Using ECOSTRESS to Observe and Model Diurnal Variability in Water Temperature Conditions in the San Francisco Estuary

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Abstract—The San Francisco Estuary and Sacramento–San Joaquin River Delta (Bay Delta) is a highly sensitive and critical habitat for the Delta Smelt, an endangered endemic fish, with water temperature being a key determinant of habitat suitability. This study investigates the relationship between open water surface and subsurface conditions from spaceborne thermal measurements (ECOsystem Spaceborne Thermal Radiometer Experiment on Space Station (ECOSTRESS) and Landsat-8) and in situ sensor data from the California Data Exchange Center (CDEC) to produce estimates of spatially continuous bulk temperature in the Bay Delta. We found that ECOSTRESS and Landsat-8 surface temperature measurements are well-correlated with bulk water temperatures ($N = 236$ and $r = 0.907$ and $N = 226$ and $r = 0.976$, respectively). For the ECOSTRESS-in situ comparison, accounting for time of day improved the correlation between surface and subsurface conditions ($r = 0.946$, 0.881, and 0.944 for morning, midday, and evening, respectively). We found that ECOSTRESS surface temperatures were warmer than bulk temperatures in the midday period (2°C peak at 2 P.M.) and cooler in the morning and evening periods (−1°C peak at 6 A.M.). We also found that a simple harmonic regression model can capture the diurnal variability of the skin effect to predict bulk water temperature (root-mean-square error (RMSE) = 0.809°C). With ECOSTRESS, we found that across the Bay Delta, including open waters and pelagic bays, temperature conditions causing stress and mortality for the Delta Smelt were persistent throughout the day during summer months. ECOSTRESS is a unique dataset capable of informing conservation efforts in the Bay Delta.

Index Terms—Aquatic habitat, Delta Smelt, diurnal patterns, ECOsystem Spaceborne Thermal Radiometer Experiment on Space Station (ECOSTRESS), Landsat-8, skin effect, water temperature.

I. INTRODUCTION

WATER temperature is a key determinant of ecosystem performance. Aquatic organisms are highly sensitive and adapted to certain temperature ranges and changes in temperature can have consequences for ecosystem composition and function. Fishes are particularly sensitive to water temperature; they have optimal temperature ranges, and if they are subjected to temperatures outside of those ranges, they may experience physiological stress responses that can affect reproduction and longevity or survival [1]–[4]. Water temperature also affects the native plant ecosystem and changes can create a more favorable environment for nonnative species [5].

Throughout USA, stream water temperatures have risen 0.009°C–0.077°C per year due to warmer air temperatures [6]. In California, warmer air temperatures, loss of snowpack, and earlier spring snowmelt have contributed to an increase in stream water temperature [7]–[9]. The San Francisco Bay and upstream Sacramento–San Joaquin River Delta (henceforth the Bay Delta) has mirrored these trends; it has regularly registered temperatures exceeding 20°C and events when temperatures reach 25°C–28°C, which is beyond some endemic species’ optimal temperature range (i.e., the Delta Smelt) [1], [10], [11]. This has contributed to declines in endemic fish populations [1], [12]–[16]. While there are other environmental factors known to be causing the decline in native fish populations (i.e., invasive species and increased salinity [17] and changes to their food web [18]), temperature is key because fishes are physiologically sensitive to water temperatures [19], [20].

Remotely sensed surface temperatures provide measurements of water temperature with greater spatial coverage than in situ measurements. However, remote sensing of water temperature only captures the skin surface temperature ($T_s$) and is temporally sparse relative to continuous in situ measurements. $T_s$ represents the temperature of the top 10–500 μm of the water surface and is regulated by conductive and diffusive heat processes [21]. Bulk water temperature ($T_b$) represents temperature measured at depth and is controlled by turbulent heat transfer processes and solar heating [21]. This difference in temperature at the surface and with depth is known as the skin effect and can be up to a few degrees depending on the diurnal thermocline [22], [23]. The diurnal fluctuations of $T_s$ are not entirely representative of the shape and magnitude of $T_b$ fluctuations, with $T_s$ being cooler than $T_b$ during the night and the reverse during the day [21]. Therefore, deriving a relationship between remotely sensed $T_s$ and $T_b$ may improve the utility of thermal remote sensing for certain ecosystem restoration and monitoring efforts.

