April reporting date (there are four reporting dates each winter for most courses), this sampling has always occurred on or within the 5 days prior to 1 April. These standard methods have remained unchanged since the establishment of formal snow course sampling in the western USA in the early 1900s; details are available in NRCS (1984). Data used in this analysis, including site metadata, are available through the NRCS's Washington Snow Survey Program (<http://www.wa.nrcs.usda.gov/snow/>).

Statistical analysis

Each time series was tested for the existence of potential breakpoints using the algorithm developed by Bai and Perron (2003) and implemented in the *strucchange* package (Zeileis et al. 2002, 2008) in R (2.10.1, R Development Core Team 2009). We chose an information theoretic approach so as to entertain the possibility that more than one model of a given time series is statistically plausible, i.e., the simplest means by which the relative likelihoods of different models (i.e., multiple working hypotheses) can be directly and quantitatively compared (cf. Burnham and Anderson 2002). The model set for each course includes seven models: stationary, OLS, and five step-stationary

models that contain between one and five potential breakpoints.

To compare these models, we used ΔBIC (BIC: Bayesian Information Criterion) values and posterior model probabilities ($P_{\text{Model}(M)|\text{Data}(D)}$; i.e., the probability that a given model is the best model, given the data) to compare plausible models. Because we assume that a “true” model can be found among the finite dimensions (i.e., years) of these data sets, BIC is the more appropriate information criterion for this work (Yang 2005). For initial model comparison and selection purposes, we used the conservative “Occam’s window” approach (Raftery 1995), where any model with a ΔBIC value of ≤ 6 is considered statistically plausible. Stationary and OLS models were included in all of the results even when they did not meet this threshold, for side-by-side comparison purposes with the plausible models. Finally, the posterior probability (P_{MID}) value provides a direct estimate of confidence (i.e., its likelihood) of a given model within the model set. We deemed the model with the highest likelihood the “most plausible” model, and models that were within 10 % of the most plausible one were classified as “essentially equivalent.”

Results and discussion

Using these methods, our analysis found 90 models that could plausibly describe the statistical structure of the 25 snow courses' time series (Table 1). Four of the

Fig. 1 Locations and most plausible model types for the 25 Olympic and Cascade Mountain NRCS snow courses evaluated in this study

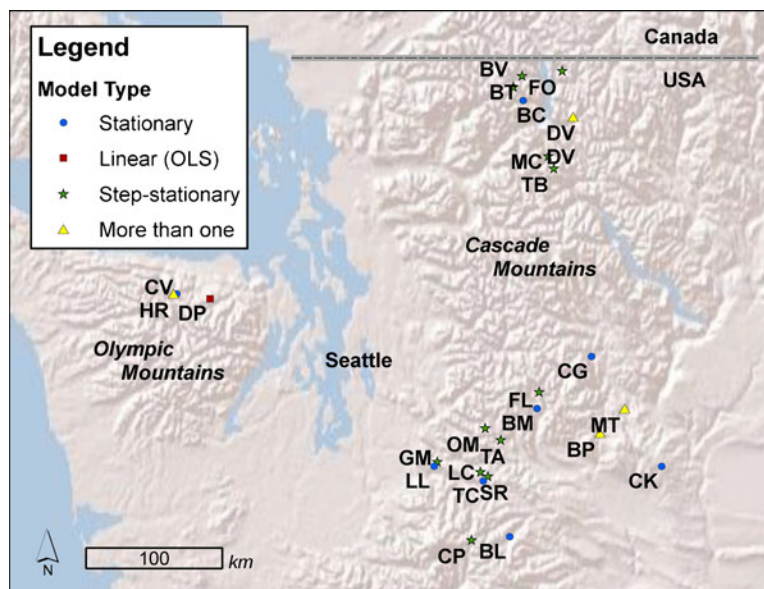


Table 1 Bayesian information theoretic-based comparisons of the four model types for 1 April SWE from the 25 Olympic and Cascade Mountains snow courses evaluated in this study

