Lake Mendocino and Upper Russian River Water Temperature Model

1. Overview/Summary

The National Oceanic and Atmospheric Administration's National Marine Fisheries Service (NOAA Fisheries) has been monitoring the upper Russian River stream temperatures and water temperature at different depths in Lake Mendocino during summer through fall (2015 - 2020). These data provide valuable information regarding temperature conditions in Lake Mendocino that greatly influence salmonid habitat temperature conditions in the upper Russian River. Based on these data, a machine learning modeling approach has been developed to estimate stream and reservoir water temperatures that influence the quality of salmonid habitat within the upper Russian River. The main objective of this study is to gain a better understanding of the effects of different reservoir storage levels on cold water pool storage in Lake Mendocino and associated water temperatures in the upper mainstem Russian River during the juvenile steelhead trout summer rearing season and the fall migration period of adult Chinook salmon.

One of the recommended actions of the preliminary viability assessment of Lake Mendocino (Forecast Informed Reservoir Operations Steering Committee, 2017) are: *"Water quality in the reservoir should be evaluated in terms of sediment load and temperature stratification as a component of further evaluation of water availability. The ability to maintain a "cold water pool" and release cooler water in late summer for salmonid migration should be evaluated."* Therefore, the scenarios modeled in this study will answer the question: How would water temperature conditions in the "cold water pool" in Lake Mendocino influence the upper Russian River cold water tailrace (zone/reach) below the reservoir and to what extent downstream? To answer this question, we investigated reservoir conditions at different storage levels during 2015 (dry year) and 2019 (wet year) water years.

1.1 Highlights

- A machine learning modeling approach has been developed to estimate stream and reservoir water temperatures that influence the quality and extent of salmonid habitat within the upper Russian River.
- The main objective of this study is to gain a better understanding of reservoir operation effects on cold water pool storage in Lake Mendocino and associated water temperatures in the upper mainstem Russian River during summer and fall.
- The modeling results demonstrate benefits of higher reservoir storage levels to maintaining cooler water temperatures during the juvenile steelhead trout summer rearing season through the fall adult Chinook salmon migration period.

1.2 Investigations and work

Description (background, state-of-the-art, applicability to FIRO)

Many modeling techniques based on physical modeling have been developed to characterize the current and future states of hydrologic systems. Sometimes, their practical applications are limited by the lack of required data and the expense of data acquisition. To overcome these limitations, hydrologists have used data driven modeling based on machine learning approach as an alternative to physically based models (Ticlavilca and McKee 2011, Ticlavilca et al. 2013, Maslova et al. 2016). Machine learning models are characterized by their ability to capture the underlying physics of the system simply by examination of the measured system inputs and outputs and their interactions. In this study, a machine learning model based on Deep Learning (DL) approach is applied.

The DL modeling approach considers the complex interactions between local climate, reservoir operation, reservoir water temperatures and associated water temperatures in the upper mainstem Russian River. The DL model consists of Input Layers, Hidden Layers and Output Layers. The hidden layers consist of a specific number of nodes that transform the data and enable statistical interactions using activations functions between the inputs and outputs of the system. The influences of the interactions are propagated layer-by-layer to the final Output Layer.

During the late fall, winter, and early spring, water stored in Lake Mendocino remains well mixed, and water released from the reservoir is well oxygenated. In addition, atmospheric conditions and tributary input help to maintain DO levels at or near saturation. However, beginning in May of most years, DO levels in the water released below the reservoir begins to decrease. This continues through the summer and early fall until the reservoir "turns over" and the process starts anew. The general pattern follows the development and depletion of the cold water pool in Lake Mendocino. Lake Mendocino has one release point at the bottom of the reservoir where the water typically remains colder than surface temperatures until mixing of the stratified water layers occurs in late summer/early fall.

Figure 1 and Figure 2 show the Lake Mendocino daily water temperature at different depths for 2015 and 2019 respectively. Figure 3 shows the temperature logger locations along the Upper Russian River.

In this study, four data sets were analyzed in Lake Mendocino:

1) Lake Mendocino Water Temperature, Surface
2) Lake Mendocino Water Temperature, 10 feet – 20 feet Average: These data correspond to the average of water temperatures at two depths: 10 feet and 20 feet.
3) Lake Mendocino Water Temperature, 40 feet - 80 feet: These data correspond to the average of water temperatures at 4 depths: 40 feet, 50 feet, 60 feet, 70 feet and 80 feet.
4) Lake Mendocino Water Temperature, Bottom.

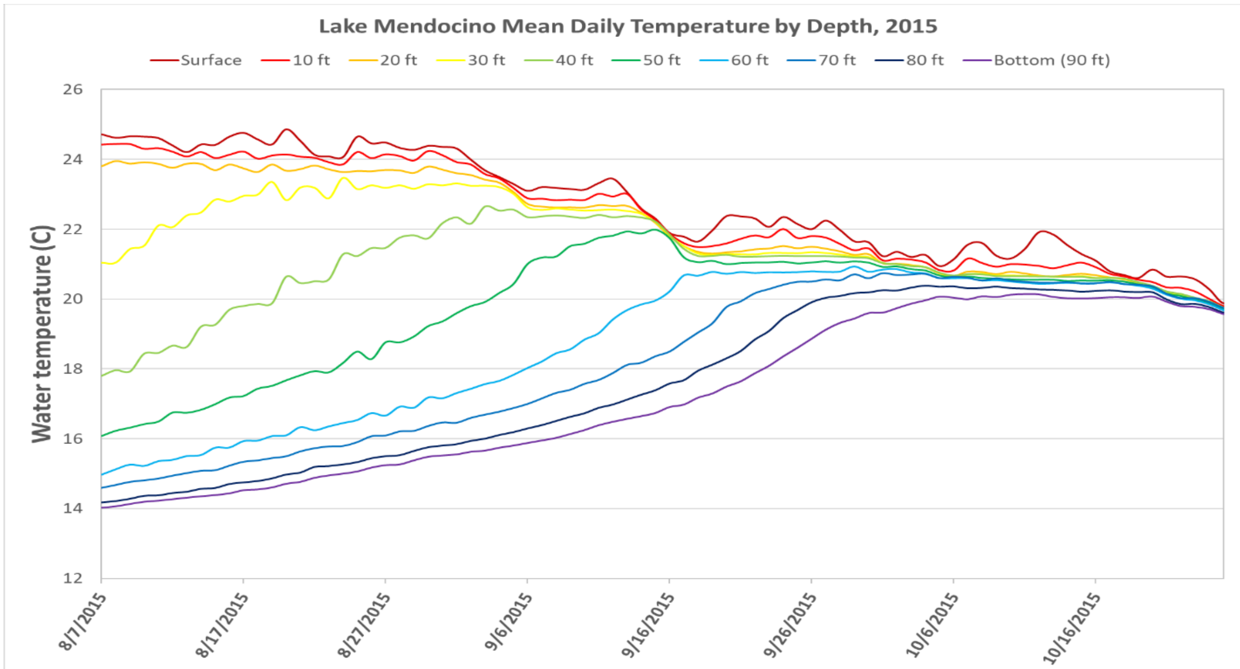

Figure 1. Daily Lake Mendocino Water Temperature at Different Depths, 2015.