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Incorporating remote sensing into decision-making provides added utility to current methods. Remote sensing represents a spatially continuous dataset that can complement spatially discrete measurements. The combination of temporally dense \textit{in situ} measurements with spaceborne thermal measurements can provide a more complete picture of the Bay Delta and habitat conditions, including about spatially variable and infrequently connected habitat refugia [24]. While station data are temporally dense, remote sensing data are more spatial complete, which may enhance system understanding given the complexity and heterogeneity of habitats such as the Bay Delta. Furthermore, NASA Earth observation products are freely available and can be a cost-efficient means of increasing monitoring. Finally, remote sensing data could replace the use of single-station data for validating models [25].

Here, we aim to better understand the complementarity between available temperature datasets within the context of aquatic ecosystems management as it relates to the Delta Smelt, an endangered fish species in the Bay Delta. To do this, we assessed aquatic temperature conditions in the Bay Delta using Landsat-8, ECOSystem Spaceborne Thermal Radiometer Experiment on Space Station (ECOSTRESS), and measurements made at depth from an \textit{in situ} sensor network obtained from the California Data Exchange Center (CDEC). We evaluated the diurnal variability of the skin effect, enabled by the variable sampling of ECOSTRESS. We then developed and applied a simple harmonic regression to predict bulk water temperature (ECOSTRESS $T_b$). Finally, we considered the spatial distribution of average diurnal temperature conditions at the surface and depth during August–September 2020. We used these months because they have the warmest afternoon temperatures, which is relevant for Delta Smelt habitat monitoring. It revealed regions with thermal conditions that could cause stress and mortality for vulnerable fish species, both at the surface and depth.

II. DATA AND METHODS

A. Site Description

The San Francisco Bay and Sacramento–San Joaquin River Delta (Bay Delta) is a heavily managed, complex estuary that serves a multitude of purposes. It is made up of the Sacramento River and San Joaquin River and their confluence forms the freshwater Delta system, which connects to the Suisun, San Pablo, and San Francisco Bays, which eventually drain to the Pacific Ocean. The watershed drains 40% of California and the rivers originate as far north as the Cascades. There are over 1400 dams throughout the watershed, and it is the center of two major water storage and delivery projects (Central Valley Project and State Water Project) [26], providing drinking water for 25 million people [27] and supporting California’s $50B agricultural industry.

The Bay Delta is a heavily regulated system and often the subject of conflict over resource management and water allocation; 62% of the water is used for agriculture [28], 16% goes to urban and industrial use, and the remaining 22% is for environmental uses, such as streamflow and wetlands [26]. Because the Bay Delta provides so many services, it is at the center of continuing policy debates about how to allocate the water to meet multiple management objectives. The Bay Delta is home to federally and state-designated endangered fish species that sometimes take priority, so fish and human needs are at times in opposition. Climate change is expected to exacerbate these conflicts as the supply diminishes and demand increases from a growing population and agricultural sector [16].

The Bay Delta is home to many endemic species, including the Delta Smelt [16]. Delta Smelt is a protected species, but its population has been in decline for decades, despite federal and state conservation efforts [29], [30]. They usually reside between San Pablo Bay and the freshwater rivers and sloughs to the east [17]. They are most abundant in low-salinity zones [31] (about two practical salinity units), cool, and turbid habitats [32]. It is projected that climate change will warm streams beyond the Delta Smelt’s optimal temperature range and cause longer and earlier spawning windows; during the juvenile life stage, climate change is projected to increase the number of days of exposure to stressful temperatures ($\geq 24$ °C) by 60–100 days and the number of days above chronic lethal thermal maximum ($> 27$ °C) by up to 50 days [1]. Climate change is also expected to favor nonnative species as the Bay Delta becomes warmer, clearer, and more saline, which will make preserving Delta Smelt habitat very challenging [16], [33]. Consequently, the Bay Delta is potentially headed for a major change in its ecosystem structure, including the extinction of Delta Smelt, due to changes in stream water quality [34].

B. Data

1) \textit{In Situ} Bulk Water Temperature: $T_b$ data from four continuous-monitoring stations were downloaded from the CDEC [35]. CDEC is a centralized hub of hydrologic data aggregated from federal, state, and local agencies in California. CDEC stores and disseminates data in real time for purposes, such as flood prediction and water management. Data are considered provisional.