Snow course	Model type	Break dates	BIC ^a	Δ BIC	$P_{M D}$ ^b	Implied change (%)
Most plausible model (stationary)						
Beaver Creek Trail	S	n/a	480.76	0.00	0.73	0
	L	n/a	484.37	3.61	0.12	-20
	1	1976	484.76	4.00	0.10	-30
	2	1976 and 1996	486.07	5.32	0.05	-2
Berne-Mill Creek	S	n/a	349.33	0.00	0.69	0
	L	n/a	353.02	3.69	0.11	7
	1	1976	354.06	4.73	0.07	-17
	2	1976 and 1968	352.61	3.28	0.13	-7
Bumping Lake New	S	n/a	353.58	0.00	0.49	0
	L	n/a	356.13	2.55	0.14	-23
	1	1976	354.48	0.90	0.31	-29
	2	1976 and 1968	357.71	4.13	0.06	-13
Chiwaukum Guard Station	S	n/a	302.69	0.00	0.75	0
	L	n/a	306.05	3.36	0.14	-18
	1	1976	306.90	4.21	0.09	-26
	2	1976 and 1968	310.40	7.71	0.02	-5
Colockum Pass	S	n/a	305.04	0.00	0.73	0
	L	n/a	307.83	2.79	0.18	-16
	1	1976	309.43	4.39	0.08	-17
	2	1976 and 1968	314.67	9.63	0.01	-4
Cox Valley	S	n/a	444.80	0.00	0.70	0
	L	n/a	448.00	3.20	0.14	-14
	1	1976	448.00	3.20	0.14	-25
	2	1976 and 1994	452.67	7.87	0.01	-14
Lynn Lake	S	n/a	330.05	0.00	0.69	0
	L	n/a	333.64	3.60	0.11	11
	1	1976	333.52	3.47	0.12	-35
	2	1976 and 1996	334.41	4.37	0.08	-13
Twin Camp	S	n/a	371.20	0.00	0.61	0
	L	n/a	373.77	2.57	0.17	-21
	1	1976	373.38	2.18	0.21	-24
	2	1976 and 1984	378.99	7.79	0.01	-20
Most plausible model (linear)						
Deer Park	S	n/a	569.60	12.20	0.00	0
	L	n/a	557.40	0.00	0.57	-55
	1	1976	558.80	1.40	0.28	-38
	2	1976 and 1994	560.10	2.70	0.15	-49
Most plausible model (step-stationary)						
Beaver Pass	S	n/a	534.20	5.54	0.05	0
	L	n/a	532.06	3.41	0.14	-36
	1	1976	528.66	0.00	0.77	-31
	2	1976 and 1996	534.24	5.59	0.05	-20

Table 1 (continued)

Snow course	Model type	Break dates	BIC ^a	Δ BIC	P_{MID} ^b	Implied change (%)
Brown Top Ridge	S	n/a	346.83	3.86	0.10	0
	L	n/a	349.66	6.69	0.02	-14
	1	1976	342.97	0.00	0.70	-32
	2	1976 and 1981	345.68	2.71	0.18	-29
Cayuse Pass	S	n/a	643.77	2.08	0.21	0
	L	n/a	644.30	2.62	0.16	-22
	1	1976	641.69	0.00	0.60	-22
	2	1976 and 1949	647.46	5.77	0.03	-11
Fish Lake	S	n/a	530.48	0.62	0.30	0
	L	n/a	531.12	1.26	0.22	-25
	1	1976	529.85	0.00	0.42	-23
	2	1976 and 1993	533.81	3.96	0.06	-11
Freezeout Creek Trail	S	n/a	423.96	2.27	0.18	0
	L	n/a	423.53	1.85	0.22	-35
	1	1976	421.69	0.00	0.56	-31
	2	1976 and 1996	426.81	5.12	0.04	-17
Grass Mountain 2	S	n/a	397.20	20.99	0.00	0
	L	n/a	388.85	12.64	0.00	-91
	1	1976	376.21	0.00	0.91	-74
	2	1975 and 1968	380.99	4.78	0.08	-69
Lester Creek	S	n/a	372.44	1.82	0.24	0
	L	n/a	374.36	3.74	0.09	-26
	1	1976	370.62	0.00	0.59	-32
	2	1976 and 1996	374.49	3.88	0.08	-18
Meadow Cabins	S	n/a	349.94	2.69	0.13	0
	L	n/a	348.21	0.96	0.32	-65
	1	1976	347.25	0.00	0.51	-57
	2	1976 and 1996	352.66	5.40	0.03	-67
Ollalie Meadows	S	n/a	544.93	12.64	0.00	0
	L	n/a	533.21	0.92	0.37	-57
	1	1976	532.29	0.00	0.58	-42
	2	1976 and 1956	537.15	4.86	0.05	-49
Sawmill Ridge	S	n/a	405.49	5.23	0.06	0
	L	n/a	404.10	3.83	0.12	-37
	1	1976	400.26	0.00	0.79	-33
	2	1976 and 1969	406.19	5.93	0.04	-27
Thunder Basin	S	n/a	450.37	4.97	0.05	0
	L	n/a	446.57	1.17	0.32	-36
	1	1976	445.40	0.00	0.57	-28
	2	1976 and 1986	449.77	4.37	0.06	-22
Tunnel Avenue	S	n/a	538.98	3.17	0.14	0
	L	n/a	538.90	3.09	0.14	-37
	1	1976	535.81	0.00	0.67	-35
	2	1976 and 1994	541.20	5.39	0.05	-21

