Ecohydrology Research Project

Tuolumne River Climate Change Analysis

BEE 6740

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CONTENTS

INTRODUCTION

Changes in climate will impact hydrological conditions in the Sierra Nevada mountains. A representative alpine river, the Tuolumne, was chosen due to its importance for urban and agricultural water supply and the availability of measured data. A reach of the river upstream of dams and other infrastructure was selected. Downscaled climate projections were used for a snowmelt model in the Tuolumne headwater watershed. As temperatures increase, there will be less alpine snowpack and modified seasonal streamflow. Albedo feedback and changes in evapotranspiration and groundwater dynamics may exacerbate these impacts. A modified hydrologic regime of this region dominated by snowpack has implications for water supply.

BACKGROUND

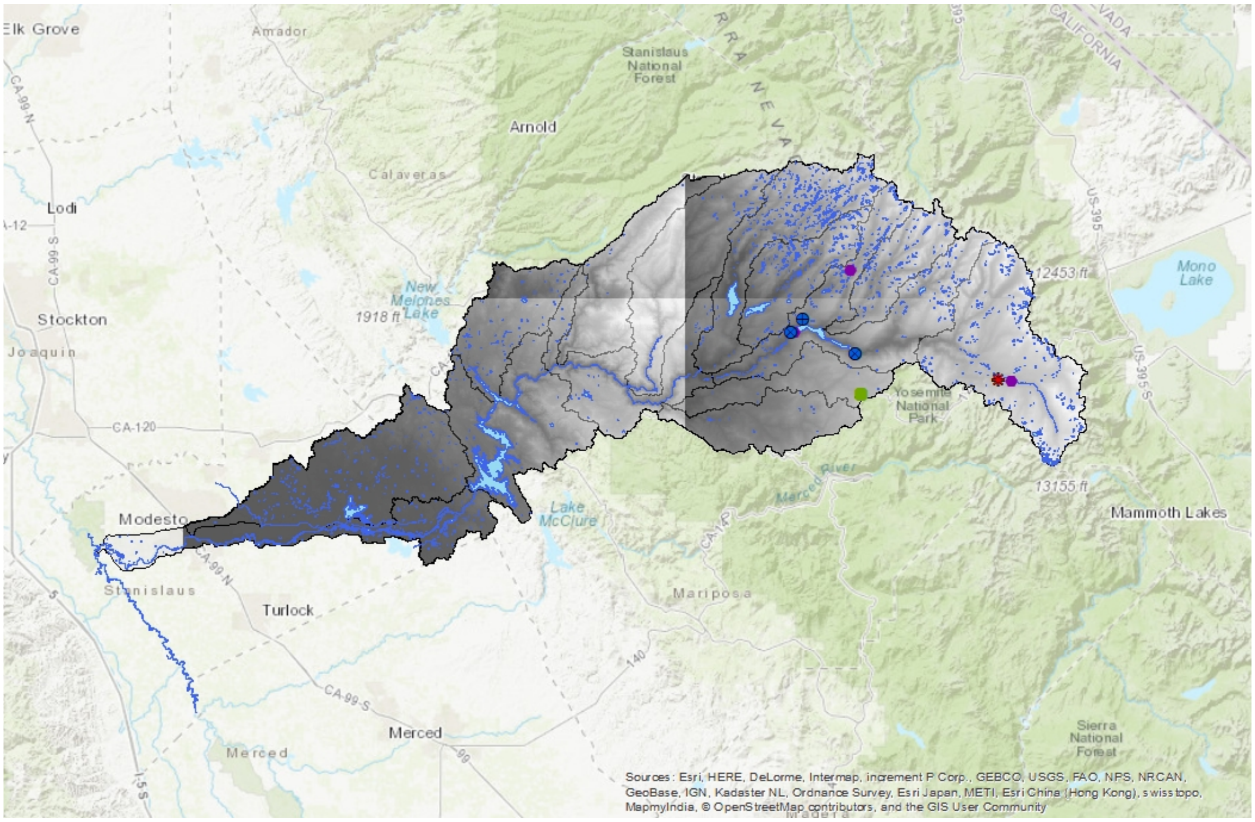
In mountainous regions such as the western United States, snowmelt is the dominant water source.[1] The Sierra Nevada region provides 60% of California's fresh water, for 23 million people.[2] Snowpack functions as a reservoir for water storage.[3] Changes in climate impact the seasonality of the hydrologic cycle. In turn, humans are impacted in terms of water supply, water quality, and hydropower.

With temperature increases by end of 21th century of 2.4^{o}C and 3.7^{o}C per emissions scenario, impacts of increased winter streamflow and deceased summer flow are predicted.[4] Higher air temperatures can result in less precipitation in the form of snowfall. Warming affects other processes such as evapotranspiration, soil storage, snowmelt processes which in turn affect stream discharge.

Outcomes relate to decrease in late winter snow and diminished spring snowpack. Decreased mean annual flow, less snowpack, and faster snowmelt runoff are expected outcomes from climate shifts.[5] Seasonal changes in streamflow with shortened winter due to higher temperatures will likely place stress on water supply and ecology in arid and semiarid regions, resulting in summer water shortage.[6]

Gaging how particular watersheds will respond to global changes is more difficult, especially given the degree of human intervention such as hydrological infrastructure in the form of dams, aqueducts, reservoirs, etc. present in an area like California. The mixed constructed-natural system provides a barrier to analysis as flow is semi-regulated, less so at its free-flowing alpine source. While it's important to approach the analysis comprehensively when analyzing supply/user impacts, this report will focus on the Tuolumne watershed headwaters as the most direct consequence of projected climate changes.

[1] Tague, 2009.
[2] Reich, et al, 2018.
[3] Green, 2016.
[4] Maurer, 2007.
[5] Null, 2010.
[6] Green, 2016



Snowpack is one of the major areas of impact for California water resources. The total water stored on average in Sierra Nevada snowpack on April 1 is 12.4 km^3, more than double the capacity of California's largest constructed reservoir.[7] Snowpack changes are among the fastest changing climate features on Earth.[8] The changes will largely depend on elevation.[9]

Snow albedo feedback (SAF) can exacerbate warming as higher temperatures result in less snowfall and earlier snowmelt.[10] Less of the land surface covered by snow reduces albedo and allows the land heat due to the absorption of more solar radiation. Largely because of SAF, the elevation in the Sierra Nevada most vulnerable to climate change are 1500 to 2500 meters.[11] Projections indicate that the impact of a shorter winter in the Sierra Nevada will cause less snow cover especially in April and May, causing significantly warmer temperatures because of SAF.

Null, et al. looked at outcomes in terms of water resource development, principally water delivery, hydropower, and mountain meadows.[12] Watersheds such as Tuolumne had increased late summer low flow duration and vulnerable mountain meadow ecosystems in their models. The alpine Tuolumne Meadows may be impacted, affecting ecological soundness and water quality. The metrics for impacts used by Null, et al. include mean annual flow (MAF) and low flow duration (LFD), used in this analysis.

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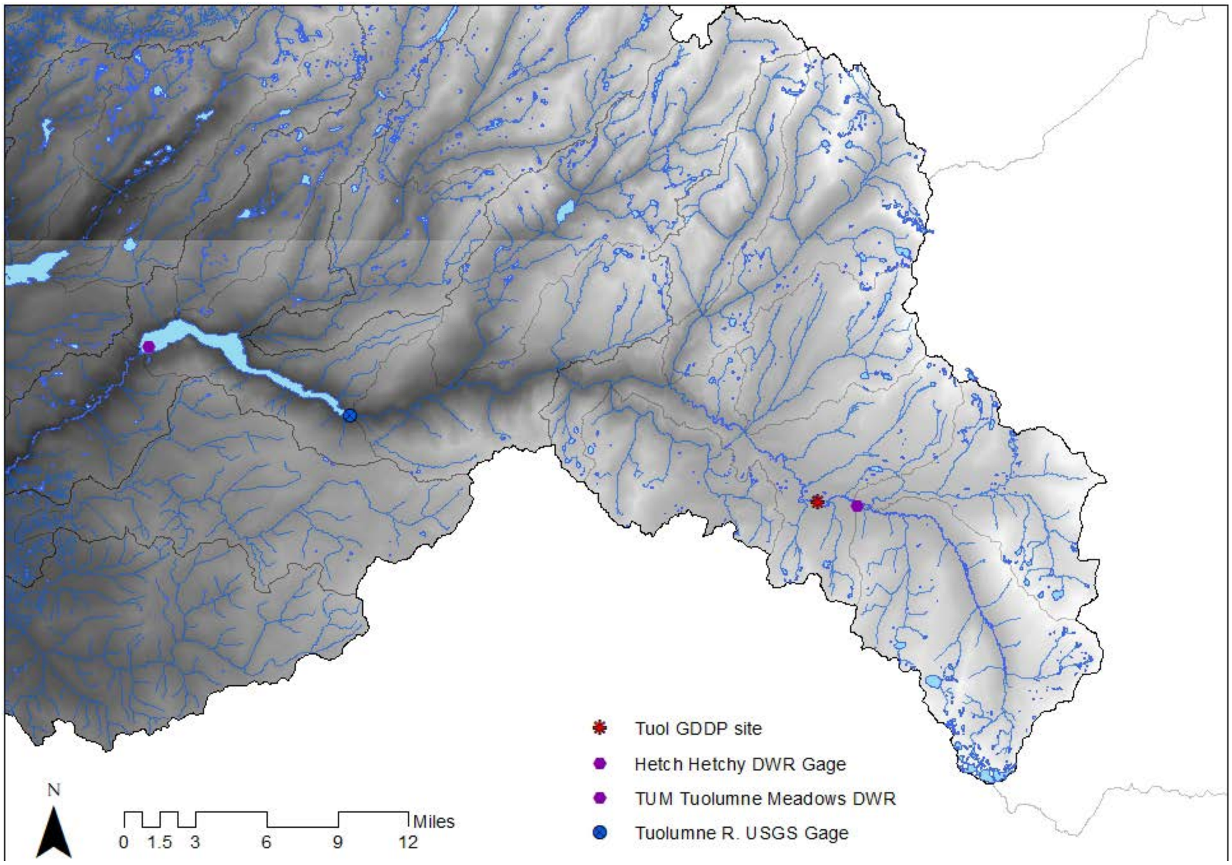
[7] Maurer, 2007.
[8] Trinh, 2017.
[9] Maurer, 2007.
[10] Walton, et al, 2017
[11] Reich, et al., 2018.
[12] Null, 2010.



The Tuolumne River begins in mountains at elevation 2618 m in Yosemite National Park. It flows into the Hetch Hetchy reservoir at elevation 875 m where it is dammed. It supplies the Hetch Hetchy aqueduct providing power and water for 2.7 million people in San Francisco.[13] The river is diverted at Hetch Hetchy then flows through a series of dams, providing agricultural irrigation water and hydropower. For the purposes of this analysis, the undammed and unmodified headwaters/upstream portion of the river will be examined.

The Tuolumne Headwaters watershed is upstream of a USGS stream gage, itself upstream of Hetch Hetchy. The watershed is 770.56 km^2 and has an average elevation of 2843.5 m. It consists of mountainous terrain, alpine meadows (Tuolumne Meadows), and the valley that terminates in Hetch Hetchy to the west.

PROCESS

The following data were imported into R for use in the Tuolumne River analysis: observed precipitation, temperature and snow depth measurements from California Department of Water Resources (DWR) site (elevation 2621 m), Tuolumne upstream discharge from USGS gage (elevation 1809 m), and projected precipitation and temperature data from NASA NEX-GDDP GCMs (the NCAR CESM1 and NOAA GFDL

[13] SF Water, 2018.