For this study, we identified CDEC stations within the Bay Delta based on their locations and representative conditions that are generally favorable for the Delta Smelt. Open water conditions were also more tractable for assessing diurnal water temperature differences with minimal interference from land adjacency and shallow water effects (see Table I and Fig. 1 for the selected stations and their locations).

Water temperature measurements in °F are made at about 1 m below the water surface; anchoring of the measurement instruments varied (some are anchored to the bed and others are on buoys). Water temperature measurements are made subhourly (every 15 min). At the stations used in this analysis, \textit{in situ} $T_b$ data were available from June 1, 2015 to present, with some gaps in the record at certain stations. We converted the temperatures to °C and then cleaned the data based on protocols described by the Interagency Ecological Program [36]. We then found the closest-in-time matches between ECOSTRESS and \textit{in situ} acquisitions, which were
As there were some temporal gaps in the in situ measurements, typically within 1 h of the ECOSTRESS overpass time. As there were some temporal gaps the in situ measurements, we removed any instances when the difference in the matched times was >1 h. Finally, we averaged the in situ \( T_b \) values that were within ±15 min from the matched time (a 30-min window) from ECOSTRESS. We used the average in situ \( T_b \) instead of the instantaneous \( T_b \) for subsequent analyses because of the possible uncertainties associated with using a single measurement.

2) ECOSTRESS Surface Temperature: We used the ECOSTRESS Level 2 Land Surface Temperature and Emissivity (L2 LSTE) product for \( T_s \) data (referred to as “ECOSTRESS \( T_s \)” [37]. The L2 product provides surface temperature, emissivity, and cloud/quality flags over land and water surfaces in the HDF5 format [38]. Because ECOSTRESS is on the International Space Station (ISS), it acquires data at variable times (each overpass is not at the same time of day), with frequent revisit (1–5 days). The product has been validated by the mission team [39]. A cold bias of about 0.9 K was observed over water bodies when considering both thermal radiometer measurements [39] and [40] reports a cold bias when comparing ECOSTRESS \( T_s \) and subsurface water temperature measurement, though did not explicitly examine diurnal variability or dependencies. The bias will be addressed in a future collection of the data.

We examined 236 ECOSTRESS LST images from July 15th, 2018 to July 20th, 2021; October–December 2018 and March–May 2019 were not available due to anomalies in the mass storage unit. ECOSTRESS images were retrieved using the Application for Extracting and Exploring Analysis Ready Samples (AppEEARS) API [41]. The request was made for all L2 product images in the area defined by a shapefile with the extent: \((-122.71, 37.36, -121.296, 38.43\). This is the area shown in Fig. 1. Through the API, the images were reprojected and provided as GeoTIFF rasters. We then applied the associated cloud masks to each of the rasters. We resampled the ECOSTRESS images to a 70-m grid spanning the Bay Delta. In addition, we masked land pixels in the surface temperature images using a land mask from the National Oceanic and Atmospheric Administration’s (NOAA) Coastal Change Analysis Program (C-CAP) open water classification [21].

To obtain ECOSTRESS \( T_s \), we extracted temperatures from a 3 × 3 grid of pixels, with the center pixel corresponding to the location of the in situ CDEC station locations. The 3 × 3 grid created a 210 m × 210 m sampling area, which accounted for potential small-scale variability in temperature. We calculated the mean temperature of the sampling area. Finally, we removed ECOSTRESS temperature outliers by grouping each set of station data by location and time of day (morning, midday, and evening, with morning being from 4:00 to 11:00, midday being from 12:00 to 19:00, and evening being 20:00 to 3:00) and then filtering out temperatures ±2 standard deviations from the mean. We removed outliers from the dataset because it is possible that all cloud-containing pixels were not fully eliminated during the masking process. Certain clouds can be difficult to detect and remove [39]. At all stations, less than 10% of ECOSTRESS measurements were deemed outliers and removed, many of which were too cold (and thus, likely clouds).