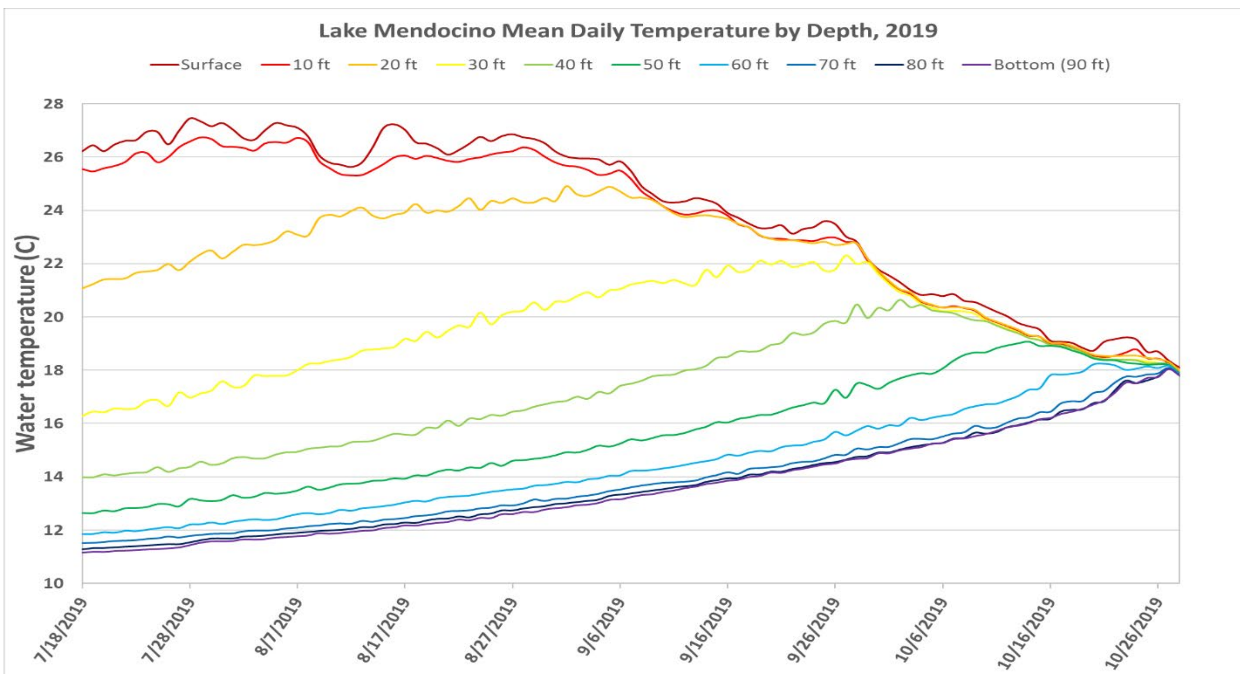

Figure 2. Daily Lake Mendocino Water Temperature at Different Depths, 2019.

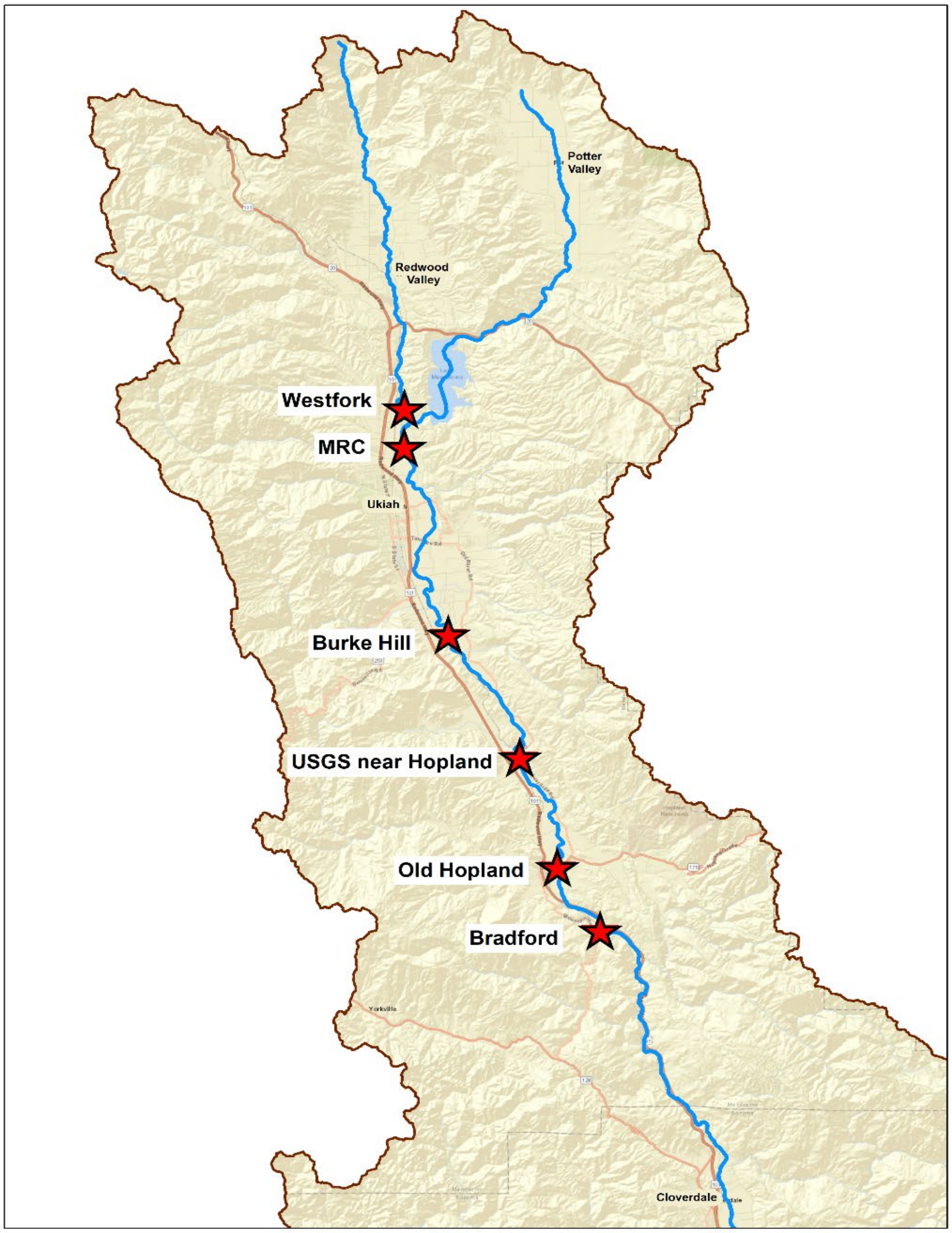

Figure 3. Upper Russian River Water Temperature Logger Locations.