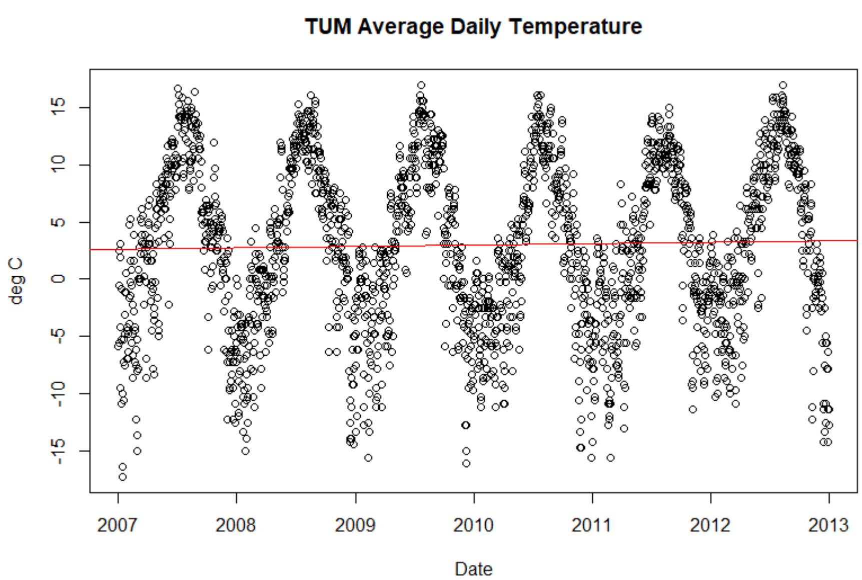
models) for an area encompassing headwater area.[14] The observed data covered the years 2007-2013 while the GCM projections ranged 1950-2005 (historical) and 2005-2100 (future). The future projections followed two greenhouse gas emissions scenarios: Representative Concentration Pathway RCP 4.5, a moderate to optimistic assumption, and RCP 8.5, a starker prediction of warming with increasing emissions.[15]

Given their large scale, there are limitations in the predictive utility of the GCMs. Their resolution is 0.25 degrees (~25 km x 25 km).[16] Since the projected average daily temperature for 2007-2013 compared to the observed data was found to be 2^{o}C higher, the GCM temperature inputs for the models were bias corrected by minus 2^{o}C. The issue likely stems from the varied geography in the region. The ideal, representative climate data site is at the mean elevation of the watershed.

Observations

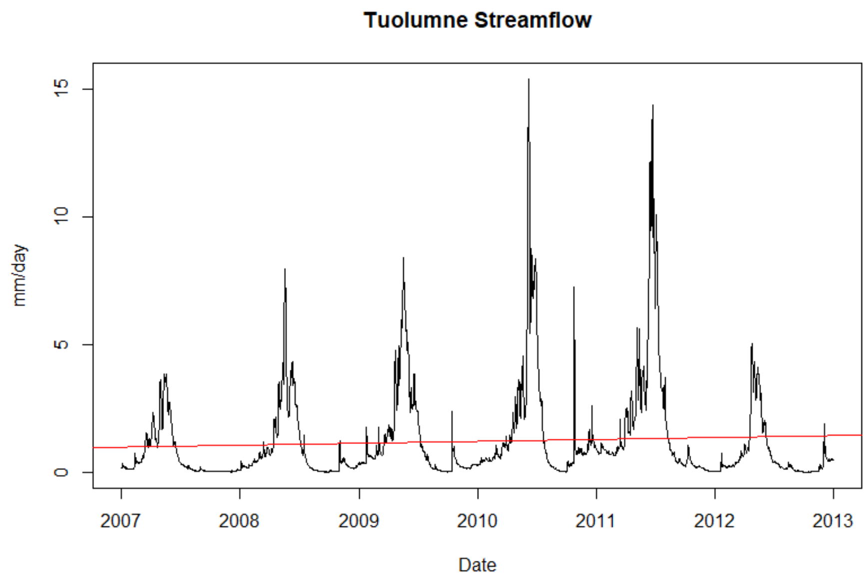
Six years of observed temperature measurements from the CA DWR site in Tuolumne Meadows is shown below. The seasonal fluctuations can be compared to the following graphs of precipitation and streamflow. All temperature values are the average of minimum and maximum daily measurements in degrees Celsius.

Statistical analysis proved fruitful in the examination of long-term trends. A linear regression trendline was used in the graphing of this data, and will be used in other figures in this report. The red trendline is the output of a simple linear regression model in which the date is the independent variable and the projected phenomenon is the dependent variable (e.g. temperature ~ date).

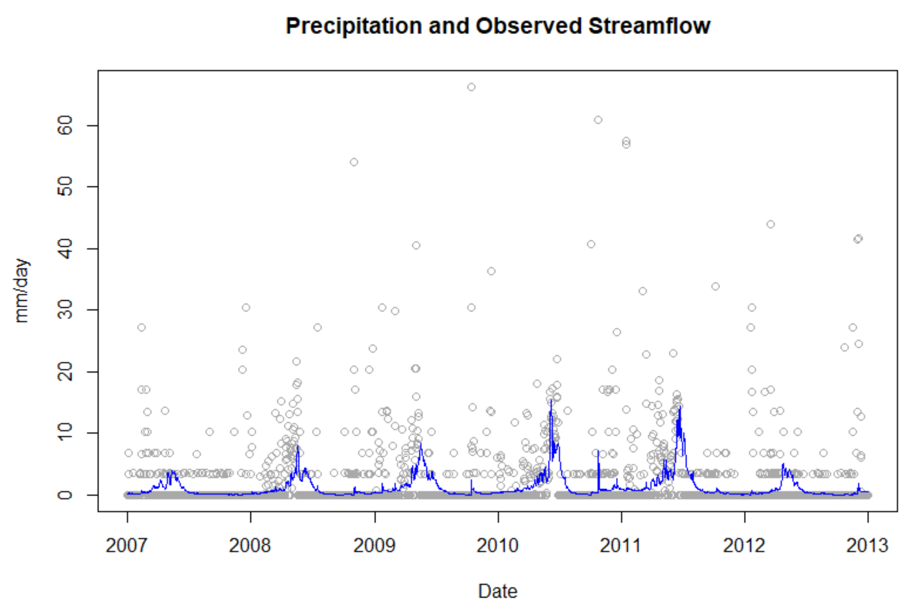


[14] CA DWR, 2018; USGS, 2018; OpenNEX / Planet OS, 2015. Climate scenarios used were from the NEX-GDDP dataset, prepared by the Climate Analytics Group and NASA Ames Research Center using the NASA Earth Exchange, and distributed by the NASA Center for Climate Simulation (NCCS). See Appendix for R code.
[15] NASA, 2014.
[16] NASA, 2015.

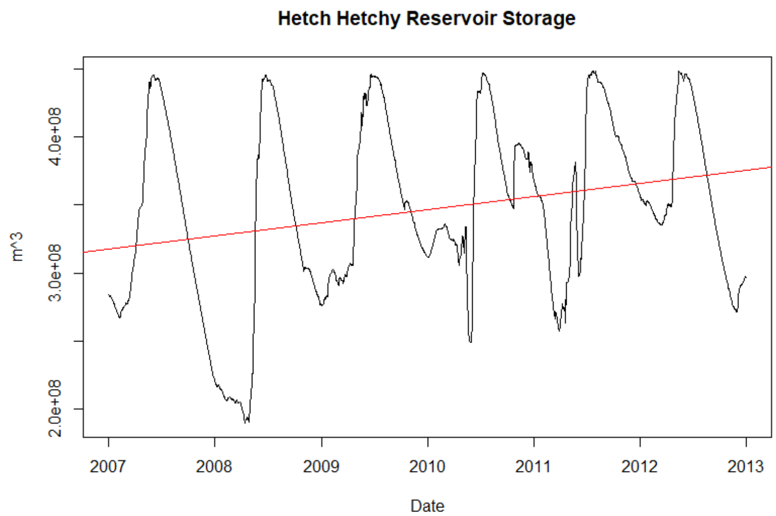
USGS stream gage data was accessed for the reach of the Tuolumne River upstream of the Hetch Hetchy reservoir and downstream of the Tuolumne headwaters. The graph below illustrates the seasonal cycle of streamflow, with marked yearly peaks in late spring.



The graph below how peaks in streamflow follow the melting of snowpack accumulated under the winter. There is a strong seasonal trend in the patterns of precipitation and streamflow. Large precipitation events predominate in the winter and spring, while peak streamflow is in the spring.



As a major source of water for urban as well as agricultural supply, the Tuolumne River is vital for Californians. The Hetch Hetchy reservoir provides storage for the drinking water of the residents of the San Francisco Bay Area. As such, the volume of water the reservoir contains is a significant hydrological indicator for the Tuolumne River. Peaks in reservoir storage appear to correspond with peaks in discharge upstream. However, since the reservoir is a managed entity with the O'Shaughnessy Dam containing it, its water levels cannot be considered as occurring in an entirely natural system. This report will look at potential impacts on the largely anthropogenic hydrology downstream of the Tuolumne Headwaters instead of analyzing particular facets or outcomes of the systems managed by the constructed infrastructure.



Model Calibration

Two models from the Ecohydrology package in R were used for the analysis, the Snowmelt Model and the Lumped VSA Model.[17] The former model is an energy balance model developed by Walter, et al. It calculates the impact of temperature on the form of precipitation, such as how much of the precipitation is snowfall, and how much snow accumulates.[18] The model includes a mechanism for albedo feedback: an increase in snow accumulation corresponds with an increase in albedo, while snowmelt will decrease albedo. The Lumped VSA Model uses precipitation output from the Snowmelt Model and incorporates soil water storage, Priestley-Taylor potential evapotranspiration, and Thornthwaite-Mather runoff water balance to generate output including, for the purposes of this analysis, modeled streamflow (flow depth over watershed area).

<u>Priestley-Taylor PET</u>[19]

$$ET_0 = \frac{1}{\lambda} \cdot \frac{s \cdot (R_n - G)}{s + \gamma} \cdot \alpha$$

l (MJ kg-1) is the latent heat of vaporization, Rn (MJ m-2 d-1) is the net radiation, G (MJ m-2 d-1) is the soil heat flux, s (kPa °C-1) is the slope of the saturation vapor pressure-temperature relationship, g (kPa °C-1) is the psychrometric constant, a is the Priestley-Taylor coefficient.

[17] Fuka, et al. 2014.
[18] Walter, et al. 2005.
[19] CRA-CIN, 2009.

Thornthwaite-Mather[20]

Situation in the Watershed	*AW*	Excess
• Soil is drying $\Delta P < 0$	$= AW_{t-1} \exp\left(\frac{\Delta P}{AWC}\right)$	$= 0$
• Soil is wetting $\Delta P > 0$ but $AW_{t-1} + \Delta P \leq AWC$	$= AW_{t-1} + \Delta P$	$= 0$
• Soil is wetting above capacity $\Delta P > 0$ but $AW_{t-1} + \Delta P > AWC$	$= AWC$	$= AW_{t-1} + \Delta P - AWC$

AWC = Available Water Capacity (soil depth) θ fc –θ wp; AW = Available Soil Water; (soil depth) ( ) θ –θ wp; ΔP = Net Precipitation; P – PET; P = Precipitation; PET = Potential Evapotranspiration [depth]

Snowpack Energy Balance[21]

$$\lambda \Delta \mathrm{SWE} = S + L_a - L_t + H + E + G + P - \mathrm{SWE}(C\Delta T_s)$$

l is the latent heat of fusion (3.35 £ 105 kJ m23), DSWE is the change in the snowpack's water equivalent (m), S is the net incident solar radiation (kJ m22), La is the atmospheric long wave radiation (kJ m22), Lt is the terrestrial long wave radiation (kJ m22), H is the sensible heat exchange (kJ m22), E is the energy flux associated with the latent heats of vaporization and condensation at the surface (kJ m22), G is ground heat conduction to the bottom of the snowpack (kJ m22), P is heat added by rainfall (kJ m22) and SWE(CDT) is the change of snowpack heat storage (kJ m22). N

Both models include multiple input parameters which represent conditions in the watershed. A DDS algorithm was used to calibrate the models and find the values which result in the closest simulation of the modeled discharge compared to observed discharge from the USGS gage.[22] The precipitation and temperature measurements from the California DWR site was used as forcing data. The best Nash-Sutcliffe Efficiency (NSE) score obtained 0.736 out of 1, 1 indicating perfect match between modeled and observed data.[23] The parameter values used to achieve that best score are listed below.