3) Landsat-8 Surface Temperature: We used the Landsat-8 Level 2 Collection 2 Surface Temperature product as an additional \( T_s \) measurement. Landsat-8 images courtesy of the U.S. Geological Survey. The Landsat-8 record spans 2013 to present, with overpasses that tend to fall within an hour block between 10 and 11 Pacific Standard Time (PST). The Landsat Level 2 LST product is distributed on a 30-m grid, downsampled from the native resolution of the Landsat thermal instruments (100 m for Landsat-8). The Level 2 Collection 2 30-m images were retrieved using the Earth Explorer API [42]. This study used all available Landsat-8 surface temperature images over the Bay Delta at path/row 044/033 and 044/034 from 2015 to 2021. We used the same water pixel identification as with ECOSTRESS but at the 30-m resolution of C-CAP and Landsat-8. At this resolution, we calculated the mean temperature of a 7 × 7 grid of pixels surrounding the station pixel to match the area sampled with the ECOSTRESS maps. We did not match the Landsat and ECOSTRESS starting dates to showcase the temporal frequency of ECOSTRESS overpasses in this area (i.e., ECOSTRESS has a three-year record and 236 usable images, while Landsat-8 had a six-year

### Table I: Stations Used for This Analysis

| Station Name | Station Code | Habitat Type | Latitude | Longitude |
|--------------|--------------|--------------|----------|-----------|
| Frank’s Tract Mid Tract | FRK | Tidal flooded island (freshwater) | 38.04642 | -121.598 |
| Grizzly Bay Busby | GZB | Tidal embayment (brackish) | 38.12315 | -122.008 |
| Grizzly Bay | GZL | Tidal embayment (brackish) | 38.12425 | -122.038 |
| Hosker Bay | HON | Tidal embayment (brackish) | 38.0724 | -121.939 |

Fig. 1. Map of the Bay Delta study location and the location within California. The map shows the whole Bay Delta with the four CDEC stations we used to evaluate the ECOSTRESS \( T_s \). These stations are within the Delta Smelt habitat area.
record and 226 usable images). Because of the length of the in situ records, we were only able to use Landsat-8 data going back to 2015.

C. Skin Effect

Skin surface temperature (\(T_s\)) represents the temperature of the top 10–500 \( \mu \)m of the water surface and bulk water temperature (\(T_b\)) represents temperature measured at depth [21]. The difference in temperature at the surface and with depth is known as the skin effect [22], [23]. The strength of the skin effect varies throughout the day and with seasons depending on environmental factors, such as air temperature, sun position, and water movement [21]. We quantified the diurnal skin effect by calculating the average difference between remotely sensed ECOSTRESS \(T_s\) and in situ \(T_b\) for every hour at each of the stations.

D. Evaluating the \(T_b\)–\(T_s\) Relationship

To compare ECOSTRESS and Landsat-8 \(T_b\) to in situ \(T_b\), we calculated the root-mean-square error (RMSE), Pearson \(r\), and \(R^2\) between \(T_b\) and \(T_s\). We calculated these statistics for all stations together and each individually. To quantify variability in performance based on time of day, we also grouped the data by morning, midday, and evening acquisitions and calculated the same statistics. Finally, we plotted linear regressions of matched Landsat-in situ and ECOSTRESS-in situ points.

We evaluated the spatial distribution of average surface temperature conditions in critical Delta Smelt habitat during the morning, midday, and evening, aggregating data collected from August to September 2020. We chose these months because they register the warmest water temperatures during the year and are therefore the most critical time for Delta Smelt conservation; we chose one year to exemplify the diurnal spatial patterns in temperatures in different areas of the Bay Delta. The Landsat-8 map is the average of all acquisitions made during that period. These ECOSTRESS and Landsat-8 maps can be used to identify regions that are persistently experiencing thermal conditions that could cause mortality to vulnerable aquatic species such as the Delta Smelt, as well as find the times of day in which this is most likely to occur.