Table 1 (continued)

Snow course	Model type	Break dates	BIC ^a	Δ BIC	P_{MID} ^b	Implied change (%)
More than one most plausible model						
Blewett Pass 2	S	n/a	427.99	2.16	0.15	0
	L	n/a	425.98	0.15	<i>0.40</i>	−37
	1	1976	425.83	0.00	<i>0.43</i>	−29
	2	1976 and 1956	431.12	5.30	0.03	−38
Devil's Park	S	n/a	476.02	0.00	<i>0.39</i>	0
	L	n/a	476.96	0.94	0.24	−22
	1	1976	476.28	0.26	<i>0.34</i>	−17
	2	1976 and 1989	481.02	5.00	0.03	−12
Hurricane	S	n/a	540.30	15.30	0.00	0
	L	n/a	525.00	0.00	<i>0.44</i>	−68
	1	1976	525.20	0.20	<i>0.40</i>	−49
	2	1976 and 1957	527.10	2.10	0.16	−59
Merritt	S	n/a	338.50	2.10	0.13	0
	L	n/a	336.69	0.29	<i>0.33</i>	−55
	1	1976	336.40	0.00	<i>0.38</i>	−43
	2	1976 and 1968	338.30	1.90	0.15	−24

Break date time is located prior to the subsequent water year/winter (e.g., a break date of 1976 implies a change prior to April 1977)

Model type—*S* stationary, *L* linear (OLS) trend, *1* step-stationary with one breakpoint, *2* step-stationary with two breakpoints

^aBayesian information criterion

^bBayesian posterior model probability (probability of the model given the data). Italicized values in this column represent the statistically most plausible model(s) of the model set

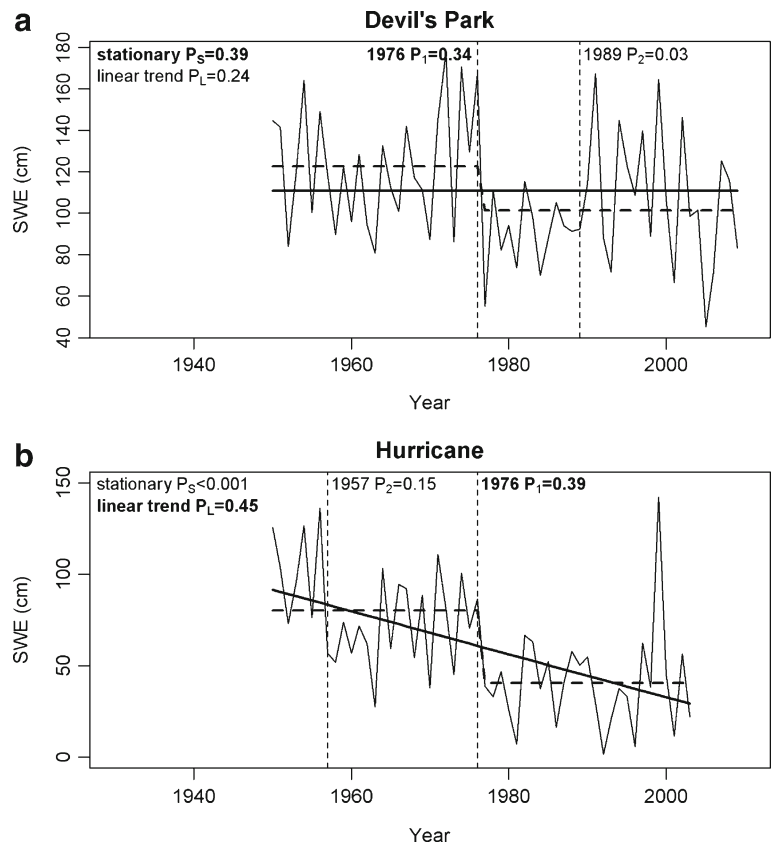
seven model types were considered plausible: stationary, linear, step-stationary with one breakpoint, and step-stationary with two breakpoints. Twenty-nine of the 90 models were classified “most plausible” based on posterior model probabilities (P_{MID}); some courses had more than one most plausible model because they were considered essentially equivalent. P_{MID} values of these “most plausible” models ranged from 0.33 to 0.91 (mean=0.58, s =0.15). Only four of these 29 models (14 %; e.g., Fig. 2a) comprised an OLS trend. The majority of these series were best represented as stationary (n =9, 31 %; e.g., Fig. 2b) or as step-stationary models with a single breakpoint (n =16, 55 %; e.g., Fig. 2c).