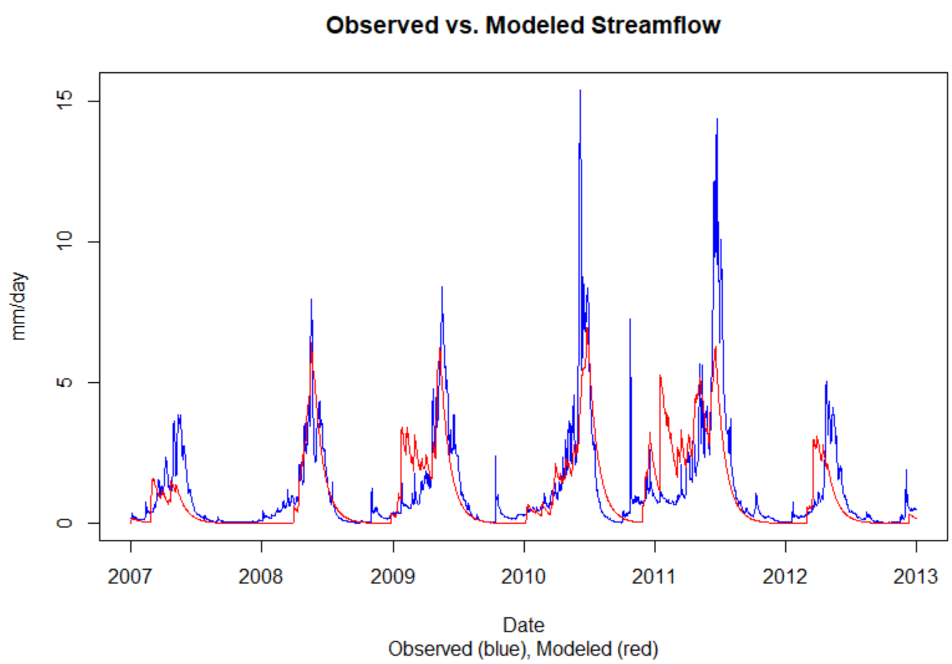
NSE Best Parameter	Value	Range	Significance
Forest Cover (0-1)	0.2968	0.1 – 0.9	Forested land cover.
Time to Peak (hours)	4.1223	1 – 12	
PET Cap (mm)	5.9821	2 – 10	Limit of evapotranspiration.
Rec Coefficient	0.0361	0.02 – 0.6	

[20] Physical Hydrology for Ecosystems, 2013.
[21] Walter, et al., 2005.
[22] Tolson and Shoemaker, 2007.

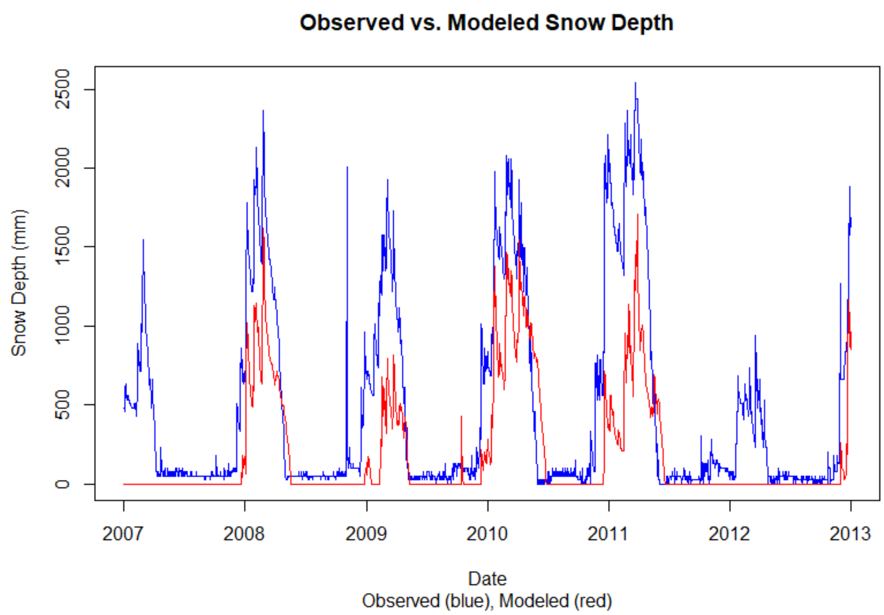
Se Min (mm)	176.231	10 – 180	
C1 Coefficient	5.6225	1 – 7	
Ia Coefficient	0.2871	0.01 – 0.3	
Ground Albedo (0-1)	0.2099	0.1 – 0.8	Albedo indicates snow cover.
Wind Speed (m/s)	4.227	0 – 7	
Surface Emissivity (0-1)	0.459	0 – 1	

COMPARISONS

The hydrographs of the modeled and observed flow were compared to understand the limitations of the Lumped VSA model. As illustrated in the graph below, the model underestimated streamflow compared to the USGS gage data. The baseflow and highest peak discharge especially diverged from the observed values. The model produced a slightly lower overall mean daily discharge depth in the watershed.



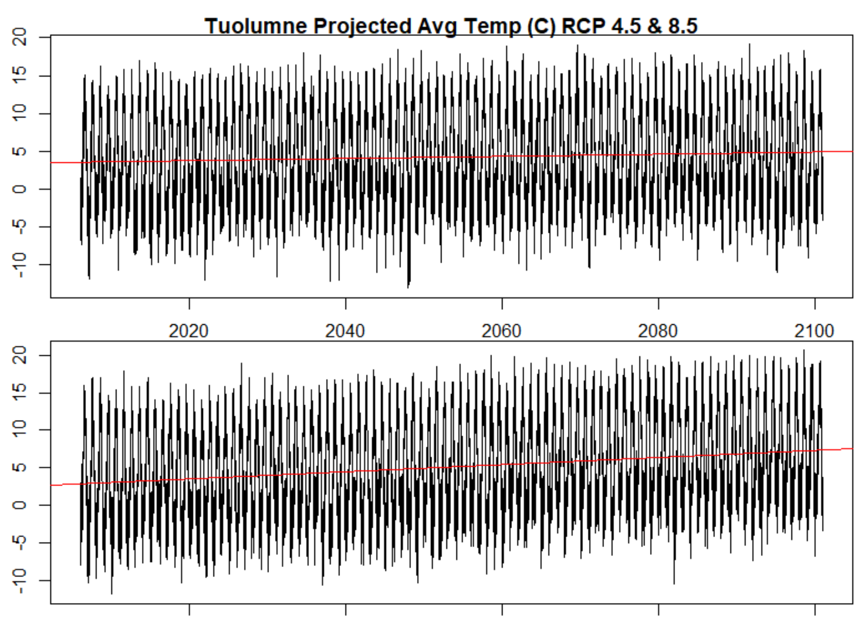
Observed vs. modeled snow depth is graphed below. The Snowmelt Model significantly underestimates snow depth to around half of observed. The model likely triggers snowmelt too rapidly and underestimates proportion of precipitation that is snowfall.



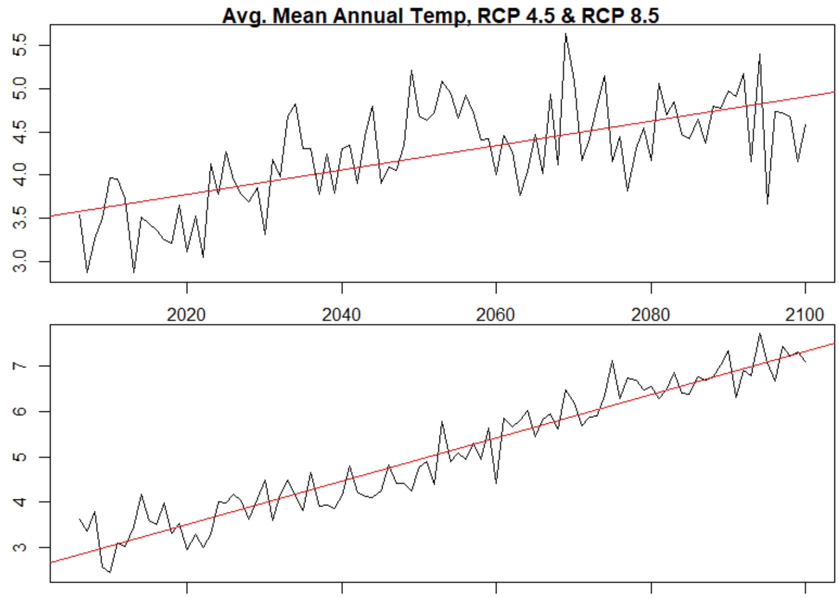
ANALYSIS

CLIMATE IMPACTS

The average daily temperatures from the GCMs are shown below. The data represents both the RCP 4.5 and RCP 8.5 emissions scenarios. There is an upward trend in warming evident in both projections, especially the high emissions scenario.

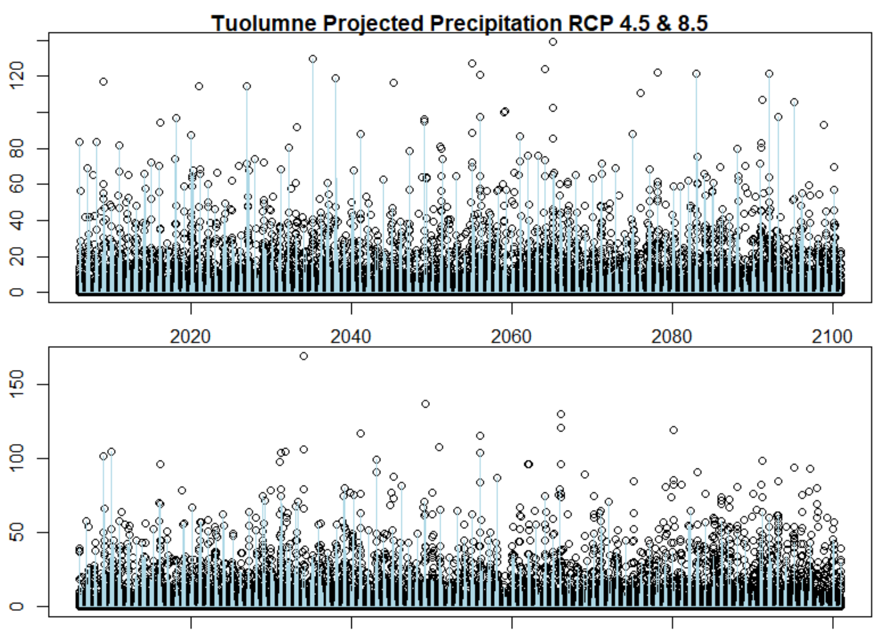


The graph below of the average annual mean temperature shows the extreme warming trend evident in the RCP 8.5 scenario, with an increase of ~4^{o}C projected by 2100, while RCP 4.5 shows an increase of ~2^{o}C for the area.

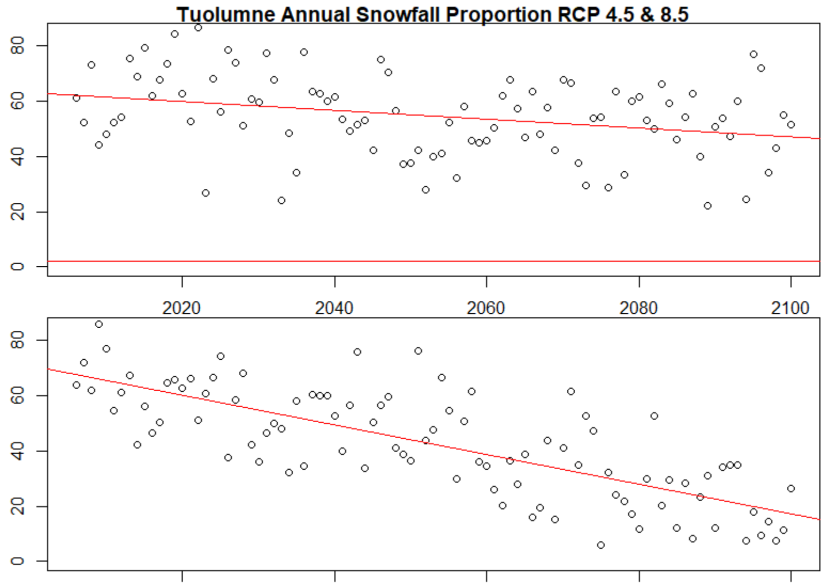


Snow Impacts

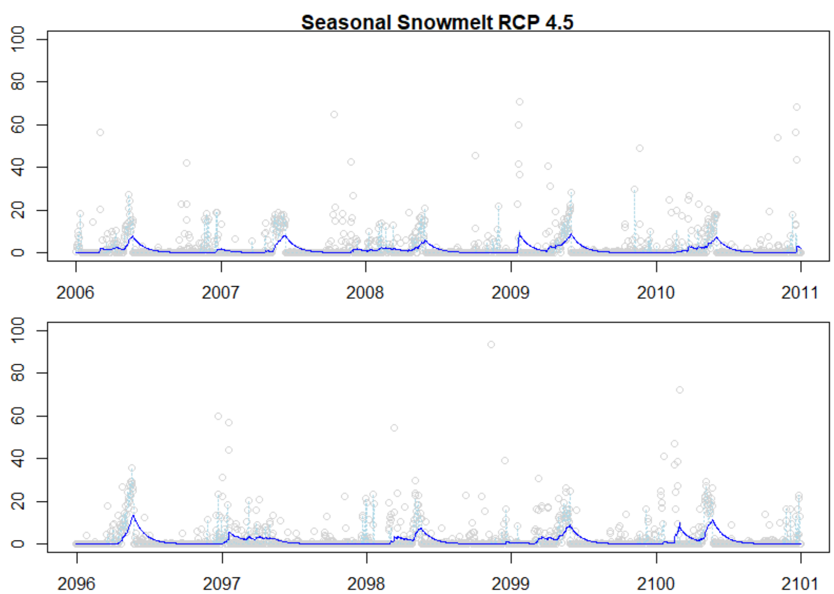
Projected perspiration for the Tuolumne Headwaters watershed is shown below in mm/day with snow in blue.



