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Climate Change Resilience Planning at the Savannah River Site, Part 2

David Werth,

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1. Introduction

In June of 2016, the Savannah River National Laboratory (SRNL) submitted a climate vulnerability screening and assessment (V S/A) (Johnson and Werth, 2016, henceforth JW2016) for the Savannah River Site (SRS) in response to a request from the Department of Energy's (DOE) Office of Environmental Management (EM). That report comprised an analysis of the effect of future climate change on energy use for heating and cooling site facilities and the health and safety of outdoor workers exposed to hot weather. In this report, we extend that work to estimate the effect of climate change on three other site assets – the SRS forest, former cooling ponds, and site steam and power production. DOE, in partnership with the US Forest Service-Savannah River Station (USFS-SR), is responsible for maintaining the SRS forest, including performing controlled burns, practicing silviculture and studying its impact, and fighting any wildfires that occur. SRS is also home to two large ponds (L-Lake and Par Pond) formerly used to cool the excess heat from reactor operations. These ponds now contain radioactive elements (primarily cesium) in the bottom sediment, and the water is employed as a natural barrier for their sequestration. Water levels are therefore required to remain above a set threshold, which could become harder to maintain as climate changes. Also on site, the Ameresco Biomass Cogeneration Facility (BCF) burns wood (mostly debris from logging and forest thinning) to boil water to produce steam and electricity, and the plant's operations could be compromised by rising water or air temperatures.

To characterize the climate-induced threats to the management of these assets, we select climate-related indices currently used to quantify the potential vulnerabilities, and apply projections from global climate models (GCMs) to determine how these indices will change. The analysis will in most respects be identical to that of JW2016 in that we will again apply the Dept. of Transportation's vulnerability assessment scoring tool (VAST) software to gauge the climate-induced risk (DOT, 2018). This involves selecting and quantifying 'exposure' indicators and estimating the asset's 'sensitivity' and 'adaptive capacity'. (A complete description of the software can be found in JW2016.) Future climate variables are taken from a set of existing GCM projections of the years 2040-2049, 'downscaled' to be consistent with variability at SRS (as described in Werth, 2018), and converted into relevant indices. With multiple GCM simulations of the period 2040-2049 and two climate forcing scenarios (RCP4.5 and RCP8.5, see JW2016 for a description), we will have a range of climate forecasts, allowing us to look for variabilities in the impacts of future climate.

2. Fire Management

The USFS-SR is responsible for fighting wildfires on site and, more importantly, maintaining the site forest in such a condition as to make wildfires less likely to start or grow rapidly. This is accomplished by the controlled burning of quick-igniting surface fuel and the selective harvesting of trees to reduce fuel continuity and loading. The potential of climate change to produce conditions favorable for an increased threat of wildfire is an ongoing concern in various parts of the world (Krawchuk and Moritz, 2012; Heilman et al., 2015; Brown et al., 2012; Luo et al., 2013; Yang et al., 2015), and we must evaluate the threat at SRS.

To apply the VAST program, we must first select 'exposure' indicators to characterize the threat, and several are available. The USFS uses several indices to quantify the potential of a wildfire starting or spreading, and for our purposes we select the variable known as the 'energy release component' (ERC). This variable is computed using temperature, humidity, and the cumulative rainfall over a period of several weeks (non-climate variables such as a site's fuel 'model', which characterizes the overall fuel load[1], are included as well). The value is recalculated each day, and indicates the ease with which an ignition can trigger a wildfire. Typical values at SRS range from about 10-25 in January and 20-40 in July (Fig. 1). The annual fuel loading is another measure of fire danger that is strongly affected by climate, and this is selected as another exposure indicator. The exposure 'score' as input to

[1] The 'models' are defined as part of the National Fire Danger Rating System (NFDRS).

VAST will be determined by comparing the current ERC and fuel-related values to those projected for the future.

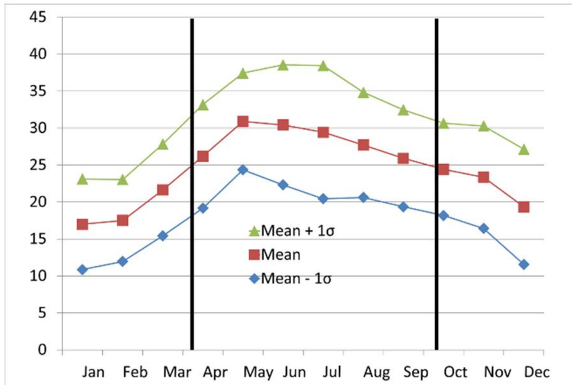

Figure 1 Annual cycle of ERC at SRS, averaged over the years 1998-2014, along with the range of variability defined by the standard deviation (σ) for each month. Data is from reports supplied by the USFS-SR[2]. The vertical lines separate the warm and cool periods.

The winter fire danger, while reduced, is nevertheless a concern to site managers because extreme wind events are more likely during this time, and can increase the potential for a fire to spread rapidly. Therefore, we select two exposure 'indicators' – the warm season ERC (wERC, equal to the April-September mean), and the cool season ERC (cERC, equal to the mean calculated over the remaining months). As described in Werth (2018), we have downscaled GCM data for SRS, including the variables precipitation, temperature, humidity and wind speed. Given that ERC is a derived variable, it was impractical to recalculate ERC exactly using this data. Instead, we establish an observed relationship between the recorded ERC values and weather variables measured at SRS. This same relationship can be applied using the future climate variables as predictors. (See Appendix A for details.) When we use the downscaled climate data for the 2040s to project ERC values, the result is a shift in the projected distribution in wERC towards *lower* values – higher values are less likely, and lower values are

[2] These ERC values were calculated assuming that SRS fits the commonly-used NFDRS 'G' fuel model ('Short needle (heavy dead)'), using the 1988 version of the model. It has been suggested that the P model ('Southern pine plantation') is actually a better fit. The climate-change analysis was done assuming both fuel models, and produced similar results. We present here the results from the G model.

more likely (Fig. A3) (i.e., an ignition producing a wildfire is less likely to occur). A similar effect is seen in the projected cERC distribution (Fig. A4).

The VAST tool requires that exposures be assigned a score of 1-4, and we have developed a way to convert a shift in the distribution for a given variable into such a rating by comparing the projected values to the mean and standard deviations of the current, observed values (JW2016). This involves assigning a rating of 1 to future risk if the future values tend to be below the current observed mean (Table 1). (See Appendix A for more information on this process.) In keeping with this, we assign an exposure score of 1 to each scenario (Table 1, Table B1), indicating a small risk of increased fire danger.