There were four snow courses that had essentially equivalent likelihoods for a most plausible model, three of which included both OLS and a single breakpoint (Hurricane (Fig. 3a), Merritt, and Blewett Pass 2), and one that included both stationary and single breakpoint models (Devil's Park (Fig. 3b)). These likelihoods ranged between the low 0.30 and the low 0.40 s ; in short, in these four cases it could be

considered no better than a “coin toss” as to which of the two choices is a better model of the time series. No two-breakpoint models were considered most plausible, and no models were found using the Occam's window selection criterion that had more than two breakpoints in the time series.

Importantly, we found that *all* 25 courses' time series could be reasonably represented by more than one model (graphs of results for all courses can be found in the Electronic supplementary material (ESM)), again given the Occam's window selection criterion. For example, the likelihood of a “second-best” model being the best model throughout all of the courses varied from 0.08 (Grass Mountain 2) to 0.37 (Olallie Meadows). A single snow course had only two statistically plausible models (Grass Mountain 2), and eight courses could be represented by three statistically plausible models. For the remaining 16 courses, all four model types had at least a small possibility of being statistically plausible representations of the time series; dismissing any of them could thus be considered arbitrary.

Fig. 2 The 1 April SWE (in centimeters) example time series for two snow courses that were best described with two essentially equivalent models: **a** stationary and step-stationary, Devil's Park (1950–2009) and **b** OLS and step-stationary, Hurricane (1950–2003). **Bold solid line and text** refer to the most plausible model. **Vertical dashed lines** represent statistically plausible breakpoints in the time series. Graphs of all 25 snow courses can be found in the [ESM](#)