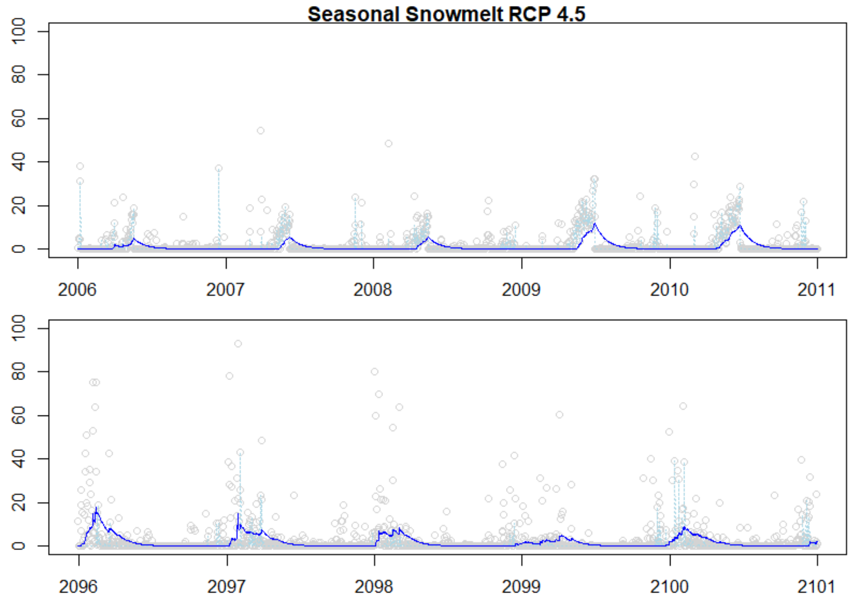
Annual snow as percent of precipitation is graphed below. There is a steady decline in snowfall in the RCP 4.5 scenario and a steeper decline in the RCP 8.5 scenario. Less snowfall would signify less seasonal storage of water and more consistent runoff conditions.



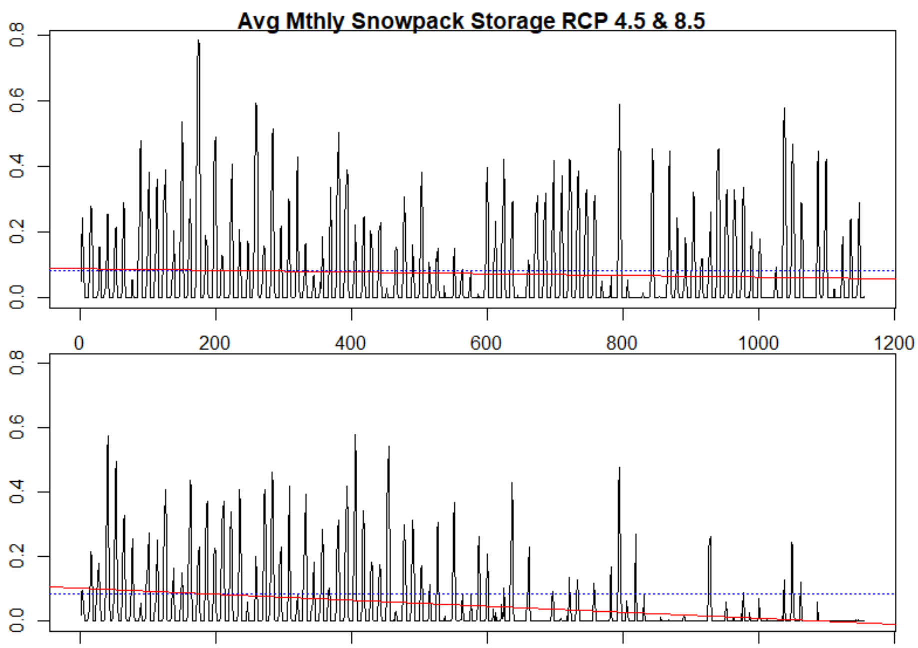
Precipitation, snowmelt, and streamflow are graphed below. Earlier onset of spring and peak flows is predicted by the end of the 21st century. At present, the April 1 snow depth is a valuable indicator of snow in the Sierra Nevada. There is a dramatic shift in seasons projected in the RCP 8.5 scenario, with all snowmelt and peak streamflow occurring during winter during the period of 2096-2101, i.e. spring arriving 2-3 months earlier, and a more modest change in the RCP 4.5 scenario showing snowmelt conditions beginning 1-2 months earlier. These results are consistent with another study predicting 25 and 50 days of earlier snowmelt runoff into mountain rivers in the high and mitigated emissions scenarios, respectively.[24]



[24] Reich, et al., 2018.



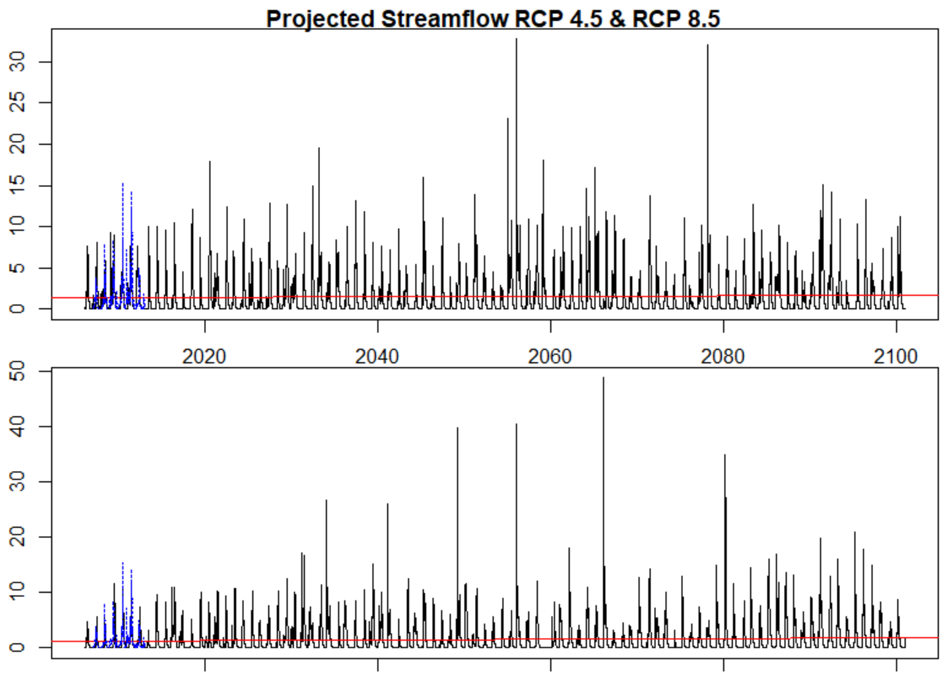
The chart below shows projected average monthly snowpack storage in km^3 for the watershed. The historic average level is in blue. There is no snowpack at the representative elevation and below (warmer) by the end of the 21st century under RCP 8.5 scenario, representing an extreme decline. The ~2^{o}C difference in temperature rise between the emissions scenarios results in a dramatic divergence in outcomes. These results seem consistent to other studies showing a 30% and 64% decline in average springtime snowpack in high and mitigated emissions scenarios, respectively, by 2100.[25]



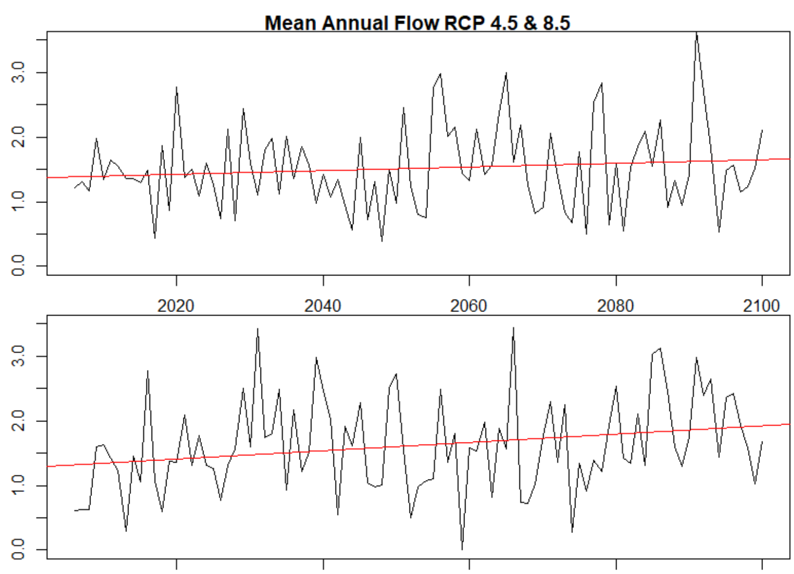
STREAM IMPACTS

[25] Reich, et al., 2018.

Sum daily discharge of the Tuolumne River is not projected to change overall. RCP 8.5 results in higher peak flow. RCP 8.5 has more flashiness with a Richards-Baker Flashiness Index of 0.059 versus 0.052 for RCP 4.5.[26] Observed discharge from the USGS gage from 2007-2013 is represented in blue.



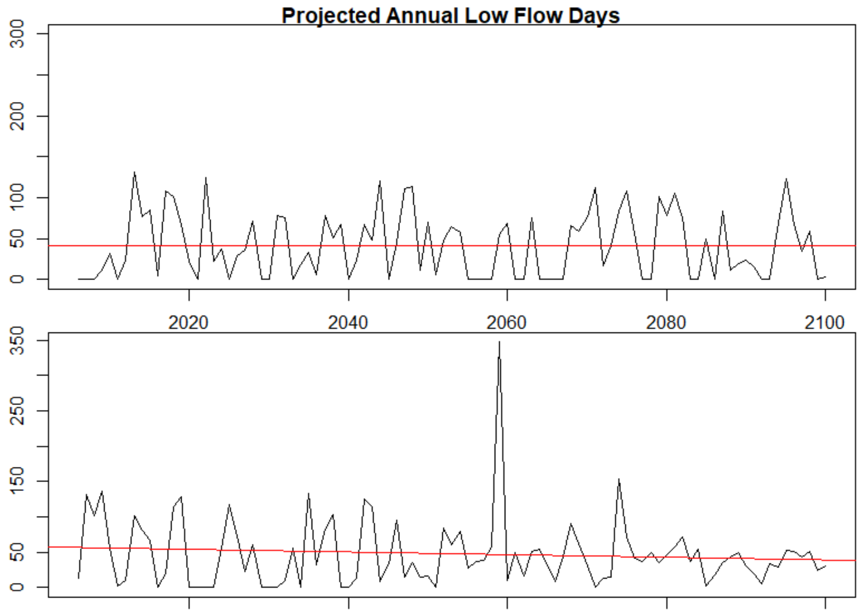
Some increase in mean annual flow is projected under both climate scenarios.



Annual low flow days are projected in the graph below with the notable caveat that the Lumped VSA Model underrepresents baseflow, so low flow days are overestimated. A midcentury drought is predicted in the RCP 8.5 scenario and less seasonal variation by end of century presumably due to less

[26] Baker, et al., 2004.

snowpack melt cycle. Low flow days are significant because the river's importance as water supply. Low flow was calculated based on the lowest 10% of daily discharge from the historic GCM projection.



LIMITATIONS

HYDROLOGICAL MODEL LIMITATIONS

There was limited observed calibration data for Lumped VSA Model. ET could be modeled better with soil water depth and other measurements. There were limitations in the models themselves. The Snowmelt Model underestimated snow depth. Aspects of certain processes like subsurface drainage were not modeled. These processes may be as significant as topographic differences for determining how mountain snow regimes respond to climate change.[27] Baseflow was especially underestimated. Because of these limitations, the observed vs. modeled streamflow NSE was imperfect.