Parameter	Current Average	$RCP_{4.5}$	Exposure Score	$RCP_{8.5}$	Exposure Score
wERC	28	< 28, 63%	1	< 28, 71%	1
cERC	21	< 21, 85%	1	< 21, 81%	1
Average Spring Temperature	65°F	67°F -69°F, 42%	3	67°F -69°F, 43%	3
Total Spring Precipitation	23”	<23”, 35%	1	23”-29”, 39%	2
P-E Par Pond	4.2 cm	-6.3 cm to 4.2 cm, 45%	1	-6.3 cm to 4.2 cm, 41%	1
Evaporation L-Lake	3710 gpm	<3710 gpm, 41%	1	<3710 gpm, 52%	1
Hot/humid days/year	16	>42, 88%	4	>42, 96%	4

Table 1 Observed climate data, along with the most likely projected values for each climate-forcing scenario, the percentage of models projecting those values, and their associated exposure scores.

VAST also requires a ‘sensitivity’ rating – an indicator of how sharply the actual danger (the risk of fire) will rise as the exposure indicator (ERC) rises. Records exist of the ERC value for each day at SRS, as well as whether or not a fire occurred. This can be used to calculate the rate at which the probability of fire increases as ERC rises. As wERC rises from 0 to 45, the probability of fire on any day with such an ERC value rises as well (from about 1% to 15%), and the two variables are strongly correlated, indicating a strong relationship. (The probability that such a fire will be large rises as well.) The relative increase is much smaller for the cool season than for the warm season, and the correlation is smaller, implying a smaller overall sensitivity to cERC. We therefore elect to assign a sensitivity rating of 4 to the warm season fire danger, and a value of 2 to that of the cool season (Table B2).

The fire risk is also related to the amount of fuel produced during the months preceding the peak fire season. Cool and dry conditions during this time will result in reduced growth and a lessening of the danger. If future spring and winter temperatures and precipitation increase, however, the additional fuel growth can make summertime fire management more difficult (Pacific Northwest National Laboratory, 2015). This could result in a shift in the site's appropriate fuel model being shifted from P to O (High pocosin, characterized by intense wildfires), with consequent increases in ERC. We use these two variables to develop an additional exposure indicator (fuel) for the fire danger. The downscaled climate data for the 2040s indicates increases in both winter/spring precipitation (Fig. A5) and (more significantly) in springtime temperatures (Fig. A6), resulting in greater fuel production. The corresponding scores are 1 or 2 for precipitation (depending on the emissions scenario), and 3 for temperature (Table 1). The overall exposure for fuel is therefore assigned a score of '3'. The three exposure scores (wERC, cERC, and fuel) must be combined into a composite score, and all three are weighted equally for a composite score of 1.7 (Table 2). Because fire danger is strongly related to fuel growth, the sensitivity rating for the fuel indicator is subjectively assigned a value of 3 (Table B2). The composite sensitivity is subjectively weighted in favor of wERC (60%), given its greater overall importance. The fuel load is weighed at 30%, with cERC weighted at 10%, resulting in a composite sensitivity of 3.5 (Table 2).

To complete the analysis, VAST will calculate an indicator of 'adaptive capacity' (AC), gauging our ability to mitigate the consequences of any increased danger. (Lower values indicate a better ability to adapt.) This requires the identification of a set of adaptive options and an estimate of how effective and practical each one is (assigning lower values to more favorable options). We evaluate three: maintaining the current practice of controlled burns and tree harvesting, increasing the rate of controlled burns, and increasing tree harvesting.

Maintaining current practices (performing controlled burns and harvesting at current rates) is the simplest option to implement, and a rating of 1 is assigned. Increases in harvesting are simple enough to implement (albeit at an increased cost), and that option is assigned a rating of 2. Controlled burns, however, are currently at their maximum practical level (John Blake, personal communication), and therefore this option is assigned a rating of 4 as an indication of its relative impracticality (Table B3). The AC rating is calculated as a weighted composite of the 3 options, depending on the estimated likelihood that they will be necessary. Given that we expect no strong increase in exposure, we can assume that it is most likely we will be able to rely on current practices, with increased harvesting and controlled burns less likely to be required. Therefore, weights of 60%, 30% and 10% are assigned to the current practice, harvesting, and burning options, respectively, for a composite of 1.6 (Table 2).

VAST combines these inputs as described in JW2016, and the result is seen in Table 2 – relatively low 'damage' (a composite of exposure and sensitivity) and adaptive capacity scores, with the asset vulnerability (a combination of the two) indicating a low risk due to climate change. Fig. 2 compares damage to adaptive capacity to gauge the overall vulnerability (indicated by the shading), and the site forest is depicted as being well away from the area of greatest danger - the high sensitivity and increased fuel load are mitigated by projections of reduced ERC values and the fact that increased harvesting can be implemented to reduce the impact of climate effects and maintain forest stability.

3. Cooling Pond Maintenance

Two bodies of water on site (L-Lake and Par Pond) are used as natural waste repositories – the sediment beneath them contains radioactive cesium, which is sequestered by the overlying water (Savannah River Nuclear Solutions, 2011). If water levels were to fall, the sediment could dry out and blow away, spreading radioactivity. SRS therefore has an interest in maintaining water levels, which could be compromised by changes in climate.

Climate controls water levels through changes in evaporation (E) and precipitation (P). Precipitation at SRS is not expected to strongly decrease (Werth, 2018), but projected temperature increases (Werth, 2018) could increase evaporation. To determine the risk due to climate change, we apply downscaled GCM data and the VAST software, with the difference between precipitation and evaporation (P-E) as the exposure indicator.

Daily precipitation values for the future were calculated as part of the GCM downscaling (Werth, 2018), but, as with ERC, evaporation is a derived variable. Along with standard meteorological data, we have evaporation data from two sources on site 1) a pan evaporation gauge, and 2) a water budget calculation. Once again, multiple linear regression is used to relate a predictand (evaporation) to a set of observed predictors that we can also get from the downscaled GCM data (Appendix A).

