Supporting Information – Coarse Climate Change Projections in a Fine-scaled World

ESTIMATING CLIMATIC TREND, VARIANCE, AND AUTOCORRELATION

There are many methods available to estimate trend, variance, and autocorrelation in both space and time. Generalized least squares (GLS) is one method that allows all three climate components to be estimated simultaneously. GLS is a method for estimating the coefficients in a linear regression that can incorporate autocorrelation into the error term. A variogram can be used to estimate the autocorrelation in both the temporal and spatial context. A variogram estimates the degree of covariance between data points separated by different amounts of time or space. The parameters of a GLS model can be estimated with the *gls* function in the *nmle* package in R (Pinheiro et al., 2015).

In the temporal context the GLS model can be fit with the focal weather variable as the response variable and time as the independent variable. The coefficient describing the slope between time and the focal weather variable is a measure of the temporal trend (Fig. B1). The range of the variogram model measures the time over which the weather variable is autocorrelated. The standard deviation of the residuals from the GLS model measures the temporal variance. Note, that climate data for species with short generation times (i.e., < 1 year) may have a seasonal signal that will need to be accounted for. In this case, the autocorrelation and variance can be estimated with a seasonal autoregressive integrated moving average (ARIMA) model and the trend can be estimated using a linear regression of the residuals from the ARIMA model.

In the spatial context, the GLS model can be fit with the focal weather variable as the response variable and the x and y spatial coordinates as the independent variables. The spatial trend can be estimated as a combination of the trend in the x and y directions:

$$\beta = \sqrt{\beta_x^2 + \beta_y^2},$$

where β is the average maximum slope, and β_x and β_y are slopes in the x- and y-directions (respectively). The variance and autocorrelation are estimated using the range of the variogram model and the standard deviation of the residuals, as in the temporal case. In the spatial context, the range of the variogram model measures the distance over which the weather variable is autocorrelated.

DOES THE CHOICE OF CLIMATE DATA AFFECT THE CLIMATE REGIME MAPS?

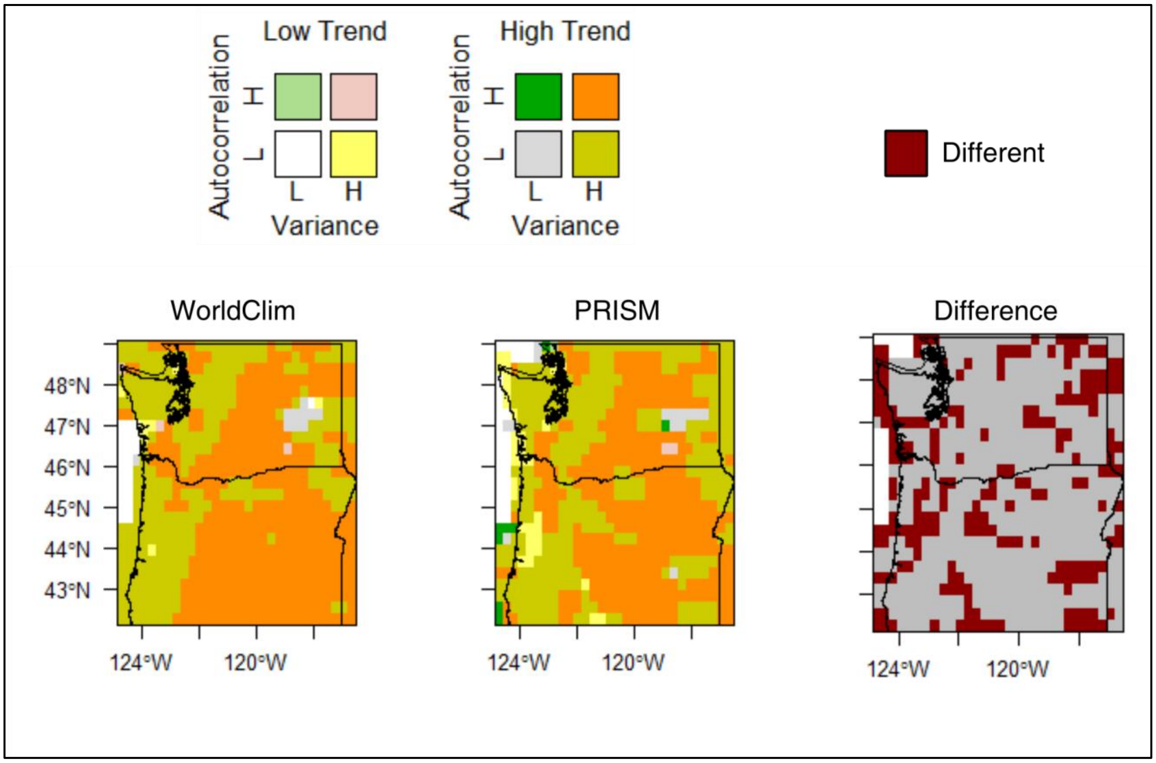

Figure S1. The location of different climate regimes in Oregon and Washington USA mapped using different climate datasets (WorldClim and PRISM 800m data) and the difference between the two maps. The climate regimes are based on different combinations of high (H) and low (L) values of spatial climatic trend, variance, and autocorrelation in mean annual temperature. The WorldClim dataset is based on a simple interpolation procedure that uses data from weather stations along with the latitude, longitude, and elevation to estimate the temperature in each cell (Hijmans et al., 2005). PRISM uses a more complicated algorithm that incorporates additional climate drivers (e.g., topographical facets, coastal effects, Daly et al., 2002). The PRISM algorithm also incorporates expert knowledge to control the local weighting of each climate driver in the interpolation procedure. Consequently, PRISM climate data produces a much more detailed picture of climate in topographically diverse areas with few weather stations such as Oregon and Washington states. WorldClim and PRISM datasets are known to differ in Oregon and Washington (Hijmans et al., 2005). Hence, they are useful in determining whether the choice of climate data affects geographical patterns in the climate regimes. The maps show similar geographical patterns; 72% of cells have the same classification between the two maps. The majority of cells (77%) with a different classification have different estimates of autocorrelation. These results suggest that the climate regime maps in Fig. 4 are robust to our choice of climate data.

References

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