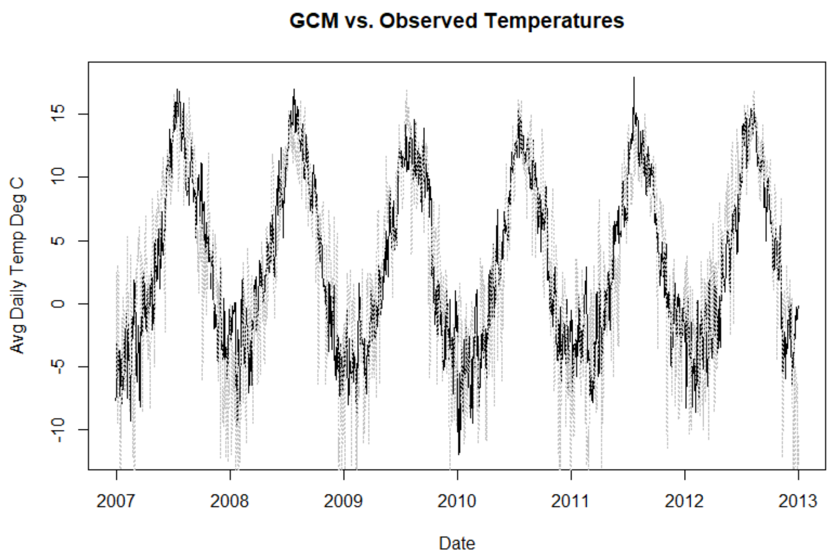
Meteorological data was limited by the date range of intact measurements. A period of 2007-2013 was chosen, and the measurement site was in an ideal location and elevation. To analyze watershed snow conditions due to climate change ideally physical data such as topography, soils, vegetation, and land use/land cover are all available as model inputs.[28] Because of limited data and model simplicity, a representative single site in the watershed was chosen and conclusions were extrapolated from the modeled results for this location. This is problematic due to the diverse topographic, ecological, geological, and climate characteristics in the Sierra Nevada. The impact assessment in this report is more apt for examining large-scale (spatial and temporal) trends than specific forecasted metrics.

CLIMATE MODEL LIMITATIONS

[27] Green, 2016.
[28] Trinh, 2017.

GCM data is limited by uncertainty and scale/resolution, especially due to alpine geography. Within the Sierra Nevada watersheds there is large variation in topography, ecology, and climate conditions. Given the large gradient of Tuolumne watershed from 1158 to 3962 meters in elevation, representative data sites (e.g. DWR site at 2621 m) close to the mean elevation (2843 m) were chosen.

Climate data was not matched perfectly to the meteorological observation site, as evidenced by comparison of observed and historical projected temperature, graphed below. The GCM data seems to be from a lower, warmer elevation than the representative elevation site chosen for observed data. GCM temperature projections concurrent with 2007-2013 data are 2^{o}C high on average compared to observed and snow is thus underestimated. All temperatures for the models incorporating GCM projections were bias corrected by -2^{o}C to compensate for this difference.



Although the Snowmelt Model incorporates a dynamic albedo process, the projection data used may not capture accelerated temperature increases or other associated climate changes due to albedo feedback GCMs often cannot model SAF due to complex topography and elevation dependent outcome, limitation of low resolution.[29]

CONCLUSION

Hydrological impacts due to climate change in California's Sierra Nevada mountains will likely increase in magnitude as the effects of warming compound. Climate projections modeled for an alpine site indicated a long-term decrease in snowfall and snowpack, which shapes the current seasonal hydrologic cycle in the Sierra Nevada, and the water usage downstream. Temperatures will continue to rise, exacerbated by albedo feedback due to diminished snowpack. Small temperature rises may cause significant changes as a result. However, total streamflow will not change significantly. Water users will need to adapt to the changing hydrologic regime, with an earlier onset of spring and less snowpack providing storage of water supply. There may be unknown impacts on water supply, water quality, and

[29] Walton, et al, 2017

potential for hydropower generation due to the limitations of climate and hydrological models, and uncertainty about the processes which they model.