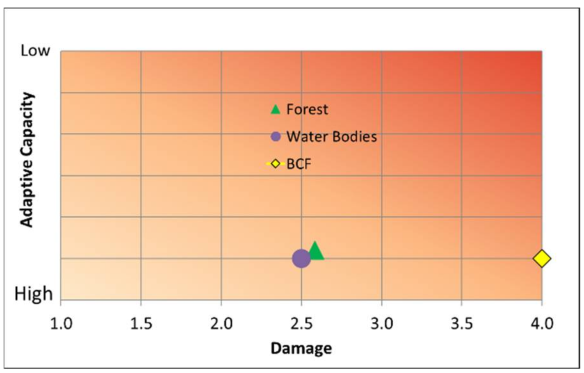

Figure 2 Vulnerability of SRS assets to climate change for the RCP4.5 and RCP8.5 scenarios. Darker shades of red indicate a greater 'vulnerability' score.

Asset Name	Exposure	Sensitivity	Adaptive Capacity	"Damage"	Vulnerability
Site Forest	1.7	3.5	1.6	2.6	2.3
Par Pond	1.0	4.0	1.5	2.5	2.2
L Lake	1.0	4.0	1.5	2.5	2.2
Cooling Tower	4.0	4.0	1.5	4.0	3.2

Table 2: Composite scores for site assets for the RCP8.5 scenario.

The dominant predictor of daily pan evaporation is the difference between the daily maximum temperature and the daily-averaged dewpoint, and the years 2040-2049 are characterized by increases in *both* variables, such that the average in the difference is only slightly larger in the 2040s than in the current observations. The overall effect is to either increase P-E by an amount that fails to be significant at the 95% level (using pan evaporation, Fig. A9), or produce a future evaporation distribution similar to that of the present (using the calculated-budget evaporation, Fig. A10). Therefore, we assign a value of 1 to this indicator for both Par Pond and L-Lake (Table 1, Table 2, Table B1).

As an independent check, we also downloaded the evapotranspiration data of Reclamation (2014). This comprised both analysis of historic values and downscaled projections of evapotranspiration from global climate models and a surface hydrology model. Comparing the historic values to the 2040-2049 values for both RCP4.5 and RCP8.5 scenarios, we again see little change, affirming the use of a low exposure score.

The sensitivity indicator for the water levels is based on the way that measured levels of Par Pond and L-Lake respond to changes in P-E on a monthly timescale (Fig. A11), and the strong correlation between the two variables (0.70 for Par Pond, 0.65 for L-Lake) causes us to assign a value of 4 (the maximum) to this indicator (Appendix A, Table 2, Table B2). The adaptive capacity (Table B3) is based on three options (SRNS, 2011) – 1) supplementing water levels with water from the Savannah River (the current practice), 2) designating the exposed area as off limits, or 3) capping exposed sediments. Given that water availability at SRS is not expected to seriously decrease below current levels[3], resupplying water to Par Pond and L-Lake can be considered a practical option (adaptive capacity = 1). Keeping people away from exposed sediment is simple enough, but is not a long-term solution, as the exposed radioactive sediment will eventually be carried over a larger area (possibly off site, with serious consequences for site management) so we assign an AC value of 2. Capping exposed sediment (or

[3] Fig. 17.11 of Carter et al., (2014), shows SC to be well outside the area of significant decrease of water availability. Additionally, the online Water Supply Stress Index Model (http://www.wassiweb.sgcp.ncsu.edu/s) does not show significant increases in water stress index (demand/supply) in the 2040s.

otherwise sequestering it) is an expensive operation, so we assign an AC value of 4. Given the fact that water levels are not expected to strongly decrease, we weight the adaptive score more heavily toward the less severe options. The option to use river water carries 70% of the total adaptive capacity score, while the use of an exclusion zone comprises 20% of the total adaptive capacity score. The impractical but unlikely requirement that we cap exposed sediment is weighted at 10%, for an overall composite score of 1.5 (Table 2).

The VAST scoring indicates that damage and vulnerability will both be relatively low (Table 2, Fig. 2). As with the forest fire potential, the analysis of water levels indicates that existing procedures to mitigate the effects of climate should be considered adequate for the future.

4. Site Energy Production

In June of 2012, the coal-burning power plant in D-area was shut down, leaving Ameresco's Biomass Cogeneration Facility (operational since January of 2012) as the sole onsite facility for producing electricity (meeting ~30% of the site's electricity needs[4]). Steam produced in the plant's boilers is allocated to three uses – powering a turbine for generating electricity, use by the site's operating facilities, and the pre-treatment of water before entering the boiler. The plant operates at a constant production level, but changing external conditions require that the amount assigned to each end user be changed. (For example, colder temperatures mandate that more steam be sent to site buildings, with less used to produce power). Water for the boiler comes from two sources – the Savannah River, and recirculated water that has already been heated to steam, forced a turbine blade, and been condensed in a cooling tower before being returned to the boiler.

Site personnel at the facility were questioned as to how climate change could adversely affect its operation. Warmer river temperatures and reduced flows are a concern for power plants that draw cooling water from them (Madden et al., 2013; HDR, 2014; DOE, 2013; DOE, 2015), but the BCF

[4] http://www.2017energyexchange.com/wp-content/tracks/track13/T13S2_Ladd.pdf

withdraws water from the river only to compensate for losses in the recirculation process, and any such withdrawal is intended to be heated in the boiler, not used for cooling. (Again, river flows are expected to remain similar to those of today (Carter et al., 2014)). Therefore, we can conclude that the risk to operations due to increasing river temperatures to be low.

The plant uses an evaporative cooling tower to cool water before being returned to the boiler. By this process, water is sprayed near the top of the tower as droplets, while air is introduced at the bottom and moved upwards by a fan. As the droplets fall, they cool through two processes: conduction of heat into the surrounding air, and, more importantly, evaporation, with the excess heat being removed by the vapor. The cooled water is then returned to the boiler.

If only the first process operated, the droplets would at a minimum cool to the temperature of the introduced air, which is drawn from the external environment. With evaporation, however, they can cool to the air's wet bulb temperature, which is often substantially lower and making evaporation the dominant cooling process. The efficiency of cooling is therefore related to the wet bulb temperature – as it increases, the cooling process becomes less efficient.

An evaporative cooling tower can still operate if the air is very hot or very humid, but not if both are true. The future climate at SRS is characterized by rising temperatures and rising humidities – both of which would raise wet bulb temperatures and threaten cooling tower operation (Werth, 2018). To characterize the risk, we make several assumptions.

1) The cooled water should not be above 83^{o}F (~28^{o}C).