E. Modeling \(T_b\)

We developed and applied a harmonic regression model using the relationship we found between in situ \(T_b\) and ECOSTRESS \(T_s\) at the four stations. To predict \(T_b\), we used the following equation:

\[
T_b = 3.755 + T_s \times 0.839 + \sin \left( \frac{\pi \times \text{hour}}{12} \right) \times -0.071 + \cos \left( \frac{\pi \times \text{hour}}{12} \right) \times 0.785 \tag{1}
\]

with \(T_s\) being the ECOSTRESS surface temperature, hour being the hour of the day between 0 and 23, and the sin and cos parameters representing the skin effect phase. Because of the periodic nature of the diurnal difference between \(T_b\) and \(T_s\) [43], we used a harmonic regression approach, which is suitable for modeling circular or directional data [44]. We evaluated the model during June–September 2020. We used the summer months because this is the key season when thermal habitat suitability is of concern for the Delta Smelt. We calculated ECOSTRESS \(T_b\) maps with (1). We then used the same process of extracting the ECOSTRESS \(T_b\) pixel values over in situ station locations and calculated the RMSE to evaluate the model. We show the average predicted ECOSTRESS \(T_b\) maps grouped by morning, midday, and evening hours that were calculated from ECOSTRESS \(T_s\) maps collected between August and September 2020. As part of the evaluation, we also show the average diurnal skin effect (ECOSTRESS—modeled \(T_b\)) calculated from both the modeled \(T_b\) and the in situ \(T_b\) at three stations from the same time period (one station was out of service during this time).

III. RESULTS

At the four stations considered in this study, both ECOSTRESS and Landsat-8 \(T_b\) showed good agreement with in situ \(T_b\), having strong positive linear relationships (Figs. 2 and 3). Both ECOSTRESS (\(r = 0.907\) and
TABLE II

| Period of Data | n  | Overall | Morning | Midday | Evening | Overall | Morning | Midday | Evening | Overall | Morning | Midday | Evening |
|----------------|----|---------|---------|--------|---------|---------|---------|--------|---------|---------|---------|--------|---------|
| ECOSTRESS (1): All Data | 236 | 0.907 | 0.946 | 0.881 | 0.944 | 1.193 | 1.046 | 1.243 | 1.253 | 0.823 | 0.895 | 0.776 | 0.891 |
| ECOSTRESS (2): 2018-07-15 - 2021-07-20 | 55 | 0.974 | NA | NA | NA | 0.619 | NA | NA | NA | 0.949 | NA | NA | NA |
| Landsat: 2015-06-01 - 2021-01-08 | 226 | 0.976 | NA | NA | NA | 1.061 | NA | NA | NA | 0.953 | NA | NA | NA |

Landsat-8 ($r = 0.976$) showed strong correlations at all locations (both with $p < 0.001$) (see the Appendix for a table of correlations at individual stations); only the ECOSTRESS $T_s - T_b$ matches were subjected to the skin effect due to the variable overpass times. ECOSTRESS ($n = 236$) had more overpasses than Landsat-8 ($n = 226$) in the study location in about half the time. With Landsat-8, there is a strong linear relationship between remotely sensed $T_s$ and in situ $T_b$ during the time of the satellite’s overpass (10–11 A.M. PST). When subset to the same hours as Landsat-8, ECOSTRESS $T_s$ showed a similar relationship to in situ $T_b$ as Landsat-8 ($r = 0.974$ versus 0.976) but had an RMSE of 0.619 °C, while Landsat-8 had an RMSE of 1.061 °C. In addition, when partitioned into acquisitions made during the morning ($r = 0.946$), midday ($r = 0.881$), and evening ($r = 0.944$), ECOSTRESS $T_s$ was more strongly correlated with in situ $T_b$ than when it was grouped together, except during the midday period. Table II gives more descriptive statistics about ECOSTRESS and Landsat’s ability to capture in situ $T_b$. Given these strong relationships, remotely sensed $T_s$ can offer a reasonable proxy of in situ $T_b$ in the Bay Delta system.

ECOSTRESS $T_s$ measurements showed seasonal water temperature patterns at all stations. ECOSTRESS retrievals were seasonally concentrated in the summer and fall months due to orbital patterns of the ISS (Fig. 4), while Landsat-8 measurements are evenly distributed throughout the year. However, ECOSTRESS provides $T_s$ measurements at different hours of the day, while Landsat-8 only measures $T_s$ between 10 and 11 A.M. PST. Fig. 5 shows this seasonal water temperature pattern averaged at the four stations over the whole ECOSTRESS record. It exhibits the frequency of ECOSTRESS acquisitions and the seasonal water temperature cycles. The combination of the two remote sensing datasets provides high temporal coverage throughout the year and day, which can be used to gain a more complete understanding of the diurnal and seasonal temperature fluctuations throughout the Bay Delta, which would not be possible with only Landsat-8.