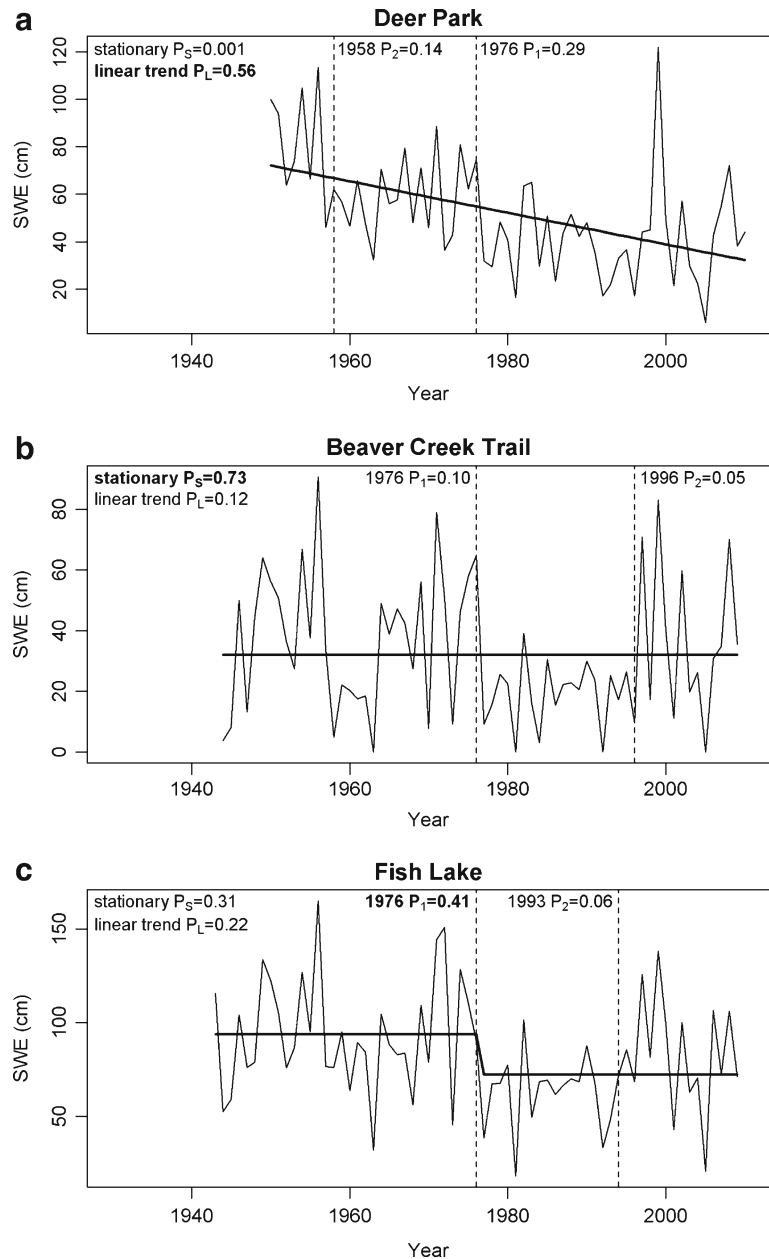


In all of the most plausible step-stationary models, the breakpoint (i.e., step change in the statistical trend) occurred between 1976 and 1977 data points, a time at which the PDO climate cycle is known to have shifted from a cool to a warm phase (Hare and Mantua 2002). The mean likelihood for these models was 0.64 ($s=0.14$, range=0.42–0.91); 1976 was a plausible break date in all but 1 of the 29 models, with a mean likelihood of 0.43 ($s=0.25$, range=0.07–0.91); the only course without a 1976 break date was Colockum Pass, which had an estimated break date of 1975. Other possible break dates that occurred within the plausible model sets included 1949 ($n=1$), a cluster between 1956 and 1958 ($n=4$), a cluster between 1968 and 1969 ($n=5$), 1981 ($n=1$), 1986 ($n=1$), 1989 ($n=1$), 1993 ($n=1$), 1994 ($n=1$), and 1996 ($n=6$). The breakpoint at 1976 is clearly correlated with the PDO shift, but other possible break dates could also indicate climate cycle effects: the early to mid-1950s experienced some of the highest La Niña index values recorded, which might account for those results while the late 1990s have been proposed as a time at which

some have suggested the PDO may have been shifting back to a cool phase (Petersen and Schwing 2003). However, Mestas-Núñez and Miller (2006) have argued that this late 1990s shift may not have really occurred, and in fact there was a recurrence of warm PDO index values through much of the mid-2000s. Because of the length of PDO cycles, it is difficult to determine when shifts in this index occur until well after the change, so to date there is no consensus on whether this cycle has shifted back toward a cool phase or whether it remains in an extended warm phase.

With respect to estimates of snowpack decline: obviously, for time series best represented by a stationary model, the estimated percent change in SWE would be zero over the period of record. Estimated average percent change based on all of the most plausible models is -27% ($s=22\%$, median= -30%). And while the “true” estimates of percent decline have important political implications (e.g., Cornwall 2007), they are not the main point of interest here—it is the differences between those estimates that are