The modeling approach consist of three machine learning sub-models. The first sub-model (sub-model 1) estimates reservoir water temperature at the surface and 10 feet – 20 feet average. The second sub-model (sub-model 2) takes the outputs of sub-model 1 (reservoir water temperature at 10 feet – 20 feet average) and reservoir storage data as inputs in order to estimate reservoir water temperatures at the cold water pool zone of Lake Mendocino (40 feet – 80 feet average and bottom). The third model (sub-model 3) takes the outputs of sub-model 2, reservoir storage, reservoir releases and streamflow data in order to estimate water temperatures at five different locations along the upper mainstem Russian River. Table 1 summarizes the inputs and outputs of the modeling approach.

Table 1. Inputs and Outputs of the Modeling Approach.

	Inputs	Outputs
Sub-Model 1	Daily Lake Mendocino Storage (AF)	Daily Lake Mendocino Water Temperature, Surface (°C)
	Daily Ukiah Max Air Temperature (°C)	Daily Lake Mendocino Water Temperature, 10ft-20ft Average (°C)
	Daily Ukiah Min Air Temperature (°C)	
Sub-Model 2	Daily Lake Mendocino Water Temperature, 10ft-20ft Average (°C)	Daily Lake Mendocino Water Temperature, 40ft-80ft Average (°C)
	Daily Lake Mendocino Storage (AF)	Daily Lake Mendocino Water Temperature, Bottom (°C)
Sub-Model 3	Daily Lake Mendocino Water Temperature, 40ft-80ft Average (°C)	Daily Russian River Water Temperature at MRC (°C)
	Daily Lake Mendocino Water Temperature, Bottom (°C)	Daily Russian River Water Temperature at Burke Hill (°C)
	Daily Lake Mendocino Storage (AF)	Daily Russian River Water Temperature at USGS Hopland (°C)
	Daily Ukiah Max Air Temperature (°C)	Daily Russian River Water Temperature at Old Hopland (°C)
	Daily Ukiah Min Air Temperature (°C)	Daily Russian River Water Temperature at Bradford (°C)
	Daily Hopland Mean Air Temperature (°C)	
	Daily West Fork Russian River Water Temperature (°C)	
	Daily Lake Mendocino Releases (cfs)	
	Daily USGS Streamflow near Ukiah (cfs)	
	Daily USGS Streamflow near Talmage (cfs)	
	Daily USGS Streamflow near Hopland (cfs)	

Each input described in Table 1 consist of the variables themselves at any day “d”, and days prior to day “d” (time lag). The total number of days prior to day “d” and DL model parameters (i.e. hidden layers, number of nodes per layer) were selected by a trial and error process. The statistics used for the selection of the optimal model is the root mean square error (RMSE). The best model was the one with the minimum RMSE corresponding to the testing phase.

In this study, two years are evaluated: 1) 2015 representing a critical dry year, and 2) 2019, representing a wet year. However, this study is dealing with relatively small dataset (daily observations from 2015 to 2019 for some months of summer and fall). It can result to a potential problem of overfitting. Overfitting is when the model performs very well on the training dataset, but the performance decreases significantly when the model is applied to a new dataset (test phase). It can lead to a wrong estimation of potential scenarios. Therefore, to minimize overfitting, the training and testing data sets are:

- 2015 Scenarios: Training dataset: 2016, 2017, 2018 and 2019, Testing dataset: 2015
- 2019 Scenarios: Training dataset: 2015, 2016, 2017 and 2018, Testing dataset: 2019

<u>Lake Mendocino storage scenarios (Figure 4) for 2015 are:</u>

- **Scenario 0:** This scenario is the baseline scenario with the 2015 observed Lake Mendocino storage and 2015 water and climate conditions (i.e. streamflow and temperature in the Westfork Russian River, air temperatures, reservoir releases and streamflow in the Upper Russian River) from May 20 to October 26.
- **Scenario 1:** Lake Mendocino storage increases by 10% on May 20.
- **Scenario 2:** Lake Mendocino storage increases by 20% on May 20.

- **Scenario 3:** Lake Mendocino storage increases by 30% on May 20.
- **Scenario 4:** Lake Mendocino storage increases by 40% on May 20.
- **Scenario 5:** Lake Mendocino storage increases by 50% on May 20.
- **Scenario 6:** Lake Mendocino storage increases by 60% on May 20.
- **Scenario 7:** Lake Mendocino storage increases by 70% on May 20.
- **Scenario 8:** Lake Mendocino storage increases by 80% on May 20.
- **Scenario 9:** Lake Mendocino storage increases by 90% on May 20 (110,742 acre-feet). It is approx. at full capacity (111,000 acre-feet).

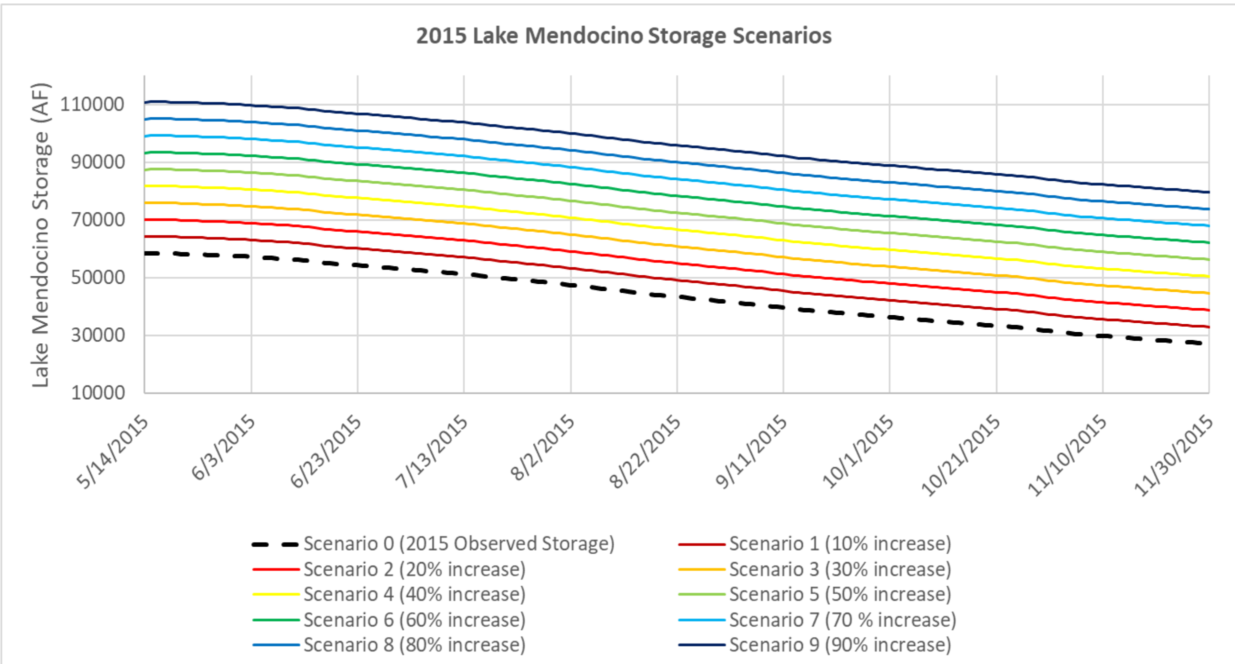

Figure 4. 2015 Lake Mendocino Storage Scenarios.