ECOSTRESS observed a diurnal pattern in the skin effect. The magnitude of the effect varied by station and time of the year; Fig. 6 shows the pattern observed at all stations, averaged over the period of record. The diurnal pattern was evident at all stations, although the magnitude varied. ECOSTRESS tends to be cooler than in situ $T_b$ during the morning and evening and warmer than in situ $T_b$ during the middle of the day. ECOSTRESS most closely matches in situ $T_b$ measurements during the late morning, having the smallest difference between in situ $T_b$ around 10 A.M.
Fig. 6. Diurnal skin effect calculated as the average difference between ECOSTRESS \( T_s \) and \( in situ \ T_b \) for each hour. The skin effect is stronger in the evening and morning.

PST and 3 P.M. PST. This pattern follows the fluctuations of air temperature, with ECOSTRESS \( T_s \) being closest to, or warmer than, \( in situ \ T_b \) during the time when the day is warmest. While other processes and mechanisms contribute to fluctuations in \( T_b \) and \( T_s \), air temperature and solar heating are two key environmental processes [25]. ECOSTRESS is uniquely capable of quantifying this diurnal skin effect because of the variable overpass times.

The simple harmonic regression model, which predicts \( T_b \) across all times of day, performed nearly as well as the linear regression predicting \( T_b \) from ECOSTRESS mid-morning only overpasses (0.809 °C versus 0.619 °C) and performed better than linear regression relating \( T_b \) from Landsat 8. In our evaluation of the model, we found an RMSE of 0.809 °C. The model was also able to capture the diurnal periodic skin effect cycles, but it did not capture the magnitude of the peak skin effect times in the early morning and around noon. However, the timing of the predicted skin effect peak matched the observed skin effect peak well. Fig. 7 shows a comparison between modeled and \( in situ \) diurnal skin effect (ECOSTRESS—\( T_b \)). The figure only shows three stations because GZB was not active during that time. On average, the model was able to capture the skin effect evolution during the critical midday and evening hours at all stations. When used to calculate bulk water temperature maps, the model was still able to capture the expected diurnal trend in the whole of the Bay Delta, with midday temperatures being warmer than morning and evening (8).

ECOSTRESS observed strong \( T_s \) gradients in both space and time in the Bay Delta. Fig. 8(a)–(d) shows the ECOSTRESS and Landsat-8 images of average \( T_s \) in the key habitat zone of the Delta Smelt during morning, midday, and evening. It illustrates the diurnal evolution of ECOSTRESS \( T_s \) and the complexity of the system’s temperature dynamics. Surface water temperatures were warmer in the smaller stream channels, relative to the rest of the Bay Delta system. These areas experienced a much greater diurnal temperature change than the open water areas, having midday temperatures greater than 26 °C and much cooler evening temperatures. In addition, it shows the different information provided by Landsat-8 and ECOSTRESS, with ECOSTRESS showing the evolution through the day. This spatial and temporal complexity in diurnal ECOSTRESS \( T_s \) cannot be captured using \( in situ \) data or Landsat-8 alone. The modeled \( T_b \) also showed the gradients and diurnal evolution although it had much smaller changes than \( T_s \) [Fig. 8(e)–(h)].

Fig. 7. Comparison of modeled and observed diurnal skin effect. The skin effect is calculated as the average difference between ECOSTRESS \( T_s \) and \( T_b \) for each hour. We only show three stations because one sensor was not collecting data during this time (summer 2020).

Fig. 8. Maps showing average surface temperatures from Landsat-8 and ECOSTRESS images captured at different hours of the day between August and September 2020. (a) Average of all Landsat-8 acquisitions. (b) Average of ECOSTRESS maps acquired from 4:00 to 11:00. (c) Average of ECOSTRESS maps acquired from 12:00 to 19:00. (d) Average of ECOSTRESS maps acquired from 20:00 to 3:00. (e)–(g) Modeled \( T_b \) from the same ECOSTRESS maps in (a)–(c). (h) Density distributions of temperatures in (a)–(g). Maps show the diurnal fluctuation in temperature not captured by Landsat-8.
IV. DISCUSSION