2) If this is to happen, either the dry bulb or wet bulb temperatures must be below 77^{o}F (25^{o}C), assuming that the cooling process is not 100% efficient and that the final temperature of the cooled water will always be several degrees (we assume 3^{o}C) above the wet bulb temperature[5]. Only if neither condition is met will the droplets be unable to cool to the desired temperature. The exposure indicator is therefore estimated as the number of days per year in which the two conditions are both not met – the

[5] http://www.kgogroup.com/wp-content/uploads/Cooling-Tower-Basics-and-Common-Misconceptions1.pdf

daily maximum temperature is greater the 25^{0}C, and the daily mean wet bulb temperature is also greater than 25^{0}C.

Using an approximation to relate wet bulb temperature to the dry bulb and dewpoint temperatures (Appendix A), we calculate the observed and projected number of days per year that the 'stress' condition is met. As indicated by Fig. A12, warm and humid days are estimated to be much more common in the 2040s, and we therefore assign a rating of '4' to the corresponding exposure indicator (Table 1, Table 2). And given the strong correspondence between the two temperatures and cooling efficiency, the sensitivity is also assigned a rating of '4' (Table 2, Table B2).

To test for variability in the assumption of the desired outlet water temperature, the analysis was repeated using wet bulb temperatures of 27^{0}C and 30^{0}C as the threshold, and in each case the result is the same – future values occurred with far greater frequency than in the observation, so our use of an exposure score of 4 is not sensitive to the threshold value selected.

In a discussion with an operator at the Biomass Cogeneration Facility (BCF), two adaptive actions were mentioned: adding towers, or increasing the capacity of the fans to move air. The first would compensate for reduced thermal efficiency by increasing the total rate at which water is moved through the cooling process, and the better mixing provided by the fans would increase the efficiency at which heat is transferred to the warmer, moister air. These were both considered to be practical, with the fans being less costly. We assigned AC values of 2 and 1 (weighted equally) to the options of more towers and improved fans, respectively (Table B3), for a composite score of 1.5 (Table 2).

After accepting this input, the VAST software outputs a risk assessment, and the vulnerability rating is shown to be the highest among the assets evaluated in this report (Fig. 2, Table 2). Projections indicate that cooling tower operations could be severely compromised in the future (high damage). The BCF can conceivably be upgraded or replaced by another facility with an enhanced cooling capacity as wet bulb temperatures rise throughout the 21st century. Given that actions to mitigate these effects are considered a normal part of operating such a facility, the overall vulnerability can still be considered moderate.

5. Conclusions

The first V S/A (JW2016) rated many site assets, such as critical buildings and outdoor workers, as being very vulnerable to climate change, with vulnerability ratings well above 2.5 (on the 1-4 scale). The current assessment, however, has vulnerability scores at or below 2.5 except for the cooling tower.

The first two evaluated site activities (forest fire management and pond operation) were seen to not be especially vulnerable to future climate change, the main reason being that the relevant climate indices (ERC and P-E, respectively) are not expected to change substantially. As temperatures and humidities rise, however, upgrades to the BCF cooling tower may be required to ensure that the plant can continue to operate. Currently, however, there is no capital investment projects scheduled to upgrade cooling tower operations. Ameresco will operate and maintain the BCF out to the year 2032, following which SRS will be responsible, so the necessity of these projected expenses should be considered in future budgeting.

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Appendix A

1. Calculation of Exposure Score

With multiple GCM simulations of several years each, we have a large number of values for the future for any climate variable in which we are interested, with some being similar to the values of today and other being much less or greater. As in JW2016, we compare the climate variable distributions of the future with those of the present in assigning the 'exposure' score. This is done by calculating the fraction of future values that fall within each of 4 bins – at or below the current mean, between the current mean and one standard deviation beyond the current mean (usually above, but possibly below if it is a variable we fear will be reduced), between one and two standard deviations beyond the current mean, and more than two standard deviations beyond the current mean. Each bin is assigned an exposure score of 1, 2, 3, and 4, respectively, and the exposure score is determined by the bin that contains the greatest fraction of the future values. If, for example, most future simulated values are greater than 2 standard deviations above the current mean, the exposure score is assigned a value of 4 (indicating the greatest threat). If the distribution shifts to lowers values, however, an exposure score of 1 is assigned.

In the following subsections, we describe in detail how the exposure indicators were calculated from the GCM data, and the calculations used to get the exposure scores of each of the exposure indicators for the three threatened site assets.

2. Forest Fire Management

i) ERC

Three predictor variables – daily maximum temperature, daily average dewpoint, and daily total rainfall, have a strong effect on both the subsequent and concurrent values of ERC. Warmer temperatures, lower humidities and reduced rainfall in the spring will increase the amount of dried out fuel for the summer, while those same conditions in summer will maintain fuel desiccation and allow nascent fires to grow and spread rapidly. For the wERC, multiple predictors were tested, and a set of three was ultimately selected – the April through August monthly mean high temperature (the most significant predictor) (Fig. A1, left), the March through August monthly mean dewpoint temperature (Fig. A1, right), and the April through July precipitation (the least significant, not shown).

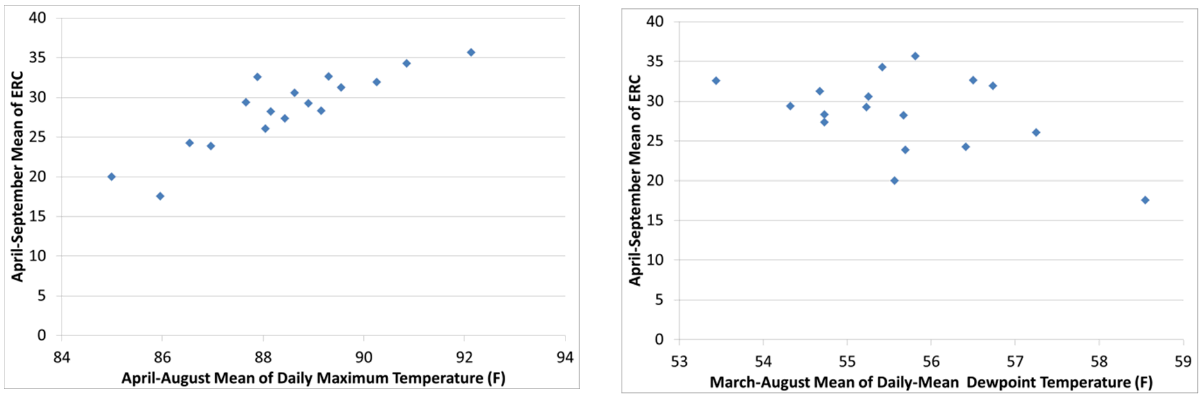
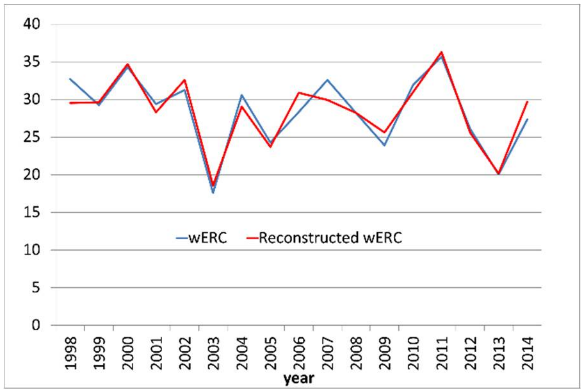