Lake Mendocino storage scenarios (Figure 5) for 2019 are:

- **Scenario 0:** This scenario is the baseline scenario with the 2019 observed Lake Mendocino storage and 2019 water and climate conditions (i.e. streamflow and temperature in the Westfork Russian River, air temperatures, reservoir releases and streamflow in the Upper Russian River) from July 18 to October 29.
- **Scenario 1:** This scenario is when the storage of Lake Mendocino starts at full capacity (111,000 AF) on July 18.
- **Scenario 2:** This scenario is when the storage of Lake Mendocino starts at 99,900 SF (Full capacity reduced by 10%) on July 18.
- **Scenario 3:** This scenario is when the storage of Lake Mendocino starts at 88,800 SF (Full capacity reduced by 20%) on July 18.
- **Scenario 4:** This scenario is when the storage of Lake Mendocino starts at 77,700 SF (Full capacity reduced by 30%) on July 18.
- **Scenario 5:** This scenario is when the storage of Lake Mendocino starts at 66,600 SF (Full capacity reduced by 40%) on July 18.

- **Scenario 6:** This scenario is when the storage of Lake Mendocino starts at 55,500 SF (Full capacity reduced by 50%) on July 18.

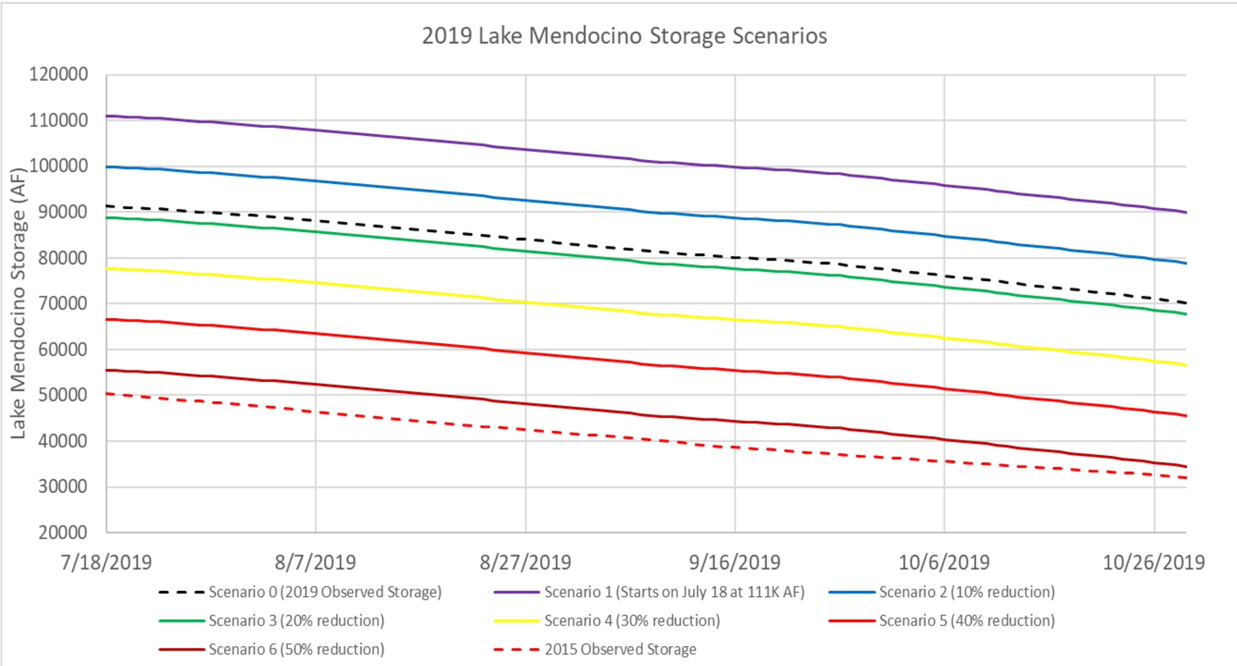

Figure 5. 2019 Lake Mendocino Storage Scenarios.

1. Results

Table 2. Number of days for each input of the model.

		Time lag (days)	
	Inputs	2015 Test	2019 Test
Sub-Model 1	Daily Lake Mendocino Storage (AF)	6	6
	Daily Ukiah Max Air Temperature (°C)	6	6
	Daily Ukiah Min Air Temperature (°C)	6	6
Sub-Model 2	Daily Lake Mendocino Water Temperature, 10ft-20ft Average (°C)	0	0
	Daily Lake Mendocino Storage (AF)	1	1
Sub-Model 3	Daily Lake Mendocino Water Temperature, 40ft-80ft Average (°C)	5	1
	Daily Lake Mendocino Water Temperature, Bottom (°C)	5	1
	Daily Lake Mendocino Storage (AF)	5	1
	Daily Ukiah Max Air Temperature (°C)	5	1
	Daily Ukiah Min Air Temperature (°C)	5	1
	Daily Hopland Mean Air Temperature (°C)	5	1
	Daily West Fork Russian River Water Temperature (°C)	5	1
	Daily Lake Mendocino Releases (cfs)	5	1
	Daily USGS Streamflow near Ukiah (cfs)	5	1
	Daily USGS Streamflow near Talmage (cfs)	5	1
	Daily USGS Streamflow near Hopland (cfs)	5	1

Table 2 shows the number of days for each input of the model. We can see that the DL model needs just 1 previous day as inputs for the 2019 test, while the DL model needs 5 previous days as inputs for the 2015 test.