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APPENDIX (CODE)

```
setwd("C:/Users/Cameron Afzal/Google Drive/M ENG SPRING 2018/Ecohydrology/Sierra research")


# TUM TUOLUMNE MEADOWS into Tuol R
# Elevation    8600.0 ft / 2621 m Latitude  37.873° Longitude     -119.35°
# Data date range: 01-01-2007 to 12-31-2012
# 2192 entries spanning 6 years
TUMprecip <- read.csv("TUMprecip2.csv")
TUMprecip$Precip_mm <- (TUMprecip$Precip_in*(25.4))
TUMprecip$Date <- as.Date(as.character(TUMprecip$Date), "%Y%m%d")
TUMsnowdepth <- read.csv("TUMsnowdepth2.csv")
TUMsnowdepth$Date <- as.Date(as.character(TUMsnowdepth$Date), "%Y%m%d")
TUMsnowdepth$Depth_mm <- (as.numeric(TUMsnowdepth$Depth_in)*(25.4))
TUMsnowdepth$Storage_m3 <- (TUMsnowdepth$Depth_mm/1000)*TuolUpstream$area_m
# TUMsnowwater$SWE_mm <- (__*(25.4))
TUMtmax <- read.csv("TUMtmax2.csv")
TUMtmax$Date <- as.Date(as.character(TUMtmax$Date), "%Y%m%d")
TUMtmax$TmaxC <- (TUMtmax$TmaxF-32)*(5/9)
TUMtmin <- read.csv("TUMtmin2.csv")
TUMtmin$Date <- as.Date(as.character(TUMtmin$Date), "%Y%m%d")
TUMtmin$TminC <- (TUMtmin$TminF-32)*(5/9)
# TUMmonthly <- read.csv("TUMsnowdepthmonthly")
# TUMmonthly$SnowDepth <- (__*(25.4))


# Overall trends
# Average daily precip
summary(TUMprecip$Precip_mm)
# Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
# 0.000   0.000   0.000   2.201   3.302 108.458
plot(TUMprecip$Date, TUMprecip$Precip_mm)
abline(lm(formula = TUMprecip$Precip_mm ~ TUMprecip$Date), col="red")


## TUOLUMNE ##
# NAME  Headwaters Tuolumne River (upstream of FC-TR) - TUM DWR site
# HUC10 1804000901
# AREAACRES    136812.51
# AREASQKM     553.66
# AVG ELEV 2937 m / 9636 ft


# NAME  Delaney Creek-Tuolumne River - dir downstream from TUM DWR site, up from RC-TR
# HUC12 180400090107
# AREAACRES    27510.78
# AREASQKM     111.33


# Register Creek-Tuolumne River - dir flow to Tuol USGS gage
# HUC12 180400090502
# AREAACRES    22576.58
```

```
# AREASQKM     91.36


## HETCH HETCHY ##
# NAME  Hetch Hetchy Reservoir-Tuolumne River - ds from RC and FC HUC12s, us from HTH
# HUC12 180400090504
# AREAACRES    22597.46
# AREASQKM     91.45


# HTH   HETCH HETCHY RESERVOIR
# Elevation    3870.0 ft Latitude    37.95°  Longitude      -119.783°
# Data date range: 2007 to 2012
HTHstorage <- read.csv("HTHstorage2.csv")
HTHstorage$Date <- as.Date(as.character(HTHstorage$Date), "%Y%m%d")
HTHstorage$Storage_m3 <- HTHstorage$StorageAF*1233.481838
plot(HTHstorage$Date, HTHstorage$Storage_m3, type="l", main="Hetch Hetchy Reservoir
Storage", ylab="m^3", xlab="Date")
abline(lm(formula = HTHstorage$Storage_m3 ~ HTHstorage$Date), col="red")


# Increase in HH Res storage? Establish correlation with snowpack storage?
# HTHmeanannualstorage


# Stream gages
# Tuolumne River
# USGS 11274790 TUOLUMNE R A GRAND CYN OF TUOLUMNE AB HETCH HETCHY (upstream of reservoir)
discharge
# Data range: 2007 to 2013
# Lat: 37.91659 Long: -119.6599
# Area: 770.56 sq km
# Gage elev: 1809.45 m
# Mean elev: 2843.5 m
# Mean annual precip: 1155.7 mm
TuolUpstream <- get_usgs_gage(11274790,begin_date = "2007-01-01", end_date = "2012-12-31")
TuolUpstream$area_m <- TuolUpstream$area*1000000
TuolUpstream$flowdata$flow_m <- TuolUpstream$flowdata$flow/TuolUpstream$area_m
TuolUpstream$flowdata$flow <- TuolUpstream$flowdata$flow_m*1000
plot(TuolUpstream$flowdata$mdate, TuolUpstream$flowdata$flow, type="l", main="Tuolumne
Streamflow", ylab="mm/day", xlab="Date")
abline(lm(formula = TuolUpstream$flowdata$flow ~ TuolUpstream$flowdata$mdate), col="red")


summary(TuolUpstream$flowdata$flow)


library(EcoHydRology)
# OBSERVED MODELS


# CALIBRATION
# Use monthly Tuol DWR files for SWE, precip, etc.
# Monthly USGS streamflow totals


# Baseflow seperation


# MODEL CALIBRATION: MONTE CARLO PARAMETER SENSITIVITY
```

```r
# MODEL CALIBRATION: DDS NSE BEST
probPeturb<-function(x, numIter){
  # Input is xBounds & numIter.
  # Returns numIter entry list with the indices which will be peturbed
  xDims<-nrow(x)
  probabilityVector<-1-log(1:numIter)/log(numIter)
  peturbIdx<-apply(matrix(unlist(lapply(probabilityVector, function(x)
as.logical(rbinom(xDims, 1, x)))), byrow=TRUE, ncol=xDims), 1, which)
  return(peturbIdx)
}


#This is the DDS Algorithm, I've coded it in full here to save us some time, Skip down to
Step 4
# Define Calibration Parameters
xBounds.df = data.frame(matrix(ncol=2,nrow=10))
colnames(xBounds.df)<-c("min", "max")


#forest
xBounds.df$min[1] = 0.1
xBounds.df$max[1] = 0.9


#Tp
xBounds.df$min[2] = 1
xBounds.df$max[2] = 12


#PETcap
xBounds.df$min[3] = 2
xBounds.df$max[3] = 10


#rec_coef
xBounds.df$min[4] = 0.02
xBounds.df$max[4] = 0.6


#Se_min
xBounds.df$min[5] = 10
xBounds.df$max[5] = 180


#C1
xBounds.df$min[6] = 1
xBounds.df$max[6] = 7


#Ia_coef
xBounds.df$min[7] = 0.01
xBounds.df$max[7] = 0.3


#groundAlbedo
xBounds.df$min[8] = 0.1
xBounds.df$max[8] = 0.8
```

```
#windSp
xBounds.df$min[9] = 0
xBounds.df$max[9] = 7


#SurfEmissiv
xBounds.df$min[10] = 0
xBounds.df$max[10] = 1.0


# Generate initial first guess
#xBounds.df<-data.frame(col1 = rep(10,10), col2=rep(100, 10))
x_init<-c(0.1, 1, 2, 0.02, 10, 1, 0.01, 0.1, 0, 0)
x_best = data.frame(x_init)


# Evaluate first cost function
NSE_init = -9999
NSE_best<-NSE_init


r= 0.2
numIter = 100
# Select which entry to peturb at each iteration


peturbIdx<-probPeturb(xBounds.df, numIter)
# Peturb each entry by N(0,1)*r(x_max - x_min) reflecting if @ boundaries
sigma<-xBounds.df$max - xBounds.df$min




for (i in 2:numIter){

  # Set up test x
  x_test<-as.matrix(x_best)

  # Get entries we will peturb
  idx<-peturbIdx[[i]]

  # Initialize vector of peturbations initially zeros with same length of x so we will add
this vector to peturb x
  peturbVec<-rep(0, length(x_test))
  # Generate the required number of random normal variables
  N<-rnorm(length(x_test), mean=0, sd=1)

  # Set up vector of peturbations
  peturbVec[idx]<-r*N[idx]*sigma[idx]

  # Temporary resulting x value if we peturbed it
  testPeturb<-x_test + peturbVec
  # Find the values in testPeturb that have boundary violations.  Store the indices in
boundaryViolationsIdx
  boundaryViolationIdx<-which(testPeturb<xBounds.df$min | testPeturb > xBounds.df$max)

  # Reset those violated indices to the opposite peturbation direction
  peturbVec[boundaryViolationIdx]<-(-
1*r*N[boundaryViolationIdx]*sigma[boundaryViolationIdx])
```

```
  # Find values still at violations of min or max and set them to the minimum or maximum
values
  testPeturb<-x_test + peturbVec
  minViolationIdx<-which(testPeturb<xBounds.df$min)
  maxViolationIdx<-which(testPeturb>xBounds.df$max)
  testPeturb[minViolationIdx]<-xBounds.df$min[minViolationIdx]
  testPeturb[maxViolationIdx]<-xBounds.df$max[maxViolationIdx]

  # Peturb the test vector
  x_test<-x_test + peturbVec

  # Run the Lumped_VSA_Model
  #Forcing Data
  #Date - Vector of dates (class Date or character) in this format: Y-m-d
  #precip_mm - Vector of precipitation in mm
  #Tmax_C - Vector of daily maximum temperature (degrees C)
  #Tmin_C - Vector of daily minimum temperature (degrees C)

  #Constants
  #lat_deg - Degrees latitude
  #slope - Overall slope of area of interest
  #aspect - Aspect of the area of interest (compass direction slope faces)
  #tempHt - height of temperature measurements (m)
  #windHt - height of wind measurements (m)

  #Parameters / Dimensions
  #groundAlbedo - Ground Albedo, 0-1 (-)
  #SurfEmissiv - Surface Emissivity, 0-1 (-)
  #windSp - Wind speed - either a vector of measured values or a single value of average
wind speed for the site (m/s)
  #forest - Forest cover (shade) - use this only when determining snowmelt under a canopy,
0-1 (-)

  #Initial Conditions
  #startingSnowDepth_m - The depth of the snow pack initially (m)

  latitudeDegrees = 37.873
  lat_deg = latitudeDegrees

  snowmelt <- SnowMelt(Date=TUMprecip$Date, precip_mm=TUMprecip$Precip_mm,
Tmax_C=TUMtmax$TmaxC, Tmin_C=TUMtmin$TminC, lat_deg=37.87*(pi/180),
                    groundAlbedo= x_test[8], windSp = x_test[9], forest=x_test[1],
SurfEmissiv=x_test[10], tempHt = 2621, windHt = 2621)

  ModelPrecip = snowmelt$SnowMelt_mm+snowmelt$Rain_mm

  # P, # Rain + Snow melt (mm)
  # Tmax, # Max daily temperature (C)
  # Tmin, # Max daily temperature (C)
  # Depth = NULL, # Average soil depth in watershed (mm) [don't need if AWC and SAT entered
directly]
  # SATper = NULL, # Porosity (fraction)
  # AWCper = NULL, # Available Water Capacity (AWC) (fraction)
  # percentImpervious = 0, # Percent of the watershed that is impervious
  # no_wet_class = 10, # The number of wetness classes for saturated area designation
  # Tp = 5, # Time to peak (hours)
  # latitudeDegrees = 42.38,
  # albedo = 0.23, # Average albedo
  #  StartCond = "avg", # Watershed conditions before first day of run ("wet", "dry",
"avg")
```

```
  #  PETin = NULL,# User has the option to enter PET values (mm/day)
  # AWC = Depth*AWCper, # AWC as a depth (mm)
  # SAT = Depth*SATper,# porosity as a depth (mm)
  # SW1 = NULL, # Soil water on the first day (depth, mm)
  # BF1 = 1, #  mm/day can use nearby watershed baseflow, ConvertFlowUnits(cfs,WA=W_Area)
  # PETcap = 5, # Does not let PET get larger than this cut off (mm)
  #  rec_coef = 0.1, # based on a study by Weiler in NY state
  # Se_min = 78, # mm
  # C1 = 3.1, # Coefficient relating soil water to Curve Number S
  # Ia_coef = 0.05, # range ~ 0.05 - 0.2
  # PreviousOutput = NULL, # Allows us to take previous model output to initiate the model
  # runoff_breakdown = RunoffBreakdown(Tp, HrPrcDelay = (Tp/2-4))
  # The proportion of runoff that reaches the outlet on a given day after the storm event.
  # Calculated from Time to peak, which is related to time of concentration

  Results <- Lumped_VSA_model(dateSeries = TUMprecip$Date, P = ModelPrecip,
Tmax=TUMtmax$TmaxC, Tmin = TUMtmin$TminC, latitudeDegrees=37.87*(pi/180),
                              Depth = 1500, SATper = 0.5, AWCper = 0.17, Tp = x_test[2],
StartCond = "avg", BF1 = 0.2,
                              albedo= x_test[8], PETcap = x_test[3], rec_coef = x_test[4],
Se_min = x_test[5], C1 = x_test[6], Ia_coef = x_test[7])

  Results$mdate = Results$Date
  AllData = merge(Results, TuolUpstream$flowdata, by="mdate")

  #Step 3: we're running a "spin-up" year to set initial conditions, but we only want to
calculate NSE on our study year
  #Calculate NSE

  numer = 0
  denom = 0
  for (j in 1:nrow(AllData))
  {numer = numer + (AllData$modeled_flow[j] - AllData$flow[j])^2
  denom = denom + (AllData$flow[j] - mean(AllData$flow))^2}
  NSE = 1 - numer/denom

  #Check if this simulation is better
  if (NSE > NSE_best)
  {
    x_best = x_test
    NSE_best = NSE
  }
  print_str = paste("Eval:",i,"   NSE:",NSE,"   NSE Best:",NSE_best)
  print(print_str)

}


print(NSE_best)
print(x_best)


# NSE Best Parameters from DDS
# NSE = 0.7361558
# [1,]   0.29680352
# [2,]   4.12232436
# [3,]   5.98211553
# [4,]   0.03619057
# [5,] 176.23104465
# [6,]   5.62254416
# [7,]   0.28712084
```

```
# [8,]   0.20997508
# [9,]   4.22714328
# [10,]   0.45915460


# Calibrated models for observed
snowmelt <- SnowMelt(Date=TUMprecip$Date, precip_mm=TUMprecip$Precip_mm,