Here, we show that $T_s$ and in situ $T_b$ are strongly correlated with two different remote sensing temperature datasets (ECOSTRESS and Landsat—$r = 0.907$ and 0.976, respectively). The differences in the relationship between ECOSTRESS $T_s$ and in situ $T_b$ when partitioned into morning, midday, and evening are likely due to the changing strength of the skin effect, with the highest RMSE values coming from grouped ECOSTRESS data (1.046 °C for the morning, 1.243 °C for midday, and 1.253 °C for evening). When considering only the mid-morning overpass time of 10–11 A.M., the RMSE value for ECOSTRESS drops to less than 1 °C, which is almost a degree less than Landsat-8’s RMSE (1.061 °C). Because this is the time of day when the skin effect appears weakest (Fig. 6), we can see that Landsat is measuring $T_s$ when in situ $T_b$ and $T_s$ are most similar, which we only know because of ECOSTRESS’s diurnal observations. These values are similar to performance values for temperature models calibrated for the Bay Delta system. For example, Vroom et al. [25] calibrated a Delft 3D-FM temperature model using CDEC in situ stations and other data sources and reported $R^2$ values ranging from 0.91 to 0.99 and RMSE values ranging from 0.62 °C to 1.35 °C. This is encouraging because it may be possible that both Landsat-8 and ECOSTRESS can be used to evaluate long-term trends of bulk water temperature for a greater spatial area than in situ measurements or support calibration and validation of current modeling approaches (i.e., [11]). However, in order to reliably detect trends in water temperature at varying time scales, additional uncertainty quantification should be explored, such as the effect of the ECOSTRESS cold bias on this skin effect quantification.

The Bay Delta has also experienced long-term changes from climate change, which may introduce additional uncertainty in quantifying the in situ $T_b$—$T_s$ relationship. Halverson et al. (accepted) used the full Landsat collection to understand long-term trends in surface water temperature in the Bay Delta and found a 0.15 °C per year increase in yearly maximum surface temperature between 1984 and 2019. Others have estimated a yearly increase in Bay Delta water temperature (0–1 m below the surface) of 0.017 °C per year since 1970 [45]; in the Western USA, rivers temperatures warmed by up to 0.046 °C per year [6]. Trends of warming water temperatures in the Bay Delta are expected to continue [11, 16]. Therefore, climate change—caused warming and other physical changes to the system are potentially additional sources of uncertainty in quantifying this relationship. Further work could remove the climate change signal from streamwater temperature warming trends to attempt to quantify the skin effect.

The Bay Delta is a highly altered and complex water system that serves a multitude of purposes, and consequently, the mixing mechanisms affecting $T_s$ and $T_b$ are decidedly variable between stations. Water temperature and mixing throughout the basin are governed by multiple processes, including temperature and salinity stratification, microclimates, inflow currents, and ocean currents, which can sometimes confound the relationship between water temperature at the surface and depth [25]. Therefore, we used characteristically similar open water stations to conduct this analysis in order to understand the relationship between $T_s$ and $T_b$ at stations where the relationship would be less confounded by other factors, including the influence of shallow water or land (i.e., channels with a width smaller than an ECOSTRESS pixel). Smaller channels may experience more frequent and stochastic impacts due to freshwater flows and are more likely to be impacted by land adjacency and shallow water temperatures [46]. In addition, open water sites are also more relevant in the context of Delta Smelt as they are an open water species [47]. Further research could explore different groupings using habitat characteristics to understand if and how the relationship varies by habitat type.

The simple harmonic regression equation likely worked reasonably well in this study area because the Bay Delta is so well mixed. Others have shown harmonic regressions to be useful for predicting river water temperature using air temperature [48]. Modeling water temperatures in the Bay Delta using physically based models can be challenging because of its physical complexities and the multitude of variables that can influence water temperatures [25]. Linear regressions could not capture the directional or circular nature of the diurnal skin effect. Therefore, given that many of the mechanisms governing water temperature (i.e., tides and incoming shortwave radiation) occur on a diurnal cycle as well, the relationship between $T_b$ and $T_s$ was better captured by the phase parameters representing hour of the day. Further work will utilize these modeled $T_b$ maps to better understand diurnal patterns in thermal habitat suitability at depth.

