todo:

include snowmelt in model run. see if it's worth including with precip and temp as a climate predictor

introduce terminology: responses = water temp, Q climatic predictors = air temp, precip, drought landscape predictors = many

Introduction

Methods

Study region

I'll probably mention anything relevant to this in the intro.

Data collection

The two response variables used in our analyses were water temperature and discharge. We obtained monthly water temperature readings from 1978 through 2015 via the Washington Department of Ecology's River and Stream Water Quality Monitoring program `cite`. In all, 24 monitoring sites within the Puget Sound region (Fig. `1`) were included, representing 19 rivers across 9 counties, and ranging from 4 to 775 m in elevation. For one site at each river, monthly discharge time series were available, either for the same location as one of the temperature monitoring sites, or for another location within 30 km on the same major reach. Discharge data were aggregated by monthly mean from the USGS Washington Water Science Center (collected daily 1978-2007) and the USGS National Water Information System (collected at 15-minute intervals 2008-2015). At least one discharge monitoring site was available for every river represented in the temperature dataset.

Potential climatic predictors of water temperature and discharge included mean and max air temperature, precipitation, and hydrologic drought, averaged by month across the response variable time series. These data are available through the U.S. Climate Divisional Dataset, developed by the National Centers for Environmental Information (NCEI) `cite`. We acquired climatic predictor data grouped by Washington State climate division, and all but two of our sites fell within divisions 3 (Puget Sound Lowland) and 4 (East Olympic/Cascade Foothills). We therefore aggregated these data by monthly mean across the two regions (after verifying their post-standardization similarity), resulting in a single dataset of four regional, climatic predictors.

For post-hoc analyses of potential sub-watershed-scale drivers of response-predictor coupling, we amassed an additional set of landscape predictor data. These were collected individually for each of the watersheds that correspond to our 24 river sites, using the EPA's StreamCat (stream-catchment) data collection `cite` and the National Hydrography Dataset (NHDPlusV2) `cite`. Land-

1

scape predictor categories include lithology, land use, population and road density, and soil type, as well as other categories summarized in Table A1.

Time series analysis

Response time series were modeled using dynamic factor analysis (DFA; Zuur et al. 2003), a multivariate technique that can be thought of as an analog to principal component analysis in the time domain. In DFA, response time series are fit with a linear combination of shared, random-walk trends (usually many fewer than the total number of response series), predictors (which can have unique effects on each response series), and random error. We chose DFA over a traditional multivariate state space approach for two reasons. First, it provides advantages in computational efficiency, as 1-5 shared trends often adequately capture variation across dozens of responses, and at much lower parameter cost. Second, in terms of identifying what drives the shared trends, having fewer trends allows greater inferential parsimony. Being a multivariate technique, DFA also provides an advantage over univariate alternatives in that covariance structure among responses can be specified and compared. All models were fit using maximum likelihood estimation by automatic differentiation, with Template Model Builder software Kristensen et al. 2015, which we called using package TMB in R R Core team 2016....

DFA takes the following form:

$$\mathbf{x}_t = \mathbf{x}_{t-1} + \mathbf{w}_t, \text{ where } \mathbf{w}_t \sim \text{MVN}(0, \mathbf{Q}) \tag{1}$$

$$\mathbf{y}_t = \mathbf{Z}\mathbf{x}_t + \mathbf{D}\mathbf{d}_t + \mathbf{v}_t, \text{ where } \mathbf{v}_t \sim \text{MVN}(0, \mathbf{R}) \tag{2}$$

$$\mathbf{x}_0 \sim \text{MVN}(0, \mathbf{\Lambda}) \tag{3}$$

At each time step t, the $m \times 1$ vector of shared trends $\mathbf{x}$ is a function of $\mathbf{x}$ in the previous step, plus normal error $\mathbf{w}$ (Eq. 1). This is the definition of a random walk. The $n \times 1$ response vector $\mathbf{y}$ at time t is a function of the shared trends and their factor loadings ($\mathbf{Z}$; $n \times m$), a $q \times 1$ vector of covariates $\mathbf{d}$ and their river-specific effects effects ($\mathbf{D}$; $n \times q$), and a second normal error term $\mathbf{v}$ (Eq. 2). $\mathbf{R}$ and $\mathbf{Q}$ are variance-covariance matrices of order m, and $\mathbf{Q}$ is set to identity for model identifiability (Harvey 1989). The initial state of the shared trend vector, $\boldsymbol{x}_0$, is multivariate-normally distributed with a mean of zero and a diagonal variance-covariance matrix with large variance (e.g. 5). Predictor data were standardized to facilitate comparison of effect sizes. Response data were centered on 0, but not scaled, to avoid error inflation cite.

Because we were interested in isolating the effects of climatic predictors on river temperature and discharge, we used fixed factors to absorb recurring seasonal variation not related to the predictors, with one factor level for each month. These factors were incorporated into the predictor matrix $\mathbf{d}$. Thus, the coefficient of $\mathbf{D}$ relating, say, air temperature and water temperature, represents the effect size of the former on the latter. In other words, it is the change in water temperature for a unit change in air temperature over the course of the

time series. We call this effect "coupling." We were also interested in coupling by month for specific predictors, which required that the focal predictor in a particular model be treated like the fixed factors of residual seasonal variation. Concretely,

$$
\begin{bmatrix}
\theta_{a1} & \theta_{a2} & \theta_{a3} & \cdots & \theta_{aT} \\
\theta_{b1} & 0 & 0 & \cdots & 0 \\
0 & \theta_{b2} & 0 & \cdots & 0 \\
0 & 0 & \theta_{b3} & \cdots & 0 \\
\vdots & \vdots & \vdots & \ddots & \vdots \\
0 & 0 & 0 & \cdots & \theta_{bT} \\
1 & 0 & 0 & \cdots & 0 \\
0 & 1 & 0 & \cdots & 0 \\
0 & 0 & 1 & \cdots & 0 \\
\vdots & \vdots & \vdots & \ddots & \vdots \\
0 & 0 & 0 & \cdots & 1
\end{bmatrix}
$$

The shared trends represent environmental variation not captured by the climatic predictors.

Appendix A

Table A1: ...at the scale of individual stream reaches (segments bounded by sources, confluences, or mouths) and their corresponding watersheds. Watersheds are calculated as land contributing flow to a reach, and have been determined for 2.6 million reaches within the conterminous United States.