Tmax_C=TUMtmax$TmaxC, Tmin_C=TUMtmin$TminC, lat_deg=37.87*(pi/180),
                     groundAlbedo= 0.2099, windSp = x_test[9], forest=0.2968,
SurfEmissiv=0.4591, tempHt = 2621, windHt = 2621)


ModelPrecip = snowmelt$SnowMelt_mm+snowmelt$Rain_mm
Results <- Lumped_VSA_model(dateSeries = TUMprecip$Date, P = ModelPrecip,
Tmax=TUMtmax$TmaxC, Tmin = TUMtmin$TminC, latitudeDegrees=37.87*(pi/180),
                            Depth = 1500, SATper = 0.5, AWCper = 0.17, Tp = 4.1223,
StartCond = "avg", BF1 = 0.2,
                            albedo= 0.2099, PETcap = 5.9821, rec_coef = 0.0362, Se_min =
176.231, C1 = 5.6225, Ia_coef = 0.2871)


Results$mdate = Results$Date
AllData = merge(Results, TuolUpstream$flowdata, by="mdate")
sim = AllData$modeled_flow
obs = AllData$flow
numer = 0
denom = 0
numer <- sum((sim - obs)^2)
denom <- sum((obs - mean(obs))^2)
NSE = 1 - numer/denom




# TUMannualprecip
summary(ModelPrecip)
TUMannualprecip <- ts((ModelPrecip), frequency = 365)
TUMyr = 2007:2012
TUMannualprecip <- aggregate(TUMannualprecip, FUN = sum)
plot(TUMannualprecip, type="l")
## Avg regional precip 1080mm/yr
# TUMmeanannualsnowwater


# TUMpercentsnow
for (i in 1:nrow(snowmelt))
{
if (ModelPrecip[i] != 0)
{
  TUMpercentsnow[i] <- snowmelt$SnowfallWatEq_mm[i]/(ModelPrecip[i])
}
}

TUMannualpercentsnow <- ts((TUMpercentsnow), frequency = 365)
TUMyr = 2007:2012
TUMannualpercentsnow <- aggregate(TUMannualpercentsnow, FUN = sum)
plot(TUMyr, TUMannualpercentsnow, type="l")


# TUMannualsnowaccum
```

```
# Precip and streamflow
plot(TuolUpstream$flowdata$mdate, ModelPrecip, col="dark grey", main="Precipitation and Observed Streamflow", xlab="Date", ylab="mm/day")
lines(TuolUpstream$flowdata$mdate, TuolUpstream$flowdata$flow, col="blue", type="l")


# Observed vs. modeled hydrographs
plot(TuolUpstream$flowdata$mdate, TuolUpstream$flowdata$flow, col="blue", type="l", main="Observed vs. Modeled Streamflow", sub="Observed (blue), Modeled (red)", xlab="Date", ylab="mm/day")
lines(TuolUpstream$flowdata$mdate, Results$modeled_flow, col="red")
summary(TuolUpstream$flowdata$flow)
summary(Results$modeled_flow)
# Analysis: Models underestimate streamflow, especially baseflow and highest peak discharge, slightly lower overall mean.


# Observed vs. modeled snow depth
snowmelt$SnowDepth_mm <- snowmelt$SnowDepth_m*1000
plot(TUMsnowdepth$Date, TUMsnowdepth$Depth_mm, type="l", col="blue", xlab="Date", ylab="Snow Depth (mm)", main="Observed vs. Modeled Snow Depth", sub="Observed (blue), Modeled (red)")
lines(TUMsnowdepth$Date, snowmelt$SnowDepth_mm, col="red")
sum(TUMsnowdepth$Depth_mm)
sum(snowmelt$SnowDepth_mm)
# Snowmelt model hugely underestimates snow depth, is around half of observed. Model likely triggers snowmelt too rapidly and underestimates proportion of precip that is snowfall


# Plot watershed mass balance P = Q + ET
# ET%
# P-Q
Q <- TuolUpstream$flowdata$flow
plot(TuolUpstream$flowdata$mdate, ModelPrecip, col="grey", main="Watershed Mass Balance", sub="Precipitation (grey), ET (green), Streamflow (blue)", ylab="mm/day", xlab="Date")
TUMet <- ModelPrecip-Q
lines(TuolUpstream$flowdata$mdate, TUMet, col="green", lty="dashed")
lines(TuolUpstream$flowdata$mdate, TuolUpstream$flowdata$flow, col="blue")
summary(Q)
summary(TUMet)
summary(ModelPrecip)


# PROJECTED DATA
# NASA NEX GDDP Data: precip and t min and t max projected
# Resolution 0.25 degrees (~25 km x 25 km)
# # -119.375   37.875
# NOAA GFDL-ESM2G model
# NCAR CESM1-BGC model, 2006-2100
# Temp : kelvin  (1.8*(K - 273.15) + 32) = F
# Precip : KG/M^2*S P*86400 = mm/day


# GFDL Historical Tuol 1950-2006
GhistPr <- read.csv("Ghisttuolpr.csv")
GhistPr$Date <- as.Date(GhistPr$Date, format = "%m/%d/%Y")
GhistPr$Prmm <- (GhistPr$Value*86400)
```

```r
GhistTmin <- read.csv("Ghisttuoltmin.csv")
GhistTmin$Date <- as.Date(GhistTmin$Date, format = "%m/%d/%Y")
GhistTmin$Tmin <- (GhistTmin$Value-273.15)

GhistTmax <- read.csv("Ghisttuoltmax.csv")
GhistTmax$Date <- as.Date(GhistTmax$Date, format = "%m/%d/%Y")
GhistTmax$Tmax <- (GhistTmax$Value-273.15)

# GFDL historical vs. observed temp, precip

# GFDL RCP 4.5 Tuol
G4Pr <- read.csv("Gtuolrcp45pr.csv")
G4Pr$Date <- as.Date(G4Pr$Date, format = "%m/%d/%Y")
G4Pr$Prmm <- (G4Pr$Value*86400)

G4Tmin <- read.csv("Gtuolrcp45tmin.csv")
G4Tmin$Date <- as.Date(G4Tmin$Date, format = "%m/%d/%Y")
G4Tmin$Tmin <- (G4Tmin$Value-273.15)

G4Tmax <- read.csv("Gtuolrcp45tmax.csv")
G4Tmax$Date <- as.Date(G4Tmax$Date, format = "%m/%d/%Y")
G4Tmax$Tmax <- (G4Tmax$Value-273.15)

# GFDL RCP 8.5 Tuol
G8Pr <- read.csv("Gtuolrcp85pr.csv")
G8Pr$Date <- as.Date(G8Pr$Date, format = "%m/%d/%Y")
G8Pr$Prmm <- (G8Pr$Value*86400)

G8Tmin <- read.csv("Gtuolrcp85tmin.csv")
G8Tmin$Date <- as.Date(G8Tmin$Date, format = "%m/%d/%Y")
G8Tmin$Tmin <- (G8Tmin$Value-273.15)

G8Tmax <- read.csv("Gtuolrcp85tmax.csv")
G8Tmax$Date <- as.Date(G8Tmax$Date, format = "%m/%d/%Y")
G8Tmax$Tmax <- (G8Tmax$Value-273.15)

# CESM1 Historical Tuol 1950-2006
ChistPr <- read.csv("Chisttuolpr.csv")
ChistPr$Date <- as.Date(ChistPr$Date, format = "%m/%d/%Y")
ChistPr$Prmm <- (ChistPr$Value*86400)

ChistTmin <- read.csv("Chisttuoltmin.csv")
ChistTmin$Date <- as.Date(ChistTmin$Date, format = "%m/%d/%Y")
ChistTmin$Tmin <- (ChistTmin$Value-273.15)

ChistTmax <- read.csv("Chisttuoltmax.csv")
ChistTmax$Date <- as.Date(ChistTmax$Date, format = "%m/%d/%Y")
ChistTmax$Tmax <- (ChistTmax$Value-273.15)
```

```r
# CESM1 Historical vs observed temp, precip


# CESM1 RCP 4.5 Tuol
C4Pr <- read.csv("Ctuolrcp45pr.csv")
C4Pr$Date <- as.Date(C4Pr$Date, format = "%m/%d/%Y")
C4Pr$Prmm <- (C4Pr$Value*86400)


C4Tmin <- read.csv("Ctuolrcp45tmin.csv")
C4Tmin$Date <- as.Date(C4Tmin$Date, format = "%m/%d/%Y")
C4Tmin$Tmin <- (C4Tmin$Value-273.15)


C4Tmax <- read.csv("Ctuolrcp45tmax.csv")
C4Tmax$Date <- as.Date(C4Tmax$Date, format = "%m/%d/%Y")
C4Tmax$Tmax <- (C4Tmax$Value-273.15)


# CESM1 RCP 8.5 Tuol
C8Pr <- read.csv("Ctuolrcp85pr.csv")
C8Pr$Date <- as.Date(C8Pr$Date, format = "%m/%d/%Y")
C8Pr$Prmm <- (C8Pr$Value*86400)


C8Tmin <- read.csv("Ctuolrcp85tmin.csv")
C8Tmin$Date <- as.Date(C8Tmin$Date, format = "%m/%d/%Y")
C8Tmin$Tmin <- (C8Tmin$Value-273.15)


C8Tmax <- read.csv("Ctuolrcp85tmax.csv")
C8Tmax$Date <- as.Date(C8Tmax$Date, format = "%m/%d/%Y")
C8Tmax$Tmax <- (C8Tmax$Value-273.15)


# GCM averages
PrH <- (ChistPr$Prmm+GhistPr$Prmm)/2
Pr4 <- (C4Pr$Prmm+G4Pr$Prmm)/2
Pr8 <- (C8Pr$Prmm+G8Pr$Prmm)/2
TminH <- ((ChistTmin$Tmin+GhistTmin$Tmin)/2)-2
TmaxH <- ((ChistTmax$Tmax+GhistTmax$Tmax)/2)-2
TavgH <- ((((ChistTmin$Tmin+GhistTmin$Tmin)/2)+((ChistTmax$Tmax+GhistTmax$Tmax)/2))/2)-2
Tmin4 <- ((C4Tmin$Tmin+G4Tmin$Tmin)/2)-2
Tmax4 <- ((C4Tmax$Tmax+G4Tmax$Tmax)/2)-2
plot(C4Tmax$Date, Tmax4, type="l", xlab="Date", ylab="Daily Max Temperature (C)",
main="Tuolumne Projected Max Temperature RCP 4.5")
abline(lm(formula = Tmax4 ~ C4Tmax$Date), col="red")


par(mfrow=c(2,1))
par(mar=c(1,2,1,2))
Tavg4 <- ((((C4Tmin$Tmin+G4Tmin$Tmin)/2)+((C4Tmax$Tmax+G4Tmax$Tmax)/2))/2)-2
plot(C8Tmax$Date, Tavg4, type="l", xlab="Date", ylab="Daily Avg Temperature (C)",
main="Tuolumne Projected Avg Temp (C) RCP 4.5 & 8.5")
abline(lm(formula = Tavg4 ~ C8Tmax$Date), col="red")


Tmin8 <- ((C8Tmin$Tmin+G8Tmin$Tmin)/2)-2
```

```
Tmax8 <- ((C8Tmax$Tmax+G8Tmax$Tmax)/2)-2
plot(C8Tmax$Date, Tmax8, type="l", xlab="Date", ylab="Daily Max Temperature (C)")
abline(lm(formula = Tmax8 ~ C8Tmax$Date), col="red")


Tavg8 <- ((((C8Tmin$Tmin+G8Tmin$Tmin)/2)+((C8Tmax$Tmax+G8Tmax$Tmax)/2))/2)-2
plot(C8Tmax$Date, Tavg8, type="l", xlab="Date", ylab="Daily Avg Temperature (C)")
abline(lm(formula = Tavg8 ~ C8Tmax$Date), col="red")


TUMtavg <- (TUMtmax$TmaxC+TUMtmin$TminC)/2


par(mfrow=c(2,1))
par(mar=c(1,2,1,2))
Tavg4meanannualtemp <- ts((Tavg4), frequency = 365)
Tavg4meanannualtemp <- aggregate(Tavg4meanannualtemp, FUN = mean)
plot(GCMyr, Tavg4meanannualtemp, type="l", main="Avg. Mean Annual Temp, RCP 4.5 & RCP 8.5")
abline(lm(formula = Tavg4meanannualtemp ~ GCMyr), col="red")


Tavg8meanannualtemp <- ts((Tavg8), frequency = 365)
Tavg8meanannualtemp <- aggregate(Tavg8meanannualtemp, FUN = mean)
plot(GCMyr, Tavg8meanannualtemp, type="l")
abline(lm(formula = Tavg8meanannualtemp ~ GCMyr), col="red")




summary(TUMtavg)
summary(TavgH)
summary(Tavg4)
summary(Tavg8)


# Temperatures: GCM average historical compared to observed average
# Average annual mean daily temp
#Observed
TUMmeanannualtemp <- ts((TUMtmax$TavgC), frequency = 365)
TUMyr = 2007:2012
TUMmeanannualtemp <- aggregate(TUMmeanannualtemp, FUN = mean)
plot(TUMyr, TUMmeanannualtemp, type="l")


# Average daily temp
TUMtmax$TavgC <- (TUMtmax$TmaxC+TUMtmin$TminC)/2
plot(TUMprecip$Date, TUMtmax$TavgC, main="TUM Average Daily Temperature", ylab="deg C",
xlab="Date")
abline(lm(formula = TUMtmax$TavgC ~ TUMprecip$Date), col="red")


plot(ChistTmin$Date, TavgH, type="l")
abline(lm(TavgH ~ ChistTmin$Date), col="red")
TavgHc <- TavgH[18248:20440]
summary(TUMtmax$TavgC)
summary(TavgHc)
# Historical projections are  2.1 deg C higher on average than measured for  range, but
range isn't ovelapping,
```

```
# indicating a lower elevation than the desired observation site for the watershed with a representative elevation,
# and/or unusually cold years for the observed data set


plot(C4Tmin$Date, Tavg4, type="l")
lines(TUMtmax$Date, TUMtavg, col="grey")
Tavg4c <- Tavg4[365:(365*7)]
summary(TUMtmax$TavgC)
summary(Tavg4c)
# RCP 4.5 avg temp projections for 2007-2013 have 2.55 deg higher mean


plot(C8Tmin$Date[365:(365*7)], Tavg8[365:(365*7)], type="l", main="GCM vs. Observed Temperatures", ylab="Avg Daily Temp Deg C", xlab="Date")
lines(TUMtmax$Date, TUMtavg, col="grey", lty=3)
Tavg8c <- Tavg8[365:(365*7)]
summary(TUMtmax$TavgC)
summary(Tavg8c)
# RCP 8.5 avg temp projections for 2007-2013 have 2.03 deg higher mean




# Bias correct GCM temps 2 deg C


# Hist Seasonal analysis: winter length / snowmelt timing (temps)
# Hannualwinterlength


# 4annualwinterlength


# 8annualwinterlength


# Caveats: low resolution downscaled, extrapolating from sites, perhaps doesn't model precip well, large elevation gradient within watersheds


# PROJECTED MODELS
# Snowmelt + VSA GCM historical
snowmeltH <- SnowMelt(Date=ChistPr$Date, precip_mm=PrH, Tmax_C=TmaxH, Tmin_C=TminH, lat_deg=37.87*(pi/180),
                      groundAlbedo= 0.2099, windSp = 4.227, forest=0.2968, SurfEmissiv=0.4591, tempHt = 2621, windHt = 2621)


ModelPrecipH = snowmeltH$SnowMelt_mm+snowmeltH$Rain_mm
ResultsH <- Lumped_VSA_model(dateSeries = ChistPr$Date, P = ModelPrecipH, Tmax=TmaxH, Tmin = TminH, latitudeDegrees=37.87*(pi/180),
                             Depth = 1500, SATper = 0.5, AWCper = 0.17, Tp = 4.1223, StartCond = "avg", BF1 = 0.2,
                             albedo= 0.2099, PETcap = 5.9821, rec_coef = 0.0362, Se_min = 176.231, C1 = 5.6225, Ia_coef = 0.2871)


# Snowmelt GCM 4.5
```

```
snowmelt4 <- SnowMelt(Date=C4Pr$Date, precip_mm=Pr4, Tmax_C=Tmax4, Tmin_C=Tmin4,
lat_deg=37.87*(pi/180),
                     groundAlbedo= 0.2099, windSp = 4.227, forest=0.2968,