Figure A1 Scatter plots comparing seasonal mean left) daily maximum temperature and right) daily mean dewpoint to seasonal mean wERC.

For cERC, the October through March means of those same three variables were selected as the predictors. For each, a linear regression was performed, and the reconstructed values of wERC and cERC compare well to the actual values (Fig. A2). We apply the same linear regression to downscaled daily climate data (described in Werth, 2018) for the years 2040-2049 for both the RCP4.5 and RCP8.5 scenarios to characterize the future fire danger at SRS.

For the future years, the temperature variable is expected to rise for both the RCP4.5 (ΔT=2.0^{o} F) and RCP8.5 (ΔT=2.36^{o} F) scenarios, which by itself would force wERC values higher (from an observed average of 28.42 to predicted values of 32.41 (RCP4.5) or 33.157 (RCP8.5)). Dewpoint temperatures, however, are projected to rise more sharply (about 5^{o}-7^{o} F), forcing ERC values downward.

The overall result is a shift in the projected distribution in wERC values towards *lower* values – higher values are less likely, and lower values are more likely (Fig. A3). A similar effect is seen in the projected cERC distribution (Fig. A4).



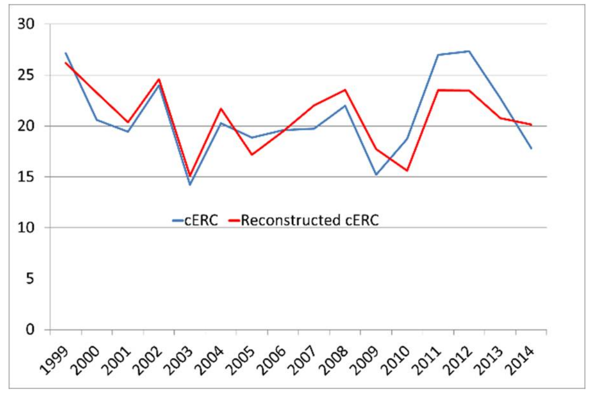
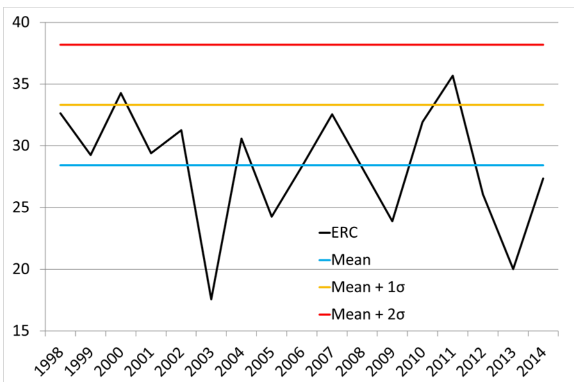


Figure A2 Observed value of wERC (left) and cERC (right), compared with the values reconstructed from the regressions.



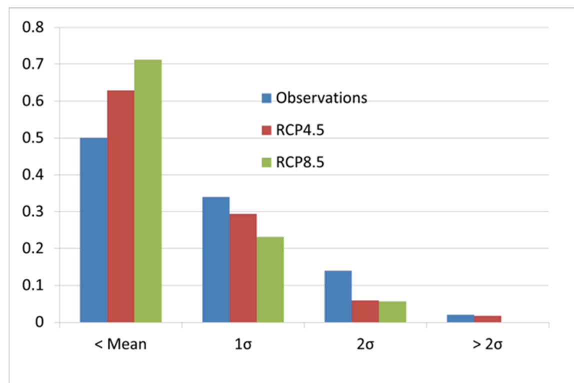
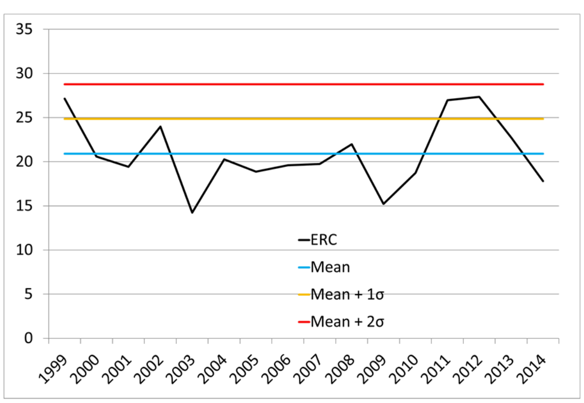


Figure A3 left) Observed (1998-2014) warm season ERC (wERC) values at SRS. Right) Fraction of future (2040-2049) simulated values of wERC below the observed mean, between the observed mean and 1 standard deviation, between 1 and 2 standard deviations above the observed mean, and beyond 2 standard deviations above the observed mean.



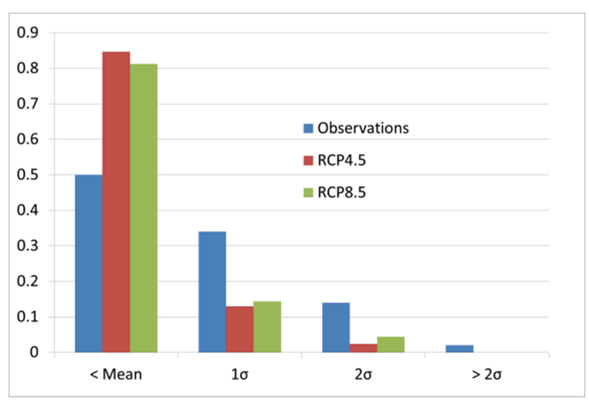


Figure A4 As in Fig. A3, but for the cool season ERC (cERC).

ii) Fuel

Projections of future temperature and precipitation are taken from the dataset of Reclamation (2014) as described in Werth (2018). The observed winter/spring (Dec-May) precipitation totals (Fig. A5) and average spring temperatures (Mar-May) (Fig. A6) are compared to the RCP4.5 and RCP8.5 projected values, and the departure from the current mean is again used to assign exposure scores.