3.1. Model Performance

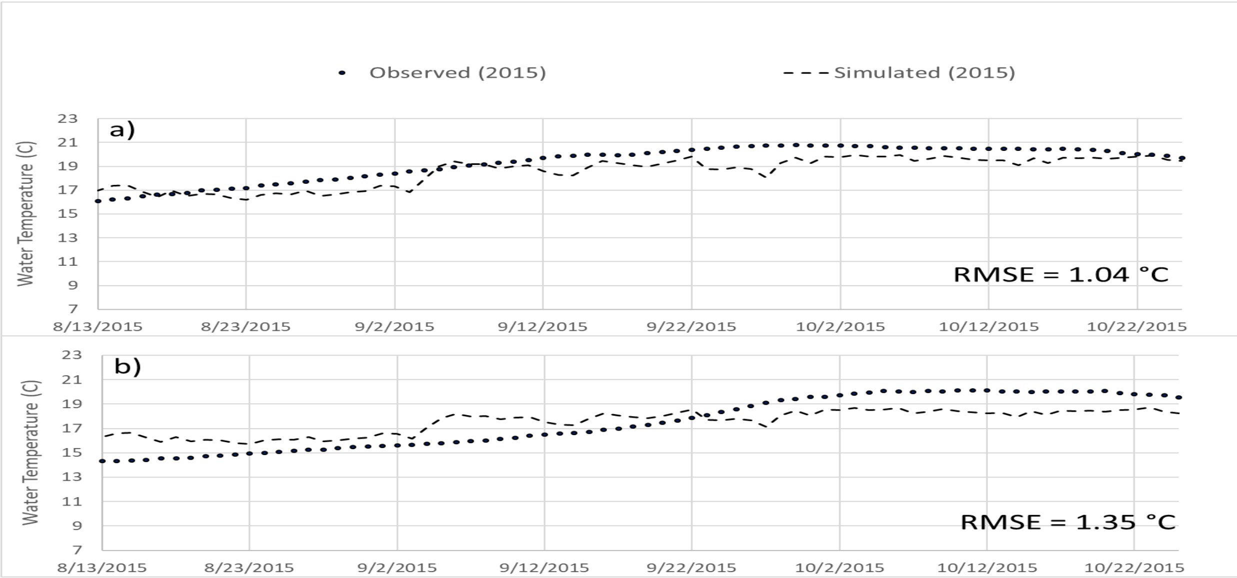

Figure 6. Observed (black dots) vs simulated (black dashed lines) water temperatures and Root Mean Square Error (RMSE) (2015 Testing Phase) of the Lake Mendocino water temperatures at depths: a) 40 feet – 80 feet Average, and b) Bottom.

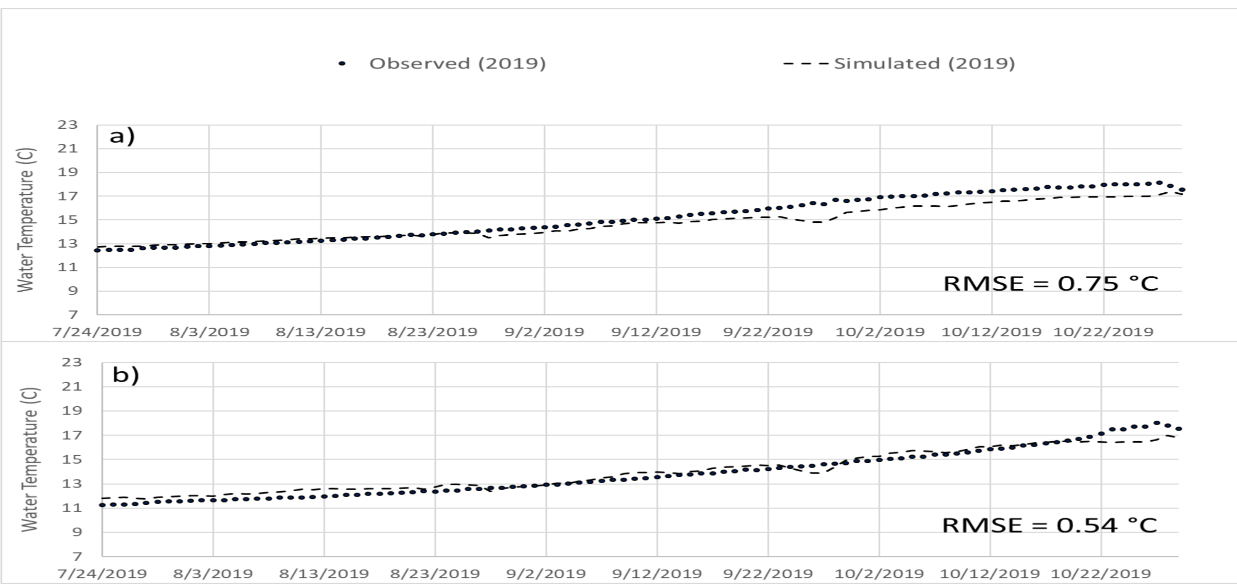

Figure 7. Observed (black dots) vs simulated (black dashed lines) water temperatures and Root Mean Square Error (RMSE) (2019 Testing Phase) of the Lake Mendocino water temperatures at depths: a) 40 feet – 80 feet Average, and b) Bottom.