SurfEmissiv=0.4591, tempHt = 2621, windHt = 2621)


ModelPrecip4 = snowmelt4$SnowMelt_mm+snowmelt4$Rain_mm
Results4 <- Lumped_VSA_model(dateSeries = C4Pr$Date, P = ModelPrecip4, Tmax=Tmax4, Tmin =
Tmin4, latitudeDegrees=37.87*(pi/180),
                            Depth = 1500, SATper = 0.5, AWCper = 0.17, Tp = 4.1223,
StartCond = "avg", BF1 = 0.2,
                            albedo= 0.2099, PETcap = 5.9821, rec_coef = 0.0362, Se_min =
176.231, C1 = 5.6225, Ia_coef = 0.2871)


# Snowmelt GCM 8.5
snowmelt8 <- SnowMelt(Date=C8Pr$Date, precip_mm=Pr8, Tmax_C=Tmax8, Tmin_C=Tmin8,
lat_deg=37.87*(pi/180),
                      groundAlbedo= 0.2099, windSp = 4.227, forest=0.2968,
SurfEmissiv=0.4591, tempHt = 2621, windHt = 2621)


ModelPrecip8 = snowmelt8$SnowMelt_mm+snowmelt8$Rain_mm
Results8 <- Lumped_VSA_model(dateSeries = C8Pr$Date, P = ModelPrecip8, Tmax=Tmax8, Tmin =
Tmin8, latitudeDegrees=37.87*(pi/180),
                             Depth = 1500, SATper = 0.5, AWCper = 0.17, Tp = 4.1223,
StartCond = "avg", BF1 = 0.2,
                             albedo= 0.2099, PETcap = 5.9821, rec_coef = 0.0362, Se_min =
176.231, C1 = 5.6225, Ia_coef = 0.2871)


# Stream flow
library(EflowStats)
library(EGRET)


# Seasonal precip and stream


par(mfrow=c(2,1))
par(mar=c(2,2,1,1))
plot(Results4$Date[1:(365*5)], ModelPrecip4[1:(365*5)], col="light grey", ylim=c(0,100),
main="Seasonal Snowmelt RCP 4.5")
lines(snowmelt4$Date[1:(365*5)], snowmelt4$SnowMelt_mm[1:(365*5)], col="light blue", lty=3)
lines(Results4$Date[1:(365*5)], Results4$modeled_flow[1:(365*5)], col="blue")


plot(Results4$Date[(365*90):(365*95)], ModelPrecip4[(365*90):(365*95)], col="light grey",
ylim=c(0,100))
lines(snowmelt4$Date[(365*90):(365*95)], snowmelt4$SnowMelt_mm[(365*90):(365*95)],
col="light blue", lty=3)
lines(Results4$Date[(365*90):(365*95)], Results4$modeled_flow[(365*90):(365*95)],
col="blue")


plot(Results8$Date[1:(365*5)], ModelPrecip8[1:(365*5)], col="light grey", ylim=c(0,100),
main="Seasonal Snowmelt RCP 4.5")
lines(snowmelt8$Date[1:(365*5)], snowmelt8$SnowMelt_mm[1:(365*5)], col="light blue", lty=3)
lines(Results8$Date[1:(365*5)], Results8$modeled_flow[1:(365*5)], col="blue")
```

```
plot(Results8$Date[(365*90):(365*95)], ModelPrecip8[(365*90):(365*95)], col="light grey",
ylim=c(0,100))
lines(snowmelt8$Date[(365*90):(365*95)], snowmelt8$SnowMelt_mm[(365*90):(365*95)],
col="light blue", lty=3)
lines(Results8$Date[(365*90):(365*95)], Results8$modeled_flow[(365*90):(365*95)],
col="blue")


# Projected stream flows
plot(ResultsH$Date, ResultsH$modeled_flow, type="l")
abline(lm(ResultsH$modeled_flow ~ ResultsH$Date), col="red")


par(mfrow=c(2,1))
par(mar=c(1,2,1,2))
plot(Results4$Date, Results4$modeled_flow, type="l", main="Projected Streamflow RCP 4.5 &
RCP 8.5")
abline(lm(Results4$modeled_flow ~ Results4$Date), col="red")
lines(TuolUpstream$flowdata$mdate, TuolUpstream$flowdata$flow, col="blue", lty=3)
summary(Results4$modeled_flow)


plot(Results8$Date, Results8$modeled_flow, type="l")
abline(lm(Results8$modeled_flow ~ Results8$Date), col="red")
lines(TuolUpstream$flowdata$mdate, TuolUpstream$flowdata$flow, col="blue", lty=3)
summary(Results8$modeled_flow)
# Slight increase in total daily flow


# Flashiness RBI
num = 0
for (i in 2:nrow(Results4))
{
  num = num + abs(Results4$modeled_flow[i] - Results4$modeled_flow[i-1])
}


RB4 = num / sum(Results4$modeled_flow)
print(RB4)


num = 0
for (i in 2:nrow(Results8))
{
  num = num + abs(Results8$modeled_flow[i] - Results8$modeled_flow[i-1])
}


RB8 = num / sum(Results8$modeled_flow)
print(RB8)


# Mean annual flow
GCMhist = 1950:2005
GCMyr = 2006:2100


par(mfrow=c(3,1))
par(mar=c(1,1,1,1))
```

```
MAFH <- ts(ResultsH$modeled_flow, frequency = 365)
MAFH <- aggregate(MAFH, FUN = mean)
summary(MAFH)
plot(GCMhist, MAFH, type="l")
abline(lm(MAFH ~ GCMhist), col="red")


par(mfrow=c(2,1))
par(mar=c(1,2,1,2))
MAF4 <- ts(Results4$modeled_flow, frequency = 365)
MAF4 <- aggregate(MAF4, FUN = mean)
summary(MAF4)
plot(GCMyr, MAF4, type="l", main="Mean Annual Flow RCP 4.5 & 8.5", ylim=c(0,3.5))
abline(lm(MAF4 ~ GCMyr), col="red")


MAF8 <- ts(Results8$modeled_flow, frequency = 365)
MAF8 <- aggregate(MAF8, FUN = mean)
summary(MAF8)
plot(GCMyr, MAF8, type="l", ylim=c(0,3.5))
abline(lm(MAF8 ~ GCMyr), col="red")
# Increase in mean annual flow


# Annual low flow days
LFO <- quantile(TuolUpstream$flowdata$flow, .1)
# 10th percentile = 0.04254
LFM <- quantile(Results$modeled_flow, .1)
# 10th percentile = 0.001167
LFH <- quantile(ResultsH$modeled_flow, .1)
# 10th percentile = 0.0017
# Models underestimate baseflow, but since same models used for GCM data, use low figure
for low flow threshold


LFDaysH <- ifelse(ResultsH$modeled_flow<0.0017,1,0)
LFDaysH <- ts(LFDaysH, frequency = 365)
LFDaysH <- aggregate(LFDaysH, FUN = sum)
sum(LFDaysH)
plot(GCMhist, LFDaysH, type="l")
abline(lm(LFDaysH ~ GCMhist), col="red")


par(mfrow=c(2,1))
par(mar=c(1,2,1,2))
LFDays4 <- ifelse(Results4$modeled_flow<0.0017,1,0)
LFDays4 <- ts(LFDays4, frequency = 365)
LFDays4 <- aggregate(LFDays4, FUN = sum)
summary(LFDays4)
plot(GCMyr, LFDays4, type="l", main="Projected Annual Low Flow Days", ylim=c(0,300))
abline(lm(LFDays4 ~ GCMyr), col="red")


LFDays8 <- ifelse(Results8$modeled_flow<0.0017,1,0)
LFDays8 <- ts(LFDays8, frequency = 365)
LFDays8 <- aggregate(LFDays8, FUN = sum)
summary(LFDays8)
plot(GCMyr, LFDays8, type="l")
abline(lm(LFDays8 ~ GCMyr), col="red")
# Increase in annual low flow days in the future
```

```
# Annual low flow duration (in weeks)
ResultsH$Lowflow = 0


for (i in 1:nrow(ResultsH))
{
  ResultsH$Lowflow[i] <- ifelse((aggregate(ts(Results4$modeled_flow[i],
frequency=7))/aggregate(ts(Results4$modeled_flow[i],
frequency=365)))<(aggregate(ts(Results4$modeled_flow[i], frequency=365))*0.01),1,0)

}




LFDH = 0
Hflowd <- data.frame(Hdate, Hflow, LFDH)
LFDH <- calc_durationLow(Hflowd, yearType = "calendar", digits = 3, pref = "mean")
get_seasonality(Hflow, yearType = "water")


Hflowannual <- makeAnnualSeries(ResultsH$modeled_flow)


Hflowweekly <- aggregate(ts(Hflowd$Hflow, frequency=7))
Hflowannual <- aggregate(ts(Hflowd$Hflow, frequency=365))
LFDH <- ifelse((Hflowweekly/Hflowannual)<(Hflowannual*0.01), 1, 0)


Hflowd$LFDH <- ifelse((aggregate(ts(Hflowd$Hflow, frequency=7))/aggregate(ts(Hflowd$Hflow,
frequency=365)))<(aggregate(ts(Hflowd$Hflow, frequency=365))*0.01),1,0)




LFDH


LFD4


LFD8


# Projected precip with snow
plot(ChistPr$Date, PrH, xlab="Date", ylab="Daily Precip (mm)", main="Tuolumne Projected
Precipitation Historic", sub="Snow (blue)")
lines(snowmeltH$Date, snowmeltH$SnowfallWatEq_mm, col="light blue")


plot(C8Pr$Date, Pr4, xlab="Date", ylab="Daily Precip (mm)", main="Tuolumne Projected
Precipitation RCP 4.5 & 8.5", sub="Snow (blue)")
lines(snowmelt4$Date, snowmelt4$SnowfallWatEq_mm, col="light blue", ylim=c(0,155))


plot(C8Pr$Date, Pr8, xlab="Date", ylab="Daily Precip (mm)")
lines(snowmelt8$Date, snowmelt8$SnowfallWatEq_mm, col="light blue")
```

```
# annual snow as percent of precipitation
snowH <- ts(snowmeltH$SnowfallWatEq_mm, frequency = 365)
snowH <- aggregate(snowH, FUN=sum)
precipH <- ts(snowmeltH$Precip_mm, frequency = 365)
precipH <- aggregate(precipH, FUN=sum)
percentsnowH <- (snowH/precipH)*100
plot(GCMhist, percentsnowH, ylab="Snow as Percent of Precip", main="Tuolumne Annual
Snowfall Proportion Historic", xlab="Year", ylim=c(0,85))
abline(lm(percentsnowH ~ GCMhist), col="red")


snow4 <- ts(snowmelt4$SnowfallWatEq_mm, frequency = 365)
snow4 <- aggregate(snow4, FUN=sum)
precip4 <- ts(snowmelt4$Precip_mm, frequency = 365)
precip4 <- aggregate(precip4, FUN=sum)
percentsnow4 <- (snow4/precip4)*100
plot(GCMyr, percentsnow4, ylab="Snow as Percent of Precip", main="Tuolumne Annual Snowfall
Proportion RCP 4.5 & 8.5", xlab="Year", ylim=c(0,85))
abline(lm(percentsnow4 ~ GCMyr), col="red")


abline(lm(formula = Pr8 ~ C8Pr$Date), col="red")
snow8 <- ts(snowmelt8$SnowfallWatEq_mm, frequency = 365)
snow8 <- aggregate(snow8, FUN=sum)
precip8 <- ts(snowmelt8$Precip_mm, frequency = 365)
precip8 <- aggregate(precip8, FUN=sum)
percentsnow8 <- (snow8/precip8)*100
plot(GCMyr, percentsnow8, ylab="Snow as Percent of Precip", xlab="Year", ylim=c(0,85))
abline(lm(percentsnow8 ~ GCMyr), col="red")
#Significant decline in yearly snowfall as percent of total precip. Almost no snowfall
at/below this elevation by end of century in RCP 8.5 scenario


# Average monthly snow storage and as SWE*watershed area
Tmth <- (1:73)
snowpack <- ts(snowmelt$SnowWaterEq_mm, frequency = 30)
snowpack <- aggregate(snowpack, FUN=mean)
snowpack <- (snowpack/1000)*.770560000
plot(snowpack, type="l", ylab="Average Monthly Snow Water Equivalent (km^3)", xlab="Month",
main="Tuolumne Watershed Snowpack Storage Observed")
abline(lm(snowpack ~ Tmth), col="red")
summary(snowpack)


Hmth <- (1:681)
snowpackH <- ts(snowmeltH$SnowWaterEq_mm, frequency = 30)
snowpackH <- aggregate(snowpackH, FUN=mean)
snowpackH <- (snowpackH/1000)*.770560000
plot(snowpackH, type="l", ylab="Average Monthly Snow Water Equivalent (m^3)", xlab="Month",
main="Tuolumne Watershed Snowpack Storage Historic")
abline(lm(snowpackH ~ Hmth), col="red")
summary(snowpackH)
# Historical avg 83820396 m^3
snowpackHavg = 0.083820396


par(mfrow=c(2,1))
par(mar=c(1,2,1,2))
GCMmth <- (1:1155)
```

```
snowpack4 <- ts(snowmelt4$SnowWaterEq_mm, frequency = 30)
snowpack4 <- aggregate(snowpack4, FUN=mean)
snowpack4 <- (snowpack4/1000)*.770560000
plot(GCMmth, snowpack4, type="l", ylab="Average Monthly Snow Water Equivalent (km^3)",
xlab="Month", main="Avg Mthly Snowpack Storage RCP 4.5 & 8.5", sub="Historic Avg (blue), LM
Trend (red)")
abline(h=snowpackHavg, col="blue", lty=3)
abline(lm(snowpack4 ~ GCMmth), col="red")


snowpack8 <- ts(snowmelt8$SnowWaterEq_mm, frequency = 30)
snowpack8 <- aggregate(snowpack8, FUN=mean)
snowpack8 <- (snowpack8/1000)*.770560000
plot(snowpack8, type="l", ylab="Average Monthly Snow Water Equivalent (km^3)",
xlab="Month", sub="Historic Avg (blue), LM Trend (red)", ylim=c(0,0.8))
abline(h=snowpackHavg, col="blue", lty=3)
abline(lm(snowpack8 ~ GCMmth), col="red")
# Extreme decline in snowpack to none by end of century in high emissions scenario, meaning
no alpine storage at/below this elevation by end of century


# Spring snow depth (April 1)
#Seasonal analysis


# Months of the year with snow cover (albedo indicator)


snowcoverH <- ifelse(snowmeltH$SnowDepth_m>0,1,0)
plot(snowmeltH$Date[0:365*5], snowcoverH[0:365*5], type="s")


snowcover4 <- ifelse(snowmelt4$SnowDepth_m>0,1,0)
plot(snowmelt4$Date[0:365*5], snowcover4[0:365*5], type="s")
plot(snowmelt4$Date[(34675-(365*5)):34675], snowcover4[(34675-(365*5)):34675], type="s")


snowcover8 <- ifelse(snowmelt8$SnowDepth_m>0,1,0)
plot(snowcover8, type="l")
mthsnowcover8 <- ts(snowmelt8$SnowDepth_m, frequency = 30)
mthsnowcover8 <- aggregate(mthsnowcover8, FUN=mean)
mthsnowcover8 <- ifelse(mthsnowcover8>0,1,0)
plot(mthsnowcover8)
plot(snowmelt8$Date[0:365*5], snowcover8[0:365*5], type="s")
plot(snowmelt8$Date[(34675-(365*5)):34675], snowcover8[(34675-(365*5)):34675], type="s")
```