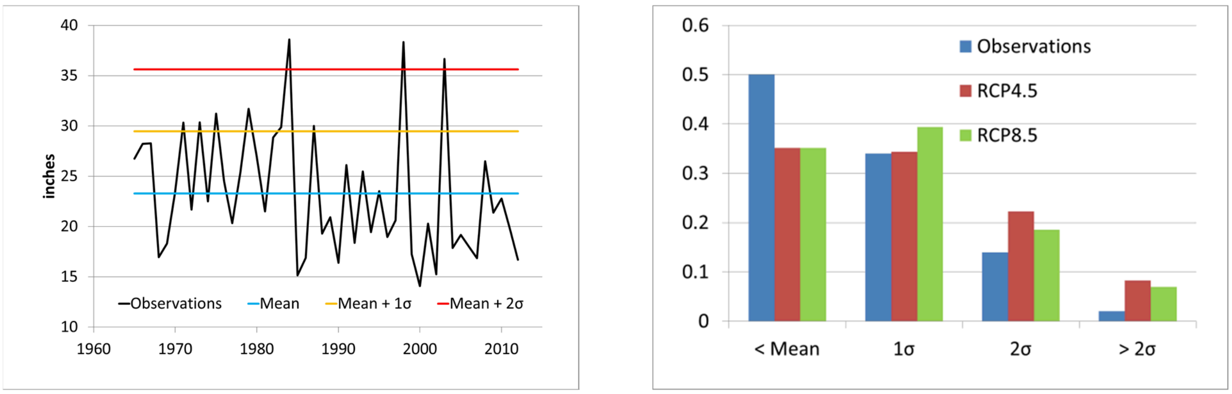


Figure A5 As in Fig. A3, but for the winter/spring precipitation total.

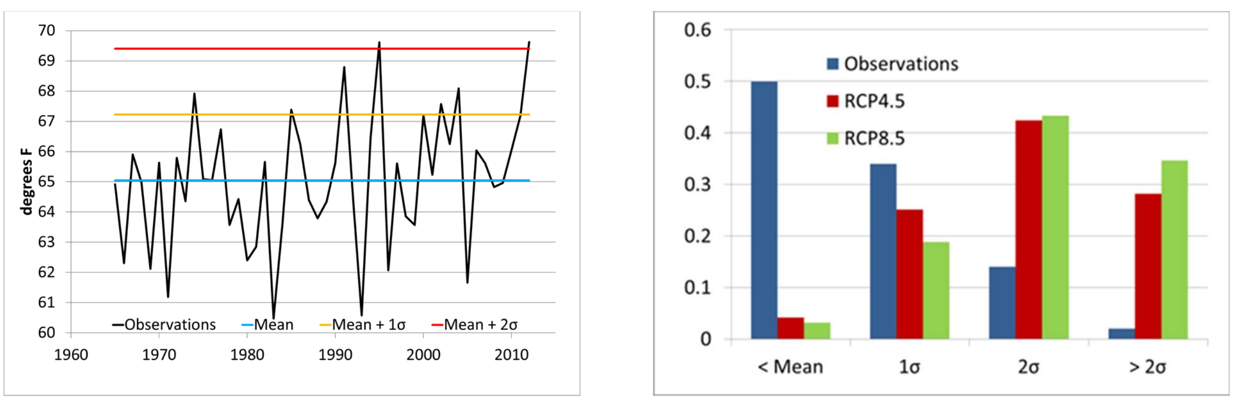


Figure A6 As in Fig. A3, but for the averaged springtime temperature.

As an exposure indicator, the winter/spring precipitation is showing a modest shift towards higher values (Fig. A5, right), but the springtime temperatures are much greater, with most simulations having values between 1 and 2 standard deviations above the current mean (Fig. A6 right), so we assign an overall value of 3 to indicate the increase in fuel.

As an additional data source, we employ the Pine Integrated Network: Education, Mitigation, and Adaptation project (PINEMAP) and its online Decision Support System[6], which allows users to map values of 'dryness index' (a ratio of vegetation water demand versus rainfall) for the years 2040-2059 under the high emissions scenario. When calculated at SRS, the current average value of 5.7 is projected to rise to 6.5+/- 2.3 (the 2σ value of the multiple model forecasts). The increase of 0.8 in the mean, however, represents a shift of 0.7σ. When we add this as an exposure indicator with a value of 2 to the analysis, the final vulnerability score changes little, so we elect not to apply this indicator in the final analysis.

3. Pond Evaporation

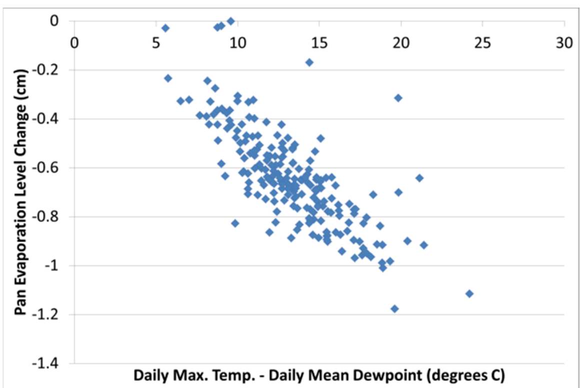
To project future evaporation from the available future climate data, we need current values of evaporation. We have two independent data sets:

i) Water levels of an evaporation pan are recorded each day, and day to day differences are used as an indicator of how much water evaporates. We create an evaporation dataset for each day in June through August for the years 2009-2013. The pan is refilled upon nearing depletion, however, and rainfall will similarly produce increases in the water level. Therefore, we exclude such days from the analysis.

ii) Controlled water inflow and outflows to L-Lake are monitored and recorded, as well as precipitation and total water amount, and this allows for the calculation of evaporation as a residual. This daily data was made available and calculated as a set of 5-day averages for June-August for the years 2009-2013, and served as a second predictand.