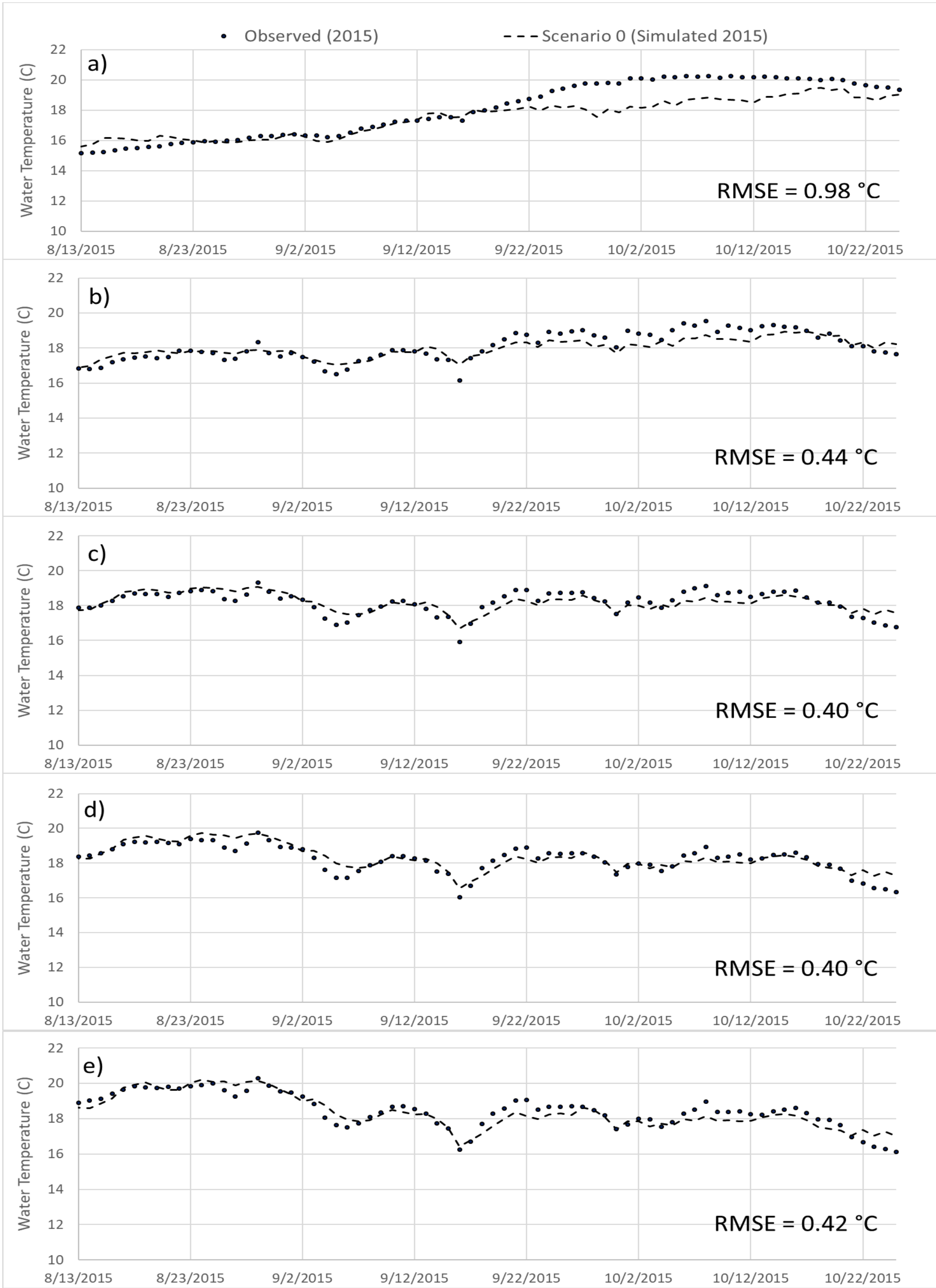

Figure 8. Observed (black dots) vs simulated (black dashed lines) water temperatures and Root Mean Square Error (RMSE) (2015 Testing Phase) of the Upper Russian River water temperatures at: a) MRC, b) Burke Hill, c) USGS Hopland, d) Old Hopland and e) Bradford

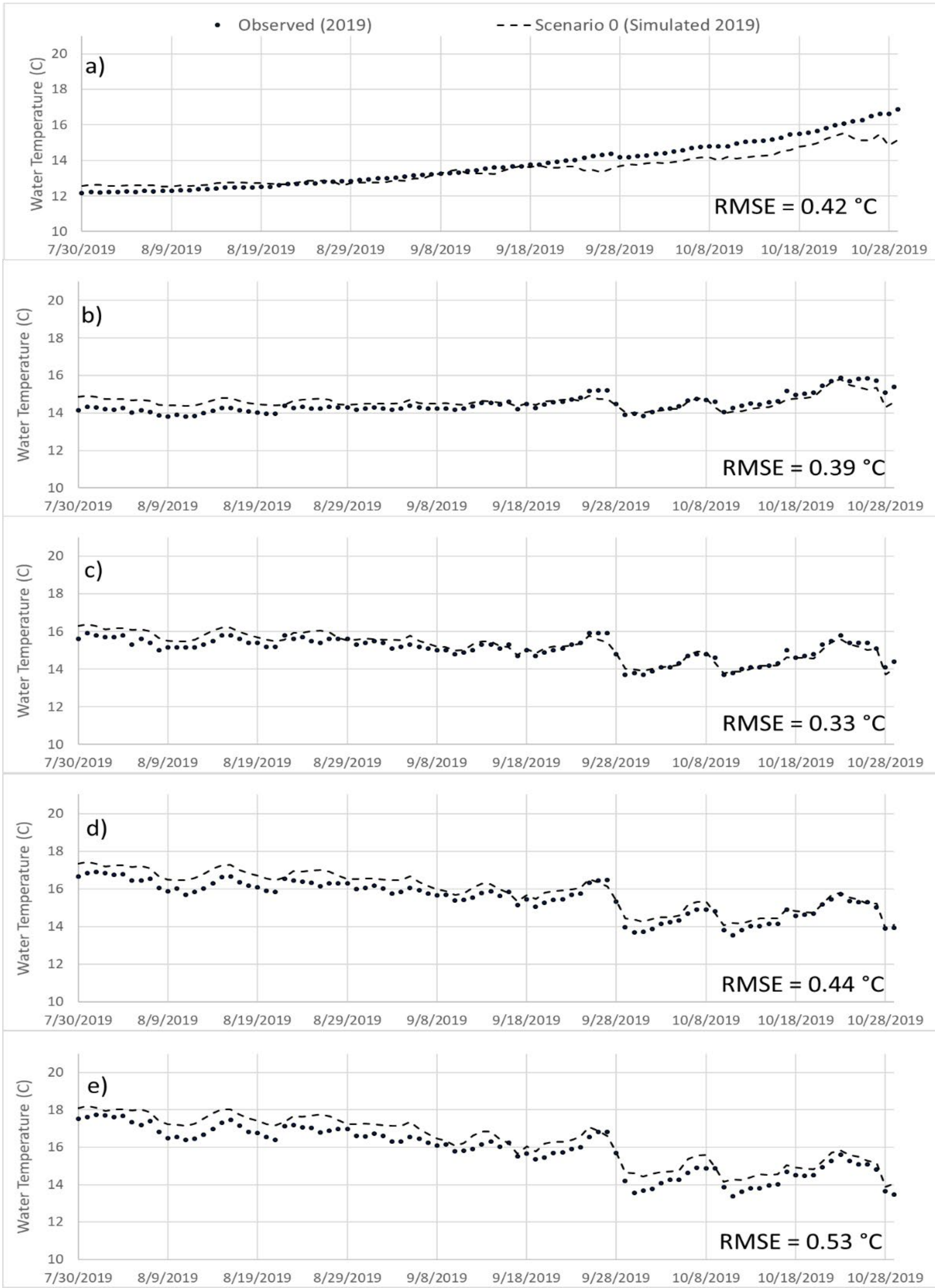

Figure 9. Observed (black dots) vs simulated (black dashed lines) water temperatures and Root Mean Square Error (RMSE) (2019 Testing Phase) of the Upper Russian River water temperatures at: a) MRC, b) Burke Hill, c) USGS Hopland, d) Old Hopland and e) Bradford

Figures 6-9 show a very good overall test performance of the DL modeling approach with low RMSE values than ranges from 0.33 °C to 1.35 °C. There are some months in which the performance of the model needs to be improved (e.g. Figures 6, 7a, 8a and 9a) and it might be due to the relatively small training data set.