Fig. 3 The 1 April SWE (in centimeters) example time series for the three most plausible models: **a** OLS model, Deer Park (1950–2010); **b** stationary model, Beaver Creek Trail (1944–2009); and **c** step-stationary model, Fish Lake (1943–2009). **Bold solid line and text** refer to the most plausible model. **Vertical dashed lines** represent statistically plausible break-points in the time series. Graphs of all 25 snow courses can be found in the [ESM](#)



instructive. For example, the differences between a stationary and a step-stationary model for the nine courses classified as stationary range from 17 to 35 % (mean = 25 %, $s=6$ %), where P_{MID} values for these less plausible models range from 0.07 to 0.31 (mean = 0.14, $s=0.08$). Differences between step-stationary classified course models and their related OLS models range from 17 % higher to 17 % lower (mean = 7 %, $s=6$ %); if you discount the implausible OLS models (i.e., $\Delta BIC, >6$),

the OLS-based estimate range changes to between 0 % and 14 % higher SWE decline than step-stationary estimates (mean = 5 %, $s=4$ %). As a final illustrative example of this issue at a single snow course, Devil's Park (Fig. 2a) has two “most plausible” models, stationary and step-stationary. While the stationary model estimates no decline in SWE over the period of record with 39 % probability, the step-stationary one suggests a 17 % decline in SWE ($P_{MID}=0.34$).

Conclusions

The question posed in the title of this paper was, of course, rhetorical. While the majority of plausible models for 1 April SWE trends in the Olympic and Cascade Mountains show that perhaps a more reasonable way than OLS to model snowpack is by using a step-stationary approach, other models are also plausible (and thus reasonable) descriptions of the statistical structure of most courses' time series. In short, there is just not enough data to state with any reasonable certainty what is impacting snowpack decline in western Washington—while the 91 % probability of a step-stationary model describing change at the Grass Mountain 2 snow course might be worth “betting the farm” on the influence of the PDO, on average most of our “most plausible” models had somewhat less than a two in three chance of being the best descriptor. While it is likely that both climate change and long-term climate cycles can be implicated in these courses' trends in SWE, the extent to which each could be more important cannot be answered at this time with the available data.

This analysis has shown that all four possible models types are plausible descriptors of the statistical structure of this 1 April SWE time series data. Importantly, neither least squares nor breakpoint models are statistically implausible. These results indicate that there would be substantial difficulty to come to general descriptions of trends in these time series across the study area. This also implies that that model outputs based on any of these models could be considered “accurate” in some sense. This ambiguity, which occurs to varying degrees in all 25 courses considered in this study, is clearly a problem with respect to attempts to characterize and forecast possible impacts of climate change on water resources using simple models, particularly for purposes of public discussion, policy development, and water management.

It is interesting that all of the courses had a possible breakpoint around the cool to warm shift in the PDO in 1977. This suggests that climate cycles *could* be more important in explaining declining snowpack in the Olympic and Cascade Mountains than human-induced climate change based on, for example, gradual and trend-based declines in snowpack and/or shifts in streamflow timing reported in many other areas (e.g., Stewart et al. 2005; Kennedy et al. 2009). However, some recent studies have suggested that the 1977 PDO shift was a combination of natural cycling as well as

increased forcing by human activities, and that such a major change would not have happened under a non-human dominated atmosphere (Meehl et al. 2009). This could further suggest that the possible late 1990s shift to a cool phase may have actually fully happened in the absence of human-caused climate forcing, but because the region has permanently shifted into a warmer regime, the shift was never fully realized. Such a conjecture is beyond the scope of this work, but it would make for an interesting modeling exercise in the future. In any case, a major point of this paper is that simple models describing trends in SWE in this region have real political implications both within and outside the scientific community (e.g., Nickels 2007; Cornwall 2007), regardless of the relative influence of an anthropogenically forced (or historically normal) PDO.

Linear OLS trends attempting to characterize a time series should be viewed with caution, even when the assumption of independence can be reasonably made (for climate data, this assumption should be automatically suspect). This study has shown that step-stationary models have the potential to more accurately characterize the current statistical structure of long-term snowpack in the Cascade and Olympic Mountains. Describing and/or estimating trends in SWE for western Washington—and thus summer streamflows—under various climate change scenarios using simple models will therefore likely require the incorporation of predictors based on step changes in climate cycles in addition to those based on climate change.

Perhaps more importantly, the use of multiple working hypotheses in an information-theoretic framework shows that more than one interpretation can plausibly be placed on a given time series, and that other researchers, journalists, and policy makers could be unduly influenced by results generated from a single model (or working hypothesis). Scientific transparency is essential in water policy and management, and approaches such as intervention analysis conducted within a multiple working hypotheses context should become part of the basic analytical toolkit for any studies of long-term SWE or other climatic time series data.

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