[6] http://climate.ncsu.edu/pinemap/index.php

For predictors, we select two – the daily average wind speed, and the difference between the daily maximum temperature and the daily-averaged dewpoint temperature (the latter is an indicator of evaporative demand). The regression reveals good linear relationships between evaporation and the two predictors (Fig. A7), although the reconstruction shows that extreme values are often missed (Fig. A8). These relationships are subsequently applied to the downscaled GCM data to estimate the daily future evaporation. We use the pan evaporation to get the monthly total precipitation-evaporation (P-E) for the summer months (June, July, August) as the exposure indicator, and calculate the distribution of future values (Fig. A9). The calculated-budget evaporation is projected in gallons per minute (and also averaged monthly for June, July, and August), and used to get a future distribution of monthly averages (Fig. A10).



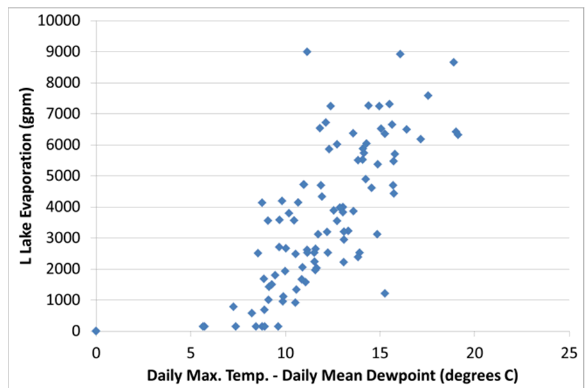


Figure A7 Scatter plots comparing the difference between the daily maximum temperature and daily mean dewpoint to daily changes in left) pan water level and right) L-Lake evaporation for June through August.

The sensitivity indicator is a measure of how Par Pond and L-Lake water levels are affected by changes in the exposure indicator (P-E). Correlations show that P-E strongly influences water levels (Fig. A11), and we assign a sensitivity rating of 4 (Table B2).

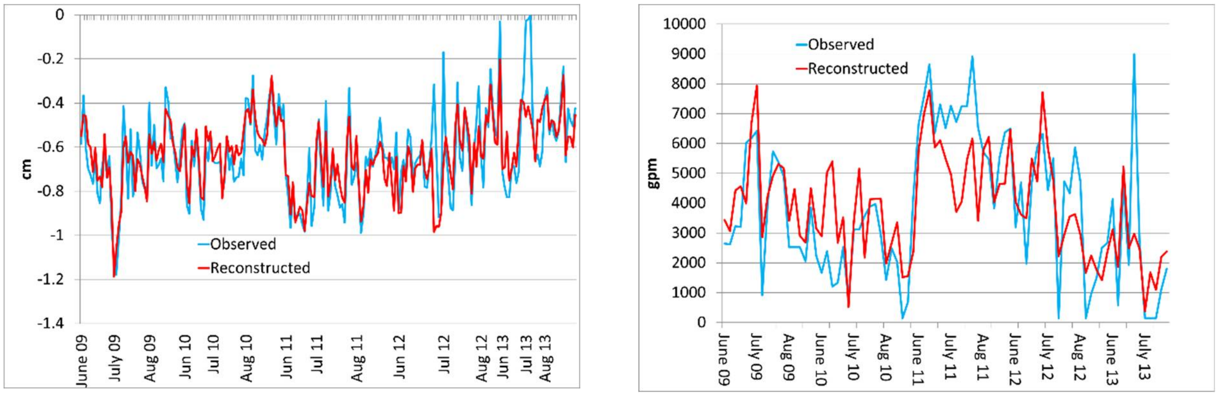


Figure A8 Observed summer (JJA) daily value of pan evaporation (left) and 5-day average evaporation from L lake (right), compared with the values reconstructed from the respective regressions.

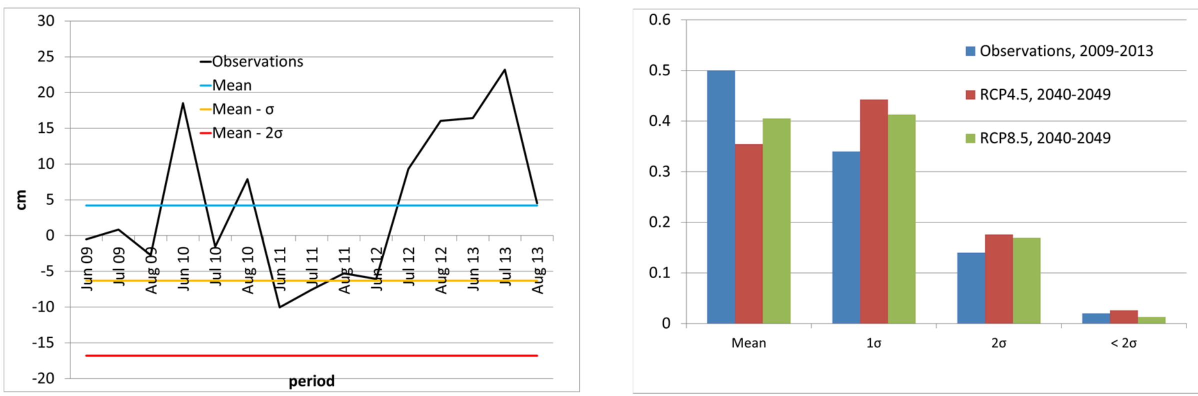


Figure A9 As in Fig. A3, but for the SRS summer (JJA) monthly-accumulated P-E (precipitation - pan evaporation), and the distribution is now for values *below* the current mean.

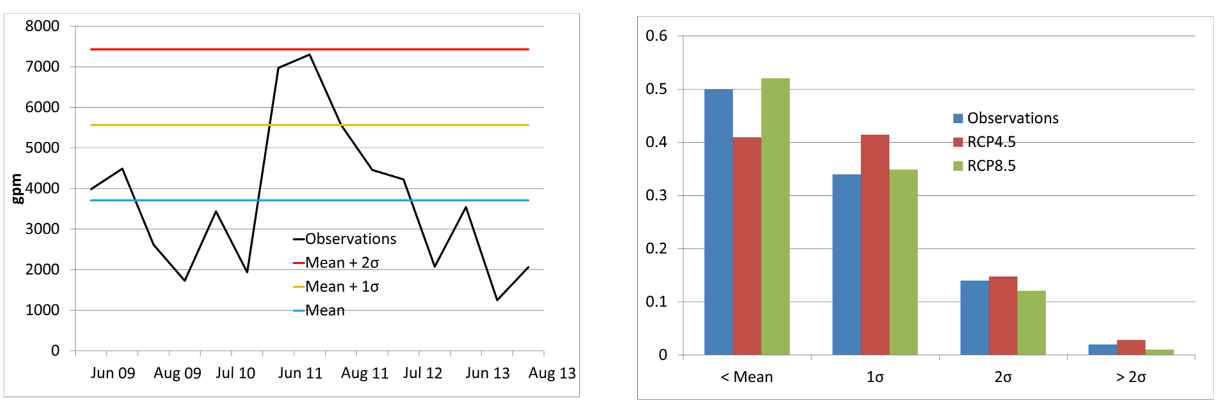


Figure A10 As in Fig. A3, but for the monthly-averaged L-Lake evaporation.