3.2 Scenario Modeling

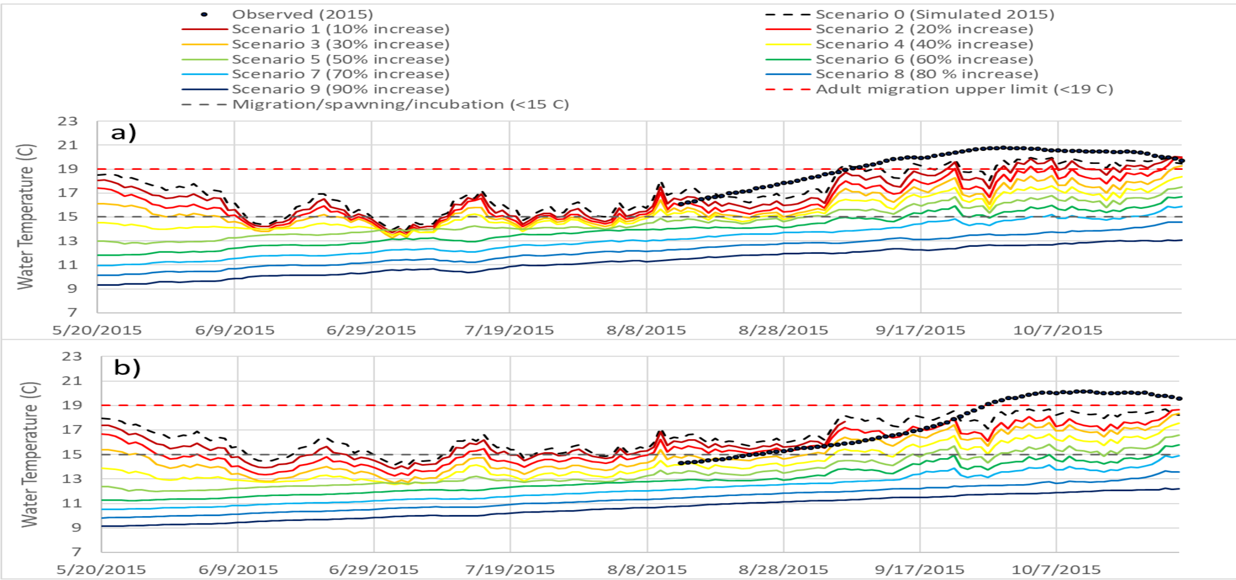

Figure 10. Scenarios for the 2015 Lake Mendocino water temperatures at depths: a) 40 feet - 80 feet Average, and b) Bottom.

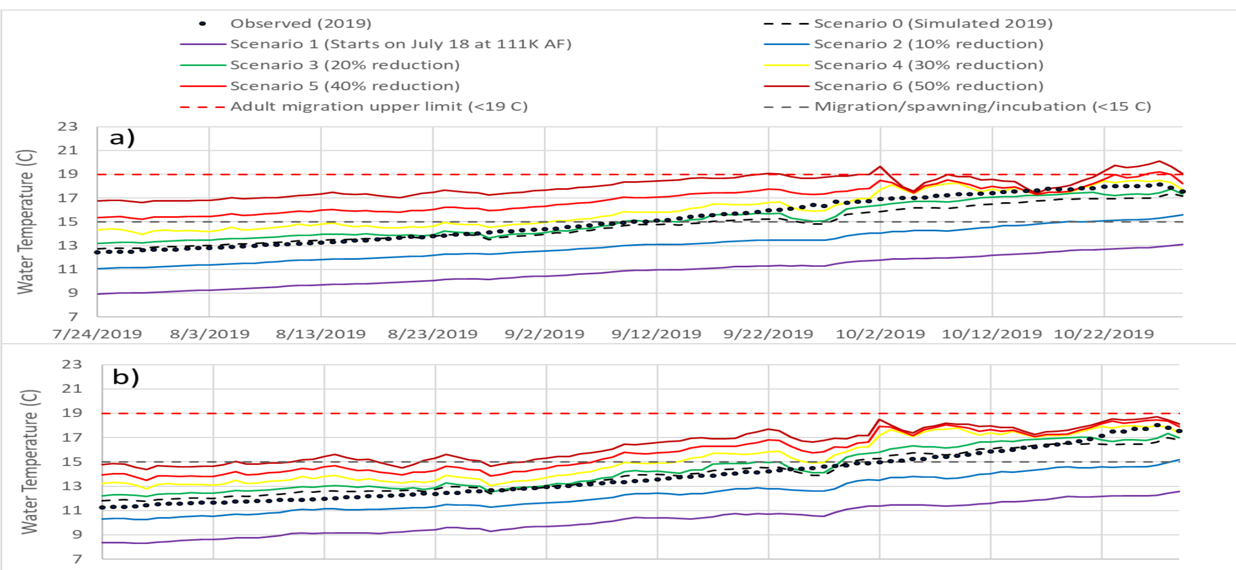

Figure 11. Scenarios for the 2019 Lake Mendocino water temperatures at depths: a) 40 feet - 80 feet Average, and b) Bottom.

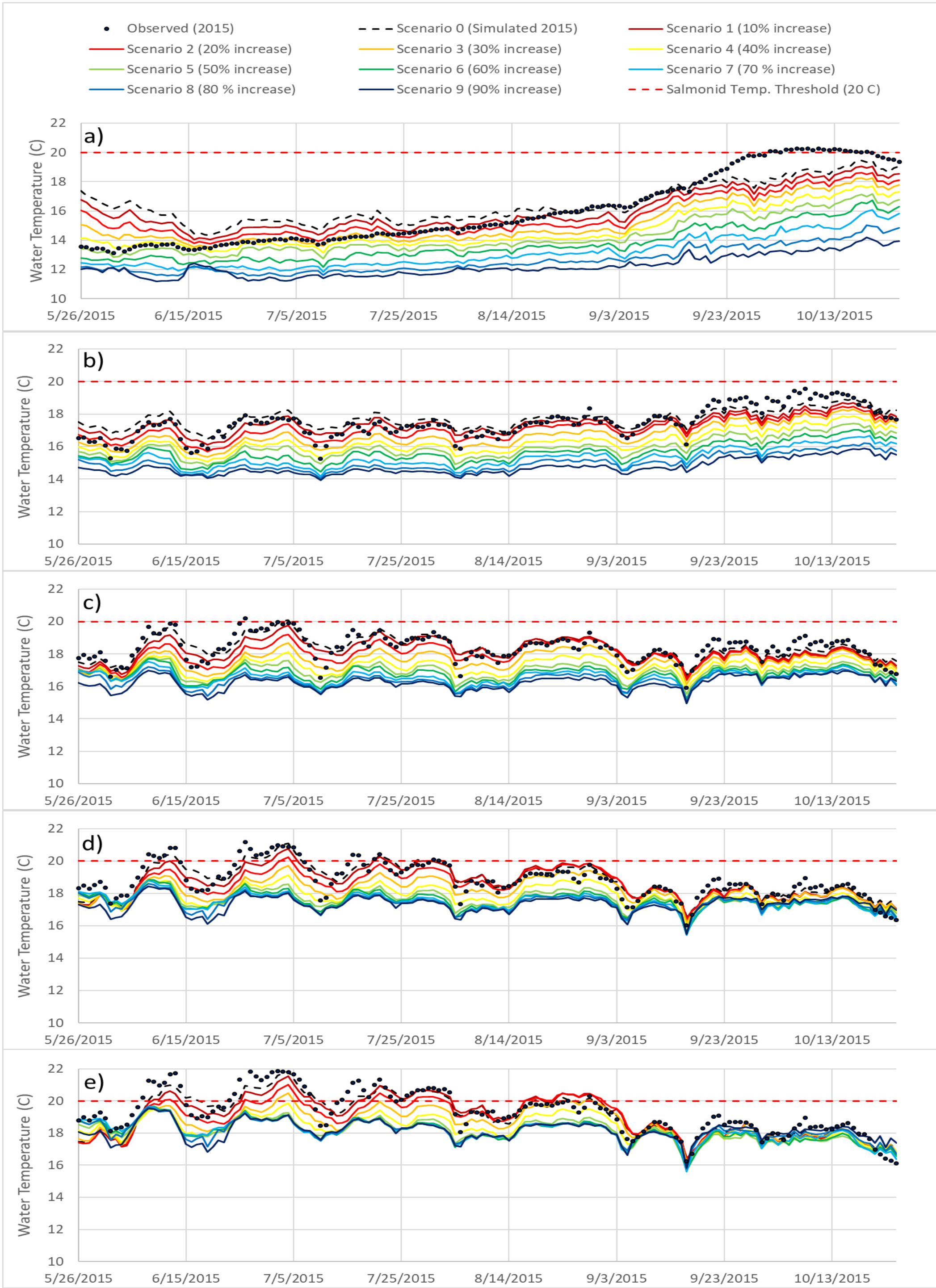

Figure 12. Scenarios for the 2015 Upper Russian River water temperatures at: a) MRC, b) Burke Hill, c) USGS Hopland, d) Old Hopland and e) Bradford