At this time, the ECOSTRESS record is only about three years. With this record, we saw that in particular locations, ECOSTRESS $T_s$ can be used to model $T_b$: we expect this trend to persist with a longer record. Availability of ECOSTRESS data in our study location was greater during summers, in part due to cloud cover and the ISS orbit, but the timing corresponds to thermal conditions most likely to present a risk to the Delta Smelt. As the $T_b$ temperature range during the winter is smaller than other seasons (i.e., smaller fluctuations in temperature), having more $T_s$ measurements during these months would provide for a fuller understanding of the $T_b$ and $T_s$ relationship.

The diurnal differences in ECOSTRESS $T_s$ and in situ $T_b$ varied by up to 2° both in terms of in situ $T_b$ exceeding ECOSTRESS $T_s$ in evenings and ECOSTRESS $T_s$ exceeding in situ $T_b$ during midday [21], [22], suggesting that localized solutions for improving ecosystem conditions by cooling water temperatures should take this effect into account. Furthermore, the consistent diurnal pattern in the covariation of ECOSTRESS $T_s$ and in situ $T_b$ at all stations could be further exploited to identify regions of greatest threat to the fish species sensitive to water temperature changes, such as the endangered Delta Smelt [17], [34], threatened longfin smelt [10], Chinook Salmon [49], and Sacramento split tail [50]. From this study, we know that the skin effect in the morning, for example, is not representative of the skin effect in the afternoon, which has strong implications for Delta Smelt...
habitat suitability during hot summer months when thermal habitat is most negatively affected (Halverson et al., accepted).

Because remotely sensed $T_s$ was a reasonable proxy of \textit{in situ} $T_h$ in this study, ECOSTRESS and Landsat-8 can be used as complementary technologies to current \textit{in situ} measurements to better inform the protection of fish habitats in the Bay Delta. For example, ECOSTRESS could be used to identify potential thermal refugia throughout the day in areas proximal to current Delta Smelt habitat zones, which is a huge management opportunity for preserving more critical habitat. Due to its longer record, the Landsat collection contributes a longer term understanding of temperature changes in the Delta, while ECOSTRESS contributes a greater understanding of diurnal and seasonal changes, with both providing additional understanding about spatial heterogeneity of thermal conditions. Combining satellite remote sensing with \textit{in situ} sensor networks gives a greater understanding of temperature dynamics in the Bay Delta.

As climate change continues to warm water temperatures in the Bay Delta, a pressing concern is preserving fish habitat. Making decisions toward preserving fish habitats will need to be balanced alongside other freshwater uses, which will likely require modifications of operational flow management [51], [52]. Thermal remote sensing represents a complementary dataset to \textit{in situ} measurements of temperature and, together, can be used to inform decision-making. Using complementary datasets can fill gaps in space and time, giving a greater understanding of climate change impacts, particularly in areas that are well-instrumented like the Bay Delta. On a global scale, there is a lack of systematic and routine observations of water temperature that has resulted in a potential under-reporting of river water temperature trends around the world [53], in which remote sensing could help address. Remote sensing can be used to support Bay Delta resource managers with decisions about allocating water for purposes, such as habitat and species conservation, drinking water, and industry [24], [54].

V. CONCLUSION

Remote sensing provides a reasonable estimate of \textit{in situ} $T_h$. Landsat-8 $T_s$ shows a strong positive linear relationship with \textit{in situ} $T_h$ ($r = 0.976$); ECOSTRESS $T_s$ also shows a strong positive linear relationship with \textit{in situ} $T_h$ ($r = 0.907$). ECOSTRESS provides greater temporal coverage than the Landsat-8 satellites, and with that coverage, we can capture diurnal skin effect patterns. These patterns persist through the year and the day. The simple harmonic regression model was able to predict $T_h$ reasonably well (RMSE = 0.809 °C) and it captured the observed diurnal skin effect. The length of the Landsat-8 $T_s$ record provides for a long-term analysis of the effects of climate change and other changes on water temperature, while ECOSTRESS can map conditions throughout the day and year. As the ECOSTRESS record becomes longer, we will be able to refine our understanding of fish habitat and conservation opportunities within the Bay Delta system.

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APPENDIX

TABLE III

| Station | Correlation Coefficient | RMSE |
|---------|--------------------------|------|
| PRK     | 0.906                    | 1.235|
| GZB     | 0.894                    | 1.107|
| GZL     | 0.899                    | 1.171|
| HON     | 0.890                    | 1.183|

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