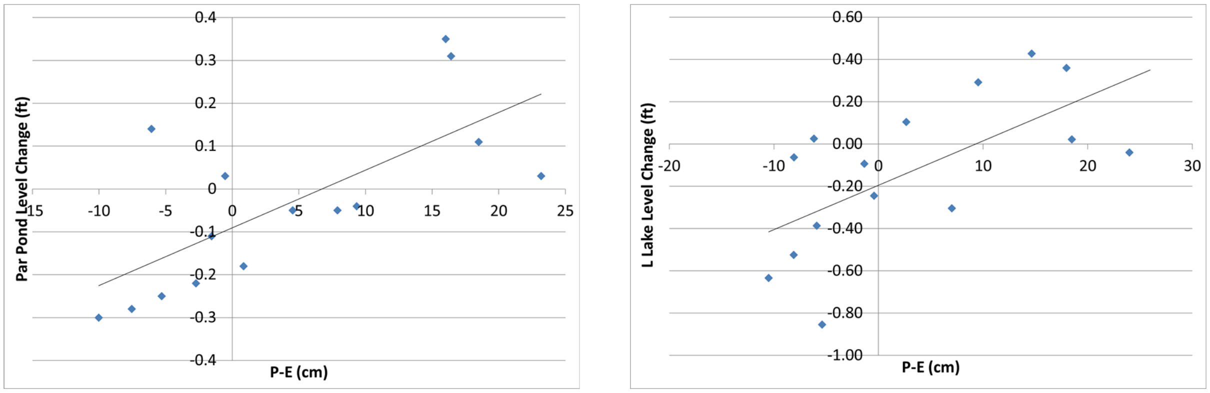


Figure A11 Comparison of changes in (left) Par Pond and (right) L-Lake levels with changes in monthly total P-E for June, July, and August. (Evaporation is from the pan data.)

4. Cooling Tower Operation

Wet bulb temperature is not a downscaled variable from a GCM, and is difficult to calculate from dry bulb and dewpoint temperatures alone. As dry bulb temperatures exceed 25^{0}C, however, we can determine what value of dewpoint corresponds to a wet bulb temperature of 25^{0}C (Table A1), and use that dewpoint temperature (along with the 25^{0}C dry bulb temperature) as the threshold for a day to qualify as hot and humid. We apply this approximation in our estimation of current and future occurrence of excessively hot and humid days (Fig. A12).

Dry Bulb Temperature (^{0}C)	Wet Bulb Temperature (^{0}C)	Dewpoint Temperature (^{0}C)
45	25	16
40	25	19
35	25	21
30	25	23
25	25	25

Table A1 Table of dry bulb and dewpoint temperatures, along with the associated wet bulb temperatures.

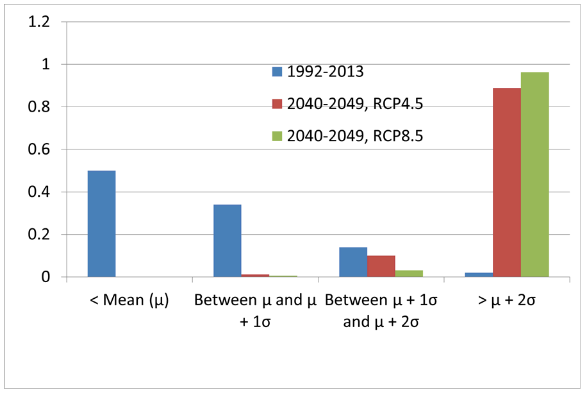


Figure A12 As in Fig. A3, but for the number of hot and humid days (dry and wet bulb temperatures both exceed 25°C).

Appendix B Supplementary Tables

	Range		Exposure Score
Fire Risk			
wERC	0	28	1
	28	33	2
	33	38	3
	38	50	4
cERC	0	21	1
	21	25	2
	25	29	3
	29	50	4
Fuel: Average Spring Temperature (degrees F)	0	65	1
	65	67	2
	67	69	3
	69	80	4
Fuel: Total Spring Precipitation (inches)	0	23	1
	23	29	2
	29	35	3
	35	40	4
SRS Cooling Ponds			
Monthly total P-E (cm) (JJA only)	4.2	10	1
	-6.3	4.2	2
	-17	-6.3	3
	-30	-17	4
Monthly averaged Evaporation (L Lake) gpm (JJA only)	0	3710	1
	3710	5568	2
	5568	7426	3
	7426	8000	4
Cooling Tower			
Annual number of hot, humid days	0	16	1
	16	29	2
	29	42	3
	42	70	4

Table B1 Value ranges and associated exposure scores for the seven climate variables.

Sensitivity Indicator	Sensitivity Score
Warm Season Fire Sensitivity	4
Cool Season Fire Sensitivity	2
Fuel amount	3
Par Pond Water Level Sensitivity	4
L Lake Water Level Sensitivity	4
Cooling Tower Sensitivity	4

Correlation Range			Sensitivity Score:
-1	0	=	1
0	.3	=	2
.3	.6	=	3
.6	1.0	=	4

Table B2: (top) sensitivity scores for the SRS assets. (Bottom) Correlation ranges and associated sensitivity scores for the water level values.

Maintain Current Practices	Increase Harvesting	Increase Controlled Burns
AC Score	AC Score	AC Score
1	2	4

River Water	Exclusion Zone	Cap Sediment
AC Score	AC Score	AC Score
1	2	4

Additional Towers	Improved Fan Capacity
AC Score	AC Score
2	1

Table B3: Adaptive options to mitigate (top) increased fire danger, (middle) low water levels, and (bottom) reduction in cooling tower efficiency, along with the associated adaptive capacity (AC) scores.