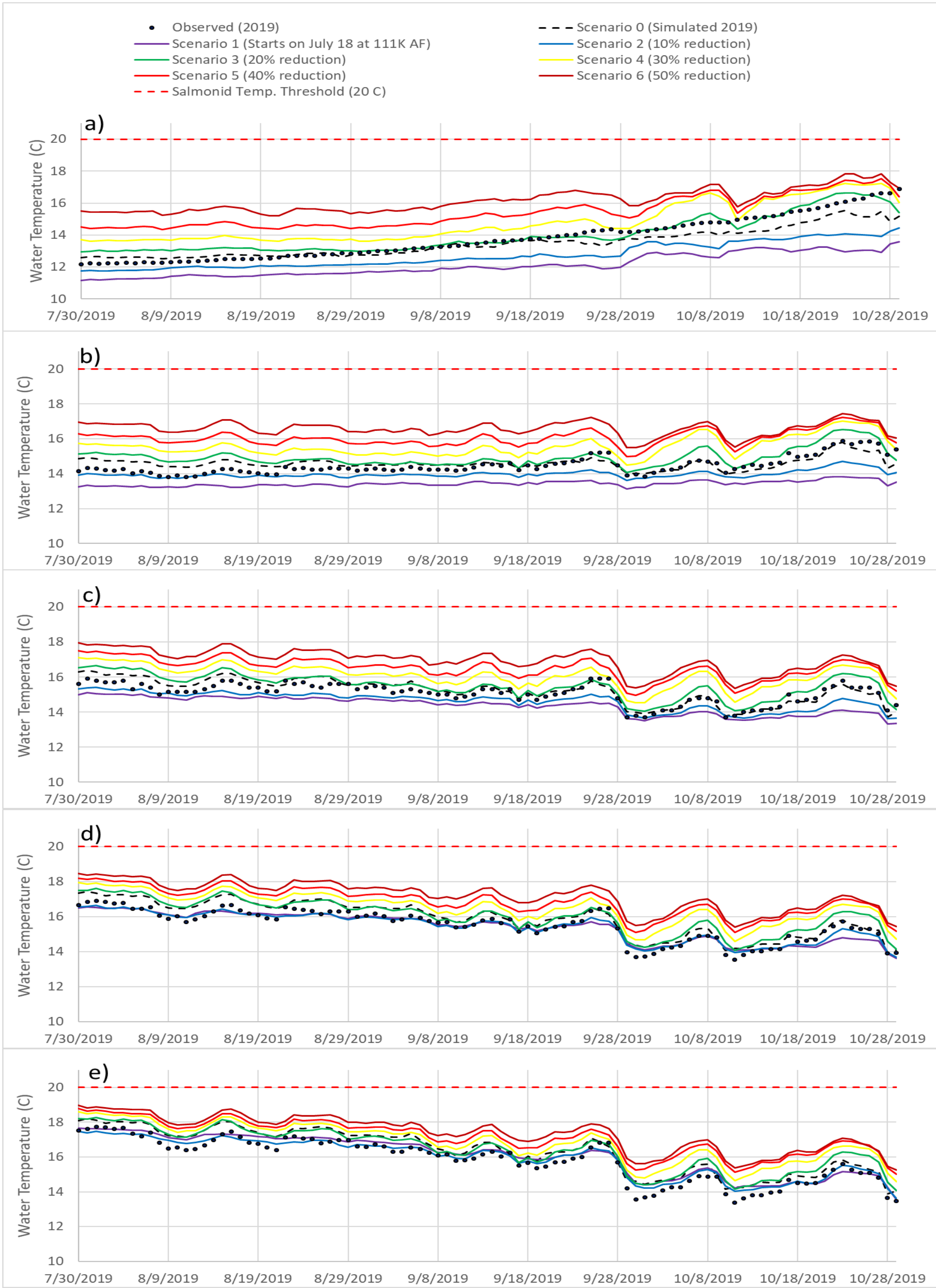

Figure 13. Scenarios for the 2019 Upper Russian River water temperatures at: a) MRC, b) Burke Hill, c) USGS Hopland, d) Old Hopland and e) Bradford.

Figures 10-13 show results for the 2015 and 2019 scenarios. In general, we can see that the temperatures at the cold water zone of the reservoir and Upper Russian River tend to be lower for the scenarios with higher reservoir storage levels (purple and blue solid lines). On the other hand, the temperatures at the cold water zone of the reservoir and Upper Russian River tend to be higher for the scenarios with lower reservoir storage levels (dark red and red solid lines).

4. Conclusions and recommendations

The modeling results demonstrate benefits of higher reservoir storage levels to maintaining cooler water temperatures during the juvenile steelhead trout summer rearing season through the fall adult Chinook salmon migration period.

5. Status and Next Steps

NOAA Fisheries continues its efforts to monitor stream temperature in the upper Russian River and water temperature at different depths in Lake Mendocino during summer through fall 2020. These new oncoming data will provide valuable information to improve the machine learning modeling approach.

Although the overall performance of the model is good, there are months in which the performance of the model needs to be improved. Therefore, NOAA Fisheries will perform the additional analysis:

- Selection of the number of lag days for different months or seasons.
- Perform additional training and validation process (e.g. cross-validation)
- Perform a sensitivity analysis to find the most relevant inputs of the model for different months or seasons.

References

Forecast Informed Reservoir Operations Steering Committee (2017). Preliminary viability assessment of Lake Mendocino.

Maslova, I., Ticlavilca A.M., and McKee M (2016), Adjusting wavelet-based multiresolution analysis boundary conditions for long-term streamflow forecasting, Hydrological Processes.

Ticlavilca AM, McKee M. 2011. Multivariate Bayesian regression approach to forecast releases from a system of multiple reservoirs. Water Resources Management 25: 523–543. DOI:10.1007/s11269-010-9712-y.

Ticlavilca AM, McKee M, Walker WR. 2013. Real-time forecasting of short-term irrigation canal demands using a robust multivariate Bayesian learning model. Irrigation Science 31(2